ACCEPTANCE AND IMPLEMENTATION OF ARTIFICIAL INTELLIGENCE IN HR PRACTICES FOR ORGANISATIONAL EFFECTIVENESS IN SELECTED INDUSTRIES

A Thesis submitted to Gujarat Technological University

for the Award of

Doctor of Philosophy

in

Management

By

Bhatt Meet Nishithkumar
209999903054

under supervision of

Dr. Priyanka Shah

GUJARAT TECHNOLOGICAL UNIVERSITY

AHMEDABAD

May – 2026

ACCEPTANCE AND IMPLEMENTATION OF ARTIFICIAL INTELLIGENCE IN HR PRACTICES FOR ORGANISATIONAL EFFECTIVENESS IN SELECTED INDUSTRIES

A Thesis submitted to Gujarat Technological University

for the Award of

Doctor of Philosophy

in

Management

By

Bhatt Meet Nishithkumar

209999903054

under supervision of

Dr. Priyanka Shah

GUJARAT TECHNOLOGICAL UNIVERSITY

AHMEDABAD

May – 2026

DECLARATION

I declare that the thesis entitled **Acceptance and Implementation of Artificial Intelligence in HR Practices for Organizational Effectiveness in Selected Industries** submitted by me for the degree of Doctor of Philosophy is the record of research work carried out by me during the period from **01/07/2021** to **13/05/2026** under the supervision of **Dr. Priyanka Shah** and this has not formed the basis for the award of any degree, diploma, associateship, fellowship, titles in this or any other University or other institution of higher learning.

I further declare that the material obtained from other sources has been duly acknowledged in the thesis. I shall be solely responsible for any plagiarism or other irregularities, if noticed in the thesis.

Signature of the Research Scholar:

Date: 13/05/2026

Name of Research Scholar: Bhatt Meet Nishithkumar

Place: Ahmedabad

CERTIFICATE

I certify that the work incorporated in the thesis **Acceptance and Implementation of Artificial Intelligence in HR Practices for Organizational Effectiveness in Selected Industries** submitted by **Ms. Bhatt Meet Nishithkumar** was carried out by the candidate under my supervision/guidance. To the best of my knowledge: (i) the candidate has not submitted the same research work to any other institution for any degree/diploma, Associateship, Fellowship or other similar titles (ii) the thesis submitted is a record of original research work done by the Research Scholar during the period of study under my supervision, and (iii) the thesis represents independent research work on the part of the Research Scholar.

Signature of the Research Supervisor: ……………………… Date: 13/05/2026

Name of Supervisor: Dr. Priyanka Shah

Place: Ahmedabad

Course-work Completion Certificate

This is to certify that Ms. Bhatt Meet Nishithkumar enrolment no. 209999903054 is enrolled for PhD program in the faculty Management of Gujarat Technological University, Ahmedabad.

(Please tick the relevant option(s))

☐ He / She has been exempted from the course-work (successfully completed during M.Phil. Course)

☐ He / She has been exempted from Research Methodology Course only (successfully completed during M.Phil. Course)

☑ She has successfully completed the PhD course work for the partial requirement for the award of PhD Degree. His/ Her performance in the course work is as follows-

Grade Obtained in Research Methodology [PHD2001]	Grade Obtained in Research and Publication Ethics [PHD2002]	Grade Obtained in Self-Study Course/ Contact Program [PHD2003]
BC	**AB**	**AA**

Supervisor's Sign

Dr. Priyanka Shah

Originality Report Certificate

It is certified that PhD Thesis titled **Acceptance and Implementation of Artificial Intelligence in HR Practices for Organizational Effectiveness in Selected Industries** by **Ms. Bhatt Meet Nishithkumar** has been examined by us. We undertake the following:

a. Thesis has significant new work / knowledge as compared already published or are under consideration to be published elsewhere. No sentence, equation, diagram, table, paragraph, or section has been copied verbatim from previous work unless itis placed under quotation marks and duly referenced.
b. The work presented is original and own work of the author (i.e. there is no plagiarism). No ideas, processes, results or words of others have been presented as Author own work.
c. There is no fabrication of data or results which have been compiled / analyzed.
d. There is no falsification by manipulating research materials, equipment or processes, or changing or omitting data or results such that the research is not accurately represented in the research record.
e. The thesis has been checked using **<u>Turnitin</u>** (copy of originality report attached) and found within limits as per GTU Plagiarism Policy and instructions issued from time to time (i.e. permitted similarity index <=10%).

Signature of the Research Scholar: ____________________ Date: 13/05/2026

Name of the Research Scholar: Bhatt Meet Nishithkumar

Signature of the Research Supervisor: ………………………………… Date: 13/05/2026

Name of the Research Supervisor: Dr. Priyanka Shah

Place: Ahmedabad

Plagiarism Report

turnitin Page 2 of 235 - Integrity Overview Submission ID trn:oid:::30110:125882070

5% Overall Similarity

The combined total of all matches, including overlapping sources, for each database.

Filtered from the Report

- Bibliography
- Quoted Text
- Cited Text
- Small Matches (less than 10 words)

Match Groups

280 Not Cited or Quoted 5%
Matches with neither in-text citation nor quotation marks

0 Missing Quotations 0%
Matches that are still very similar to source material

0 Missing Citation 0%
Matches that have quotation marks, but no in-text citation

0 Cited and Quoted 0%
Matches with in-text citation present, but no quotation marks

Top Sources

2% Internet sources
4% Publications
2% Submitted works (Student Papers)

Integrity Flags

0 Integrity Flags for Review

No suspicious text manipulations found.

Our system's algorithms look deeply at a document for any inconsistencies that would set it apart from a normal submission. If we notice something strange, we flag it for you to review.

A Flag is not necessarily an indicator of a problem. However, we'd recommend you focus your attention there for further review.

turnitin Page 2 of 235 - Integrity Overview Submission ID trn:oid:::30110:125882070

Ph.D. Thesis Non-Exclusive License to

GUJARAT TECHNOLOGICAL UNIVERSITY

In consideration of being a Research Scholar at Gujarat Technological University, and in the interests of the facilitation of research at the University and elsewhere, I, **Ms. Meet Nishithkumar Bhatt** having **209999903054** hereby grant a non- exclusive, royalty free and perpetual license to the University on the following terms:

a. The University is permitted to archive, reproduce and distribute my thesis, in whole or in part, and/or my abstract, in whole or in part (referred to collectively as the "Work") anywhere in the world, for non-commercial purposes, in all forms of media;
b. The University is permitted to authorize, sub-lease, sub-contract or procure any of the acts mentioned in paragraph (a);
c. The University is authorized to submit the Work at any National / International Library, under the authority of their "Thesis Non-Exclusive License";
d. The Universal Copyright Notice (©) shall appear on all copies made under the authority of this license;
e. I undertake to submit my thesis, through my university, to any Library and Archives. Any abstract submitted with the thesis will be considered to form part of the thesis.
f. I represent that my thesis is my original work, does not infringe any rights of others, including privacy rights, and that I have the right to make the grant conferred by this non-exclusive license.
g. If third party copyrighted material was included in my thesis for which, under the terms of the Copyright Act, written permission from the copyright owners is required, I have obtained such permission from the copyright owners to do the acts mentioned in paragraph (a) above for the full term of copyright protection.
h. I understand that the responsibility for the matter as mentioned in the paragraph (g) rests with the authors / me solely. In no case shall GTU have any liability for any acts
/ omissions / errors / copyright infringement from the publication of the said thesis or otherwise.
i. I retain copyright ownership and moral rights in my thesis, and may deal with

the copyright in my thesis, in any way consistent with rights granted by me to my University in this non-exclusive license.

j. GTU logo shall not be used /printed in the book (in any manner whatsoever) being published or any promotional or marketing materials or any such similar documents.

k. The following statement shall be included appropriately and displayed prominently in the book or any material being published anywhere: “The content of the published work is part of the thesis submitted in partial fulfilment for the award of the degree of Ph.D. in Management of the Gujarat Technological University”.

l. I further promise to inform any person to whom I may hereafter assign or license my copyright in my thesis of the rights granted by me to my university in this nonexclusive license. I shall keep GTU indemnified from any and all claims from the Publisher(s) or any third parties at all times resulting or arising from the publishing or use or intended use of the book / such similar document or its contents.

m. I am aware of and agree to accept the conditions and regulations of Ph.D. including all policy matters related to authorship and plagiarism.

Date: 13/05/2026

Place: Ahmedabad Signature of the Research Scholar

Recommendation of the Research Supervisor: YES

Recommendation of the Co-Supervisor (if any): …………………………………………………..

Signature of the Research Supervisor

Signature of the Co-Supervisor (if any)

Thesis Approval Form

The viva-voce of the PhD Thesis submitted by **Ms. Bhatt Meet Nishithkumar** Enrollment No. **209999903054** entitled "**Acceptance and Implementation of Artificial Intelligence in HR Practices for Organizational Effectiveness in Selected Industries"** was conducted on Wednesday, 13/05/2026 (day and date) at Gujarat Technological University.

(Please tick any one of the following options)

☑ The performance of the candidate was satisfactory. We recommend that he/she be awarded the PhD degree.

☐ Any further modifications in research work recommended by the panel after 3 months from the date of first viva-voce upon request of the Supervisor or request of Independent Research Scholar after which viva-voce can be re-conducted by the same panel again.

(briefly specify the modifications suggested by the panel)

☐ The performance of the candidate was unsatisfactory. We recommend that he/she should not be awarded the PhD degree.

(The panel must give justifications for rejecting the research work)

13/05/2026

Dr. Priyanka Shah
Name and Signature of Supervisor with Seal

1) Dr. Anukool Hyde
(External Examiner 1) Name and Signature

13/05/26

2) Dr. Mayank Bhatiya
(External Examiner 2) Name and Signature

ABSTRACT

The term "Artificial Intelligence" (AI) refers to the process of transferring human intelligence to machines through programs and algorithms that mimic human abilities. When applied to human resource (HR) practices, artificial intelligence will assist organisations in achieving their goals with more effectiveness and efficiency. Artificial Intelligence in HR Practices will help in automating the repetitive task of HR Function like resume sourcing and primary screening of candidate by using automated AI Powered Software (ATS), using AI enabled Predictive Analytics for HR planning, turnover ratio, skill gap analysis, payroll as per market scenario, turnover intention & Succession Planning, using sentiment analysis tools to understand employee engagement and retaining them by understanding the actual needs of employees, providing personalized training & development opportunities by measuring precise skill gap using performance management data, reducing performance bias and personalized feedback, Chatbots for employee assistance and so on. AI will assist in making good use of the HR data that is currently available with organizations, making data-driven decisions using Machine learning, Deep Learning & Neural Networks and Natural Language Processing (NLP) to understand the data and recognize the patterns available like humans and try to simulate the reasons like human HR, and implementation routine HR tasks like hiring, payroll, and performance with ease and efficiency. This will cause HR employees to strategically focus on the company's decisions, which will further increase their efficacy.

The study uses a combination of the Technology Acceptance Model (TAM), the Technology-Organization-Environment (TOE) Framework, and the Unified Theory of Acceptance and Use of Technology (UTAUT) model, variables such as Technology Characteristics, Positive Attitude Towards Change, Creativity, Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Social Characteristics & Performance Expectancy, Effort Expectancy, Social Influence, External Support & Facilitating Conditions, and Behavioural Intention. The major goal of the study, which was to develop a conceptual framework for the perceived acceptance and perceived implementation of artificial intelligence in HR Practices and organisational Effectiveness, was accomplished using the aforementioned factors. The research is descriptive in nature. Tools such as Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), and Structural Equation Modelling (SEM) were used to evaluate how artificial intelligence in HR practices affected the effectiveness of the company. MANOVA with Post-Hoc Tukey HSD was used to examine the differences between the chosen industries and AI factors. The same test was used to examine the differences between the selected industries and organisational effectiveness. A MANOVA test was used to examine the relationship between artificial intelligence variables and demographic constraints as well as organisational effectiveness and demographic variables.

The results, which included respondents from over 1245 employees of selected industries such as Information Technology / Information Technology Enabled Services (IT/ITES), Hospitality & Healthcare, Consumer Durables & Telecommunications, Banking, Insurance & Financial Services (BFSI) and Management Consultancy Firms, unequivocally demonstrated that employing AI in HR practices improves organisational effectiveness.

For the variables influencing AI perceived acceptability and perceived AI implementation in HR practices, the study developed a very comprehensive and reliable measuring Model. The strong psychometric qualities and detailed factor structure of the scales provide researchers with a solid empirical basis for understanding how artificial intelligence adoption works. Early in the investigation, it was discovered that the data did not follow a normal distribution, which facilitated the selection of appropriate analytical methods. The findings offer compelling empirical evidence that integrating AI into HR procedures significantly boosts an organization's effectiveness. The study's primary and most significant finding is that the business may benefit greatly from the proper use of AI tools in HR practices. Although there is a high correlation between employing AI and increasing an organization's effectiveness, the overall model fit suggests that other factors may also have an impact. People's perceptions of AI in HR, how they interact with it, and how they rank a company's effectiveness are influenced by their demographics. The study explicitly demonstrates that factors such as age, experience, education, income, management level, organisational size, location, and gender have a significant impact on people's perceptions of technology characteristics, Behavioural intention, perceived acceptance, implementation, and opinions on an organization's effectiveness. This demonstrates how crucial it is for businesses to develop customized AI implementation and change management strategies that take into account the various demographic characteristics of their workforce.

Keywords: Artificial Intelligence (AI), Human Resource (HR) Practices, Perceived AI Acceptance, Perceived AI Implementation, Organizational Effectiveness (OE)

Dedication

I, Ms. Meet Nishithkumar Bhatt, humbly dedicate this thesis to my beloved family, whose love, sacrifices, and support have been the foundation of my journey. This work is first and foremost dedicated to my beloved father, Late Dr. Nishithkumar Y. Bhatt (Retired Head of the Department and Associate Professor, Department of Geology, M. G. Science Institute, Ahmedabad), whose passing on 5th November 2025 left an irreplaceable void, but whose life, values, and unwavering belief in me continue to guide my journey. He was not only an exceptional academician and mentor to many but also my greatest source of strength, wisdom, and encouragement. His constant support, guidance, and quiet sacrifices shaped my character, nurtured me, and instilled the confidence to pursue knowledge with integrity and perseverance. Every step of my academic journey carries his influence, and every achievement reflects the lessons he imparted through his actions and words. Though he is no longer physically present, his ideals, discipline, and compassion remain deeply embedded in my life and work. This thesis is a tribute to his enduring legacy and a heartfelt acknowledgment of the profound role he played in shaping the person I am today. His memory continues to inspire me to strive for excellence, humility, and purpose in all that I do. I also lovingly dedicate this thesis to my mother, Mrs. Manalee Nishithkumar Bhatt, whose selfless love, unwavering support, and constant encouragement have been the strongest foundation of my life. Through every phase of my journey, she stood by me with strength, patience, and resilience. Her sacrifices, often made silently, enabled me to continue my education and pursue my aspirations. Without her continuous belief in me and her unconditional support, I would neither have been able to complete my studies nor even take the first step toward enrolling in the PhD program. She has been my source of emotional strength, my motivation in moments of doubt, and my anchor during the many ups and downs of life. This work is as much hers as it is mine. I dedicate this thesis to her with deep gratitude, love, and respect, for being the pillar of my life and for shaping my journey with compassion, strength, and unwavering devotion. I also dedicate this thesis to my husband, Mr. Ishan Trivedi, whose constant presence, understanding, and unwavering support have been a source of immense strength throughout my journey. He stood by me at every moment I needed him especially during times of uncertainty, exhaustion, and self-doubt offering reassurance, patience, and encouragement when I felt at my lowest or broken. He has been my emotional anchor, my motivator, and my steady support system, reminding me of my resilience and helping me find the courage to move forward even in the most challenging moments. His belief in my abilities, even when I struggled to believe in myself, gave me the strength to persevere and continue this journey. This thesis carries not only my academic efforts but also the quiet strength and emotional support he provided along the way. I dedicate this work to him with deep gratitude, love, and appreciation for being a constant source of comfort, motivation, and unwavering companionship. Lastly, I dedicate this thesis to my younger sister, Shaival Bhatt, for her love, invaluable guidance, and untiring support. She patiently taught me research tools and methodologies and consistently pushed me forward with the care and strength of a mother. Her encouragement and belief in me played a vital role in helping me complete this journey. I offer this work to her with deep gratitude and affection. Lastly, I am thankful to my in-laws, Mr. Yashaswin Trivedi & Mrs. Rupa Trivedi for their understanding, encouragement, and quiet support throughout this journey. Their faith in me and their constant goodwill provided a sense of stability and reassurance, allowing me the space and strength to remain focused on my academic goals. This thesis is a reflection of the love, strength, and belief each of you placed in me. I dedicate it with deep gratitude, respect, and love.

Acknowledgement

I express my deepest gratitude to my Ph.D. guide, Dr. Priyanka Shah (Associate Professor, Chimanbhai Patel Institute of Management & Research, Ahmedabad) for her invaluable guidance, constant encouragement, and unwavering support throughout this research. Her insightful suggestions, constructive feedback, and scholarly expertise played a pivotal role in shaping this study and strengthening its academic rigor. Her patience, approachability, and clarity of thought helped me navigate the complexities of research with confidence. She consistently motivated me to think critically, refine my ideas, and maintain high academic standards, while also providing the reassurance needed during challenging phases of this journey. I am truly thankful for her mentorship and support, which not only contributed to the successful completion of this thesis but also enriched my understanding of research and academic discipline. It has been a privilege to work under her guidance.

I express my sincere gratitude to my DPC members, for their valuable guidance and support throughout my research journey. I am especially thankful to Dr. Anu Gupta (Associate Professor, Chimanbhai Patel Institute of Management & Research, Ahmedabad), who has been a guiding light throughout my journey not only as a mentor for life and an informal second guide, but as a constant source of care, encouragement, and strength. Her belief in me, her wisdom, and her nurturing presence at the institute made her an irreplaceable support system and someone I will always look up to with deep respect and gratitude. I also extend my heartfelt thanks to Dr. Meetali Saxena (Associate Professor, LJ School of Management, Ahmedabad) for her guidance, insightful inputs, and continued support, timely encouragement which contributed meaningfully to this research.

I express my sincere gratitude to the Director of Chimanbhai Patel Institute of Management & Research, Prof. (Dr.) Abhinava Singh, for his guidance, encouragement, and continued support throughout the course of my research. His leadership, insightful direction, and positive encouragement provided valuable support in successfully completing this work. I extend my sincere gratitude to all the faculty members of the CPIMR family for their constant encouragement, academic support, and positive guidance throughout my doctoral journey. Their collective knowledge, cooperation, and supportive environment greatly contributed to the successful completion of this research. I am deeply grateful to my friends and colleagues, Dr. Minti Sinha and Dr. Kajal Mehta, for standing by me through every high and low of this journey. Their constant encouragement, heartfelt understanding, and unwavering belief in me gave me strength when I needed it most and made this path far less lonely.

I respectfully acknowledge the Vice Chancellor of Gujarat Technological University (GTU), the Registrar, and the PhD Section for providing the necessary academic support, administrative assistance, and institutional facilities that enabled the smooth progress and completion of this doctoral research.

I extend my warm gratitude to my content validators Mr. Jay Hulani (Manager, Samsung) & Dr. Vishal Dahiya (Director, iMCA, SVGU) for reviewing the framework & questionnaire and giving me appropriate suggestions.

I sincerely thank all the respondents who participated in the survey and contributed their valuable time and insights, as well as everyone who supported and assisted me during the data collection process. Their cooperation and willingness to share information made this research possible and are gratefully acknowledged.

I am sincerely thankful to all those who, directly or indirectly, supported and contributed to the completion of this research. Their guidance, encouragement, and goodwill at various stages of this journey are gratefully acknowledged.

Meet Nishithkumar Bhatt

Table of Contents

List of Abbreviation

AI – Artificial Intelligence

HR - Human Resource

HRM – Human Resource Management

IoT – Internet of Things

ML – Machine Learning

NLP – Natural Language Processing

ES – Expert Systems

KMS – Knowledge Management Systems

MIT - Massachusetts Institute of Technology

HRIS – Human Resource Information Systems

E-HRM – Electronic – Human Resource Management

ROI – Return on investment

T&D – Training & Development

PMS – Performance Management Systems

KPI – Key Performance Indicators

HR Analytics – Human Resource Analytics

TAM – Technology Acceptance Model

TOE – Technology-Organization-Environment Model

DOI – Diffusion of Innovation Theory

UTAUT - Unified Theory of Acceptance and Use of Technology

EFA – Exploratory Factor Analysis

CFA – Confirmatory Factor Analysis

SEM - Structural Equation Modelling

PLS-SEM - Partial Least Squares Structural Equation Modelling

CB-SEM – Covariance Based Structural Equation Modelling

IT/ITES - Information Technology / Information Technology Enabled Servies

BFSI - Banking Insurance and Financial Services

List of Figures

List of Tables

List of Annexures

CHAPTER - 1 INTRODUCTION

Acceptance and Implementation of Artificial Intelligence in HR Practices for Organizational Effectiveness in Selected Industries

1.1 Background of the Study

The rapid advancement of digital technologies has fundamentally transformed how organizations operate, compete, and manage human capital. Among these technologies, Artificial Intelligence (AI) has emerged as one of the most influential general-purpose innovations, reshaping organizational processes by enabling automation, prediction, personalization, and data-driven decision-making. AI systems, encompassing machine learning, natural language processing, robotic process automation, and predictive analytics, are increasingly embedded within organizational workflows across industries. (Erik Brynjolfsson and Andrew McAfee, 2017; Samuel Fosso Wamba et al., 2021)

Human Resource Management (HRM), traditionally viewed as a people-centric and judgment-intensive function, is undergoing a significant transformation due to AI adoption. Organizations are increasingly deploying AI-enabled tools in HR practices such as recruitment and selection, performance management, learning and development, employee engagement, workforce planning, and retention analytics. These applications promise greater efficiency, consistency, and strategic alignment of HR functions with organizational goals. (Jöhnk et al., 2021a; J. Marler et al., 2017)

Despite its growing diffusion, AI adoption in HR is not merely a technological shift. It represents a socio-technical transformation that alters decision rights, redistributes authority between humans and algorithms, and reshapes employee perceptions of fairness, control, and trust. Consequently, the success of AI in HR practices depends not only on technological sophistication but also on how employees perceive, accept, and experience AI systems in their daily work lives. (Kellogg et al., 2020; Raghavan et al., 2020)

In this context, organizational effectiveness becomes a critical outcome variable. While AI can automate tasks and improve efficiency, its contribution to organizational effectiveness is realized only when AI is meaningfully implemented, ethically governed, and accepted by employees. Organizational effectiveness, therefore, must be understood as a multidimensional construct encompassing goal achievement, internal efficiency, adaptability, employee satisfaction, and long-term sustainability. (Daft, 2016; Pestonjee, 1988a)

1.2 Artificial Intelligence in Human Resource Practices

Artificial Intelligence has developed steadily over a period of nearly sixty years and has become increasingly widespread, particularly during the last two decades. In recent years, AI technologies have shown rapid growth and have gained significant importance across a wide range of fields. These include areas such as healthcare, engineering, agriculture, organizational management, tourism, transportation, and many other sectors. Today, AI is no longer limited to research laboratories or experimental use; instead, it has become an essential part of both public services and business environments. (Chatterjee et al., 2022)

Artificial Intelligence should not be viewed as a single or universal solution applicable to all problems. Rather, it represents a collection of diverse tools and technologies, each designed to perform specific tasks and functions. These tools are commonly delivered in the form of software applications or intelligent devices that are well-designed and offer user-friendly interfaces, making them accessible to a wide range of users. The successful application of AI largely depends on how effectively these tools are selected and implemented for tasks. This responsibility lies with AI developers and professionals, who must carefully choose appropriate technologies based on the nature of the work and organizational requirements. (Leung, 2015a)

With continuous improvements in design, usability, and performance, AI technologies are becoming easier to adopt and integrate into everyday activities. As a result, Artificial Intelligence is expected to soon become a regular and unavoidable part of daily life, like how the internet and social media have become deeply embedded in modern society. Its growing presence suggests that AI will continue to influence how individuals, organizations, and industries operate in the future.(Nawaz et al., 2024; Raghavan et al., 2020)

The rapid advancement of Artificial Intelligence is expected to significantly change individuals' personal lives as well as the way organizations interact with their employees and customers. This emerging technological revolution is fundamentally reshaping organizations and workplace structures. Innovations such as AI are redefining the nature of work by influencing the timing, methods, locations, and the individuals responsible for performing various job tasks.(R Jesuthasan & 2017, 2017) Industries are experiencing major digital changes, with an increasing emphasis on adopting Artificial Intelligence in decision-making processes to support organizational growth and long-term success.(P. S Varsha, 2023) Organizations are required to improve their operational processes and enhance the skills of their human resources in order to achieve the best possible organizational performance. Over the past few years, organizations have increasingly acknowledged the unavoidable role and growing importance of Artificial Intelligence in managing human resources to adapt to a rapidly changing business environment and remain competitive. As AI technologies have become widespread across various sectors, there has been a growing emphasis on developing strategic human resource management practices supported by AI-based systems.

Organizations worldwide are under constant pressure to reduce operational costs and improve time efficiency. In this context, the integration of advanced technologies such as Artificial Intelligence, machine learning, and connected digital systems into management processes has been recognized as a strategic approach to addressing these challenges. These technologies enable organizations to streamline HR operations, improve decision-making, and enhance workforce management.

Although Artificial Intelligence offers strong potential and promising opportunities for Human Resource Management, its implementation is not without difficulties. AI systems can perform effectively only when they are supported by accurate, high-quality data. Additionally, concerns related to data security and the possible misuse of sensitive organizational information present significant challenges. Therefore, while AI holds substantial benefits for HR practices, careful planning and responsible implementation are essential to ensure its successful adoption.

Despite the challenges associated with Artificial Intelligence, organizations continue to show strong interest and invest considerable effort in adopting AI within human resource functions, as the advantages of AI-driven HR practices are seen to outweigh the existing limitations.(George* & Thomas, 2019) Organizations can fully realize the benefits and potential of Artificial Intelligence when they prepare their workforce to work effectively alongside intelligent systems. Although this transformation requires time and effort, it is expected to deliver substantial long-term advantages.

During the lockdown period and the disruption caused by the COVID-19 crisis, human resource departments shifted their focus away from performance measurement and placed greater emphasis on flexibility, resilience, and the ability to recover from challenges. While overall productivity levels were largely sustained during the pandemic, organizational leaders were more concerned about employees' stress levels and overall well-being. The crisis accelerated the process of digital transformation, leading to a rapid shift in HR operations toward digital and automated platforms. Almost every stage of human resource management, including recruitment, onboarding, training, and performance evaluation, was restructured, and carried out through digital systems.

Artificial Intelligence in Human Resource Management offers several promising opportunities, ranging from the automation of routine and repetitive tasks to the improvement of HR processes by reducing human bias. As AI continues to reshape modern workplaces, organizations are increasingly realizing the importance of modernizing their HR practices to achieve higher performance and remain competitive. (Nguyen & Le, 2022a; Venkatesh & Davis, 2000b)

Although there is general conceptual awareness of Artificial Intelligence, automation, and robotics, academic and practical research on the actual application of AI in organizational management remains limited. Human Resource Management, as a professional field, is currently experiencing significant disruption, making it essential for both researchers and HR practitioners to rethink and redesign traditional HR processes. Despite the recognized benefits of AI in reducing HR managers' workload and enabling a greater focus on strategic activities that enhance organizational productivity, many organizations still lack a clear and comprehensive understanding of AI technologies and their effects on both organizational outcomes and individual employees.

The adoption of AI-driven work environments has the potential to improve employee satisfaction, support better work–life balance, and increase overall productivity. Therefore, there is a growing need for deeper insight into the expected outcomes of implementing AI in HRM and the relationships among these outcomes to ensure informed and effective adoption.

1.3 What is AI (Artificial Intelligence)

Artificial Intelligence (AI), is called that it stimulates the human intelligence in machines and enable them in solving various problems, recognizing different patterns, understanding languages, decision making, learning from experience, performing various tasks which required human intelligence, perform cognitive functions such as perceptions, reasoning and learning. Devices which are equipped with AI can see and identify the objects. They understand the human language and respond too. It works independently and takes no help of human intelligence and intervention from human.

Definition: Artificial Intelligence (AI) is a computer science, it is concerned with the study and the creation of computer systems, which exhibits some form of intelligence or features which are associate with the intelligence in human behavior.

1.4 Concept of Artificial Intelligence:

Artificial Intelligence (AI) refers to a technology that allows machines and computer systems to carry out tasks that normally require human intelligence. It enables systems to learn from data, identify patterns, and make informed decisions to solve complex problems. AI is widely applied across various sectors such as healthcare, finance, e-commerce, and transportation, where it supports personalized recommendations, automated services, and advanced technologies like autonomous vehicles.

Artificial Intelligence is built upon several core concepts and technologies that enable machines to learn, reason, and make independent decisions. One of the most important concepts is Machine Learning, which allows systems to learn from data and improve their performance over time without being explicitly programmed for every task. Machine learning algorithms identify patterns in large datasets and use these patterns to make predictions or decisions with minimal human involvement. Another key concept is Generative Artificial Intelligence, which focuses on creating new and original content such as text, images, audio, or videos. Unlike traditional AI systems that primarily analyze or classify information, generative AI uses learned patterns from vast datasets to produce entirely new outputs, thereby extending AI capabilities beyond recognition to creation.

Additionally, Natural Language Processing (NLP) enables machines to understand, interpret, and respond to human language in a natural manner. NLP combines linguistic principles with computational techniques to support applications such as voice assistants, language translation, sentiment analysis, and real-time communication. Another significant concept is Expert Systems, which are designed to replicate the decision-making abilities of human experts. These systems rely on structured knowledge bases and predefined rules to provide solutions or recommendations in specialized domains where expert knowledge is essential but not always easily accessible.(*What Is Artificial Intelligence (AI) - GeeksforGeeks*, n.d.)

1.4.1 How It Works:

1.1.1.1 Collection of Data:

AI depends on the data, which are in large sets. This data sets include text, images and sensor reading. For example, to recognize the dogs, we have to collect a set of data, which are labelled dog's images.

1.1.1.2 Processing and Learning:

To identify the data patterns and for the analysis it uses the algorithms. For Example, it identifies the characteristics of the objects. To identify the shape of dogs, its ears and helps in understanding the data.

1.1.1.3 Model Training:

To improve its predictions, AI is trained and use data, adjust the internal settings. To give the more accurate predictions, it uses more data and becomes better in recognisation. For Example, unseen images of the dogs.

1.1.1.4 Decision Making:

After being trained, it uses what it learned in making decisions. For Example, It could find the new image which include the dogs, which is based on the patterns which it has learned during the training time.

1.1.1.5 Improvement:

After getting the feedback it could be improved, it could improve in reinforcement learning. Improving the decisions over the period of time, AI receives multiple rewards and penalties.

1.4.2 Types of Artificial Intelligence:

1.1.1.6 Based on the Capabilities

- **Narrow AI:** To perform the narrow task and specific task such as voice assistants and recommendation systems, this AI type is designed specifically. This type of AI lacks general intelligence.
- **General AI:** AI perform the task any intellectual task that a human performs such as reasoning, understanding multiple domains and track a variety of tasks.
- **Superintelligent AI:** This type of AI surpasses the intelligence of human. It performs the task in all areas more efficiently and effectively as compared to humans.

1.1.1.7 Based on the Functionalities

- **Reactive Machines:** this type of AI system responds to the specific task without experience. It responds in a set way. For Example, Chess playing AI evaluates the board and makes the move on the current position.

- **Limited memory:** This AI system use historical data to improve potential decisions. For Example, Self driving car, it uses data which is of previous trips to navigate roads and avoid obstacles.
- **Theory of Mind:** It is the theoretical type of AI which would understand emotions, intentions, beliefs, and mental states. AI is allowed to interact with the humans in a natural and empathetic manner.
- **Self-Aware AI:** In this type AI will have Consciousness and self-awareness. It would be having understanding of its own and would make the decision on the basis of awareness.

1.4.3 Advantages:

- **Efficiency and Automation:** AI stream lines workflows by automating the repetitive works. It minimizes the error of human and focuses on innovative activities and strategic activities.
- **Improved Decision Making:** AI supports data driven and informed decisions across sectors like finance, retail and healthcare. It has the ability to process and analyze the vast datasets.
- **Personalization:** AI enables personalized experience by analyzing user preferences and give recommendations and improve the satisfaction of the user of Netflix, Amazon and social media.
- **24/7 Availability:** AI functions continuously without fatigue and make them well suited for operations round the clock like customer support, security surveillance and the data collections.
- **Advanced Data Analysis and Pattern Recognition:** AI examine the large volume of data and also identify the complicated pattern which may be difficult for the humans to detect the supporting applications like medical diagnostics, fraud detection and the market analysis.

1.4.4 Real World Applications of AI:

- **Healthcare:** AI is very useful in healthcare. It detects the disease in early phase and plans the treatment by analyzing medical images, patient records, and clinical data, thus strengthen preventive and productive healthcare.
- **Retail:** AI increase the experience of shopping by recommending the personalized product which is based on customer behaviour. AI improves the management of inventory and demand forecasting, ensure optimal stock levels and the higher customer satisfaction.
- **Customer Service:** Ai offer 24 /7 assistance, manage routine queries and route the complex issues to human representatives. It improves efficiency, reduce the time of response and enhance customer experience.
- **Manufacturing:** AI Improve the operational efficiency by forecasting maintenance requirements, reducing equipment downtime, and optimizing supply chain processes through accurate demand forecasting and reduction of waste.

- **Finance:** AI help in detection of fraud, market analysis, and management of risk. Its support personalized investment advice for informed financial decision making.

1.4.5 Challenges of AI:

- **Data Privacy and Security:** AI depends on large dataset, which raises the concern regarding the privacy of data and protection as well. AI is very helpful but still in protecting the sensitive information and data and the maintaining the trust of users are the major challenges.
- **Bias and Fairness:** AI models which are used may inherit biases in data, which result in unfair outcomes. AI addresses biases to ensure the objectives and decision making.
- **Lack of Transparency:** Many AI models operate as Black Boxes, so it makes it difficult to understand and making decisions. Lack of transparency is the concern in critical fields like law enforcement and healthcare.
- **Job Displacement:** AI automates the work, which was traditionally done by the humans. Supporting the workforce transition through reskilling and upskilling is important.
- **Ethical Concern:** AI is a sensitive domains like surveillance, Autonomous weapons and automated decision making raises ethical issues. Technological advancement with ethical responsibility continues to be a challenge in AI development.

1.5 Evolution of Artificial Intelligence:

Artificial Intelligence (AI), the idea of it goes back to thousands of years, where ancient philosopher was considering the questions of life and death. In ancient time, the invention made which was called ‘automatons,’ it was mechanical and working independently without the help of human. The word ‘automaton’ was coined from Greek word, which means ‘acting of one’s own will.’ The earliest record of automation is dated back to 400 BC. In 20th century, engineers and scientists started working towards Modern day AI.

Artificial Intelligence has evolved over several decades, progressing from theoretical concepts to practical applications that influence almost every aspect of modern life. The idea of creating intelligent machines dates to the mid-20th century when researchers began exploring whether machines could simulate human thinking and problem-solving abilities. Early developments in Artificial Intelligence were primarily theoretical and focused on symbolic reasoning, logic, and rule-based systems. During this period, AI research aimed to replicate human intelligence through explicitly programmed rules and structured decision-making processes.

Table 1-1: Stages of AI Evolution

Year	***Stages***	***Description***
1940s – 1950s	Birth & Early Concepts	**1943:** First artificial neutral network was described by Pitts & McCulloch. **950:** To assess the machine Intelligence turning test was proposed. This test was propped in the book named 'Computing Machinery and Intelligence' by Alan Turing. **1952:** In this year Arthur Samuel had developed a checkers program that could be learned. **1956:** The term 'Artificial Intelligence' was coined at Dartmouth Workshop by John McCarthy, where, Ai was launched as a field officially.
1950s – 1970s	Golden Age	During this decade, researchers were focusing on the reasoning, creating programmes like the logic theorist. **1966:** An Chatbot, named ELIZA, was created by Joseph Weizenbaum. **1969:** The first book, published by Minsky & Papert's, which highlighted limitations of the early neutral networks.
1970s – 1980s	AI Winters & Expert system	Due to limited power of computing and poor to meet the expectations lead to the reduction of fundings. **1980:** Expert systems, resurged. This system was designed to mimic the human decision making in specific domains.
1990 - present	The modern Era	**1990s:** The computing power was increased and data enabled advanced learning algorithms. **1997:** Deep Blue beat world chess champion Garry kasparov by IBM. **2000s -Present:** Growth was rapid due to Machine learning, deep learning and vast datasets which led the advancements in recognition of image and speech.

1.5.1 The Dawn of Artificial Intelligence (1950s-1960s)

The 1950s are widely regarded as the foundational period in the development of Artificial Intelligence, as several important milestones were achieved during this decade. In 1950, a landmark study on machine intelligence introduced the concept of evaluating a computer's ability to exhibit intelligent behavior, later known as the Turing Test. This idea laid the groundwork for future research in artificial intelligence.

A breakthrough occurred in 1956 when the term "Artificial Intelligence" was formally introduced during a research workshop held at Dartmouth College, marking the beginning of AI as a distinct field of study. During the late 1950s and 1960s, early AI research primarily focused on representing human knowledge in computer programs using symbolic reasoning and logic-based systems. Researchers aimed to simulate human problem-solving by encoding rules and structured logic into machines.

However, progress during this early stage was limited due to insufficient computing power, lack of large datasets, and restricted technological resources. As a result, the development of early AI systems, which relied heavily on symbolic thinking and logical reasoning, advanced at a slower pace. These constraints significantly influenced the initial growth of artificial intelligence, shaping its gradual and experimental evolution in its formative years.

1.5.2 AI's Early Achievements and Setbacks (1970s-1980s)

This period was marked by both significant progress and notable challenges in the development of Artificial Intelligence. During the 1970s, expert systems emerged as an important advancement in AI research. These systems were designed to replicate the decision-making abilities of human experts by using rule-based frameworks and predefined guidelines to solve specific problems within various domains.

Despite their initial success, expert systems had several limitations. They struggled to manage uncertainty, adapt to complex or dynamic situations, and operate beyond narrowly defined problem areas. As a result, their practical applications remained limited.

Between the 1970s and early 1980s, Artificial Intelligence experienced a phase commonly referred to as the "AI Winter." This period was characterized by reduced research activity and declining investment, largely due to unmet expectations and slow progress in delivering practical and scalable AI solutions.

1.5.3 Machine Learning and Data-Driven Approaches (1990s)

The 1990s marked a major shift in the development of Artificial Intelligence, bringing a data-driven transformation to the field. During this period, there was a clear movement away from rule-based systems toward machine learning approaches. Machine learning techniques enabled computer systems to learn from data using methods such as neural networks, decision trees, and support vector machines, allowing for more flexible and accurate problem-solving.

Neural networks, inspired by the structure and functioning of the human brain, gained widespread recognition during this decade. They were increasingly applied to tasks such as speech recognition, stock market prediction, and recommendation systems. The rapid growth of computing power and the increased availability of digital data further accelerated the advancement of data-driven AI models.

As a result, new application areas began to emerge, including recommendation systems, image recognition, and natural language processing. This period is often regarded as a significant phase in AI development, as intelligent systems demonstrated improved performance in areas such as speech processing, predictive analysis, and personalized recommendations. Advancements in processing capabilities and data availability played a crucial role in enhancing the effectiveness and accuracy of AI technologies.

1.5.4 The AI Boom: Deep Learning and Neural Networks (2000s-2010s)

The 21st century has marked a significant phase in the evolution of Artificial Intelligence with the rapid advancement of deep learning and neural network technologies. During the 2000s and 2010s, deep learning emerged as a powerful branch of machine learning that is inspired by the structure and functioning of the human brain. This approach enabled AI systems to process complex data more effectively through multi-layered neural networks.

Advanced neural networks achieved remarkable success in areas such as image recognition, natural language processing, and game-based intelligence. These technological developments led to major improvements in speech recognition, language understanding, and computer vision. At the same time, large technology companies made substantial investments in AI research and development, accelerating innovation and large-scale adoption of AI technologies.

Artificial neural networks, which are built on interconnected computational nodes resembling human neurons, formed the foundation of deep learning advancements. The combination of sophisticated algorithms, increased computing power, and large datasets played a critical role in driving the rapid progress of Artificial Intelligence during this period.

1.5.5 Generative Pre-trained Transformers: A New Era (GPT Series)

One of the most significant recent developments in Artificial Intelligence is the emergence of Generative Pre-trained Transformer models. These advanced language models are trained on massive amounts of textual data and have attracted global attention due to their remarkable language generation capabilities. Among them, GPT-3 represented a breakthrough by significantly improving natural language processing through its ability to generate human-like text and perform language translation tasks with high accuracy.

Generative Transformer models learn by processing large-scale text data, which enables them to understand linguistic structure, context, tone, and even humor. Beyond basic translation tasks, these models function as intelligent writing assistants capable of producing essays, poetry, summaries, and other forms of original content.

The latest generation of generative AI systems, including models such as Bard, ChatGPT, and Bing Copilot, demonstrates the expanding potential of this technology. These systems are capable of writing, translating, summarizing, and generating original content while also providing meaningful and context-aware responses. Such advancements continue to push the boundaries of Artificial Intelligence, highlighting its growing role in content creation, creative applications, and advanced language-based services.

1.6 Role of AI in HRM:

The role of Artificial Intelligence in Human Resource Management has been steadily expanding, leading to substantial changes in the way core HR activities are designed and executed. With organizations generating and managing vast amounts of data related to business operations, employee performance, workforce planning, and organizational outcomes, AI has emerged as a vital tool for handling complex and data-intensive HR functions. The incorporation of AI into HR processes supports the development of sustainable business models by enhancing accuracy, consistency, and efficiency in decision-making. By automating routine administrative tasks and enabling data-driven insights, AI allows HR professionals to focus more on strategic initiatives that contribute to long-term organizational effectiveness and operational excellence.(Votto et al., 2021)

The application of AI in HRM significantly improves talent acquisition by enabling organizations to identify, screen, and attract highly skilled candidates more effectively. AI-powered recruitment tools help analyze large applicant pools, match candidate profiles with job requirements, and reduce time-to-hire, thereby increasing the overall efficiency and quality of recruitment processes.(Rajani Meshram & Librarian, 2023) Beyond recruitment, advanced AI technologies introduce innovative approaches to managing human resources by improving workforce planning, enhancing organizational performance, and creating multiple opportunities for effective performance management. These technologies support objective evaluations, continuous feedback mechanisms, and predictive performance analysis, which contribute to better employee engagement and productivity. In the area of training and development, AI-driven learning systems enable organizations to transform into knowledge-oriented enterprises. Such systems offer personalized training programs based on individual skill gaps, learning preferences, and career goals, thereby improving the relevance and quality of employee development initiatives. By facilitating adaptive learning and continuous skill enhancement, AI-based training platforms strengthen organizational learning capabilities and support workforce readiness in a rapidly evolving business environment.

The growing adoption of Artificial Intelligence in Human Resource Management is largely influenced by its capacity to create value for multiple stakeholders, including employees, customers, and organizations. For employees, AI enhances learning opportunities, career development, and work experiences. For organizations, it improves efficiency, strategic decision-making, and competitive advantage, while customers benefit from improved service quality driven by a more capable and engaged workforce. As a result, AI has transformed HR functions from primarily administrative roles into strategic partners that contribute meaningfully to organizational performance and long-term sustainability.

1.6.1 Potential Outcomes of Artificial Intelligence in Human Resource Practices:

1.1.1.8 Improved HR efficiency and cost reduction:

AI automates repetitive HR activities such as resume screening, payroll processing, attendance management, and employee query handling, thereby reducing administrative burden, operational costs, and human errors while enabling HR professionals to focus on strategic roles (Bersin, 2018; Kaur & Sharma, 2021).

1.1.1.9 Enhanced recruitment and talent acquisition

AI-enabled recruitment tools help organizations identify, screen, and select suitable candidates more accurately by analyzing large volumes of applicant data, leading to faster hiring decisions and improved quality of hires (Kaur & Sharma, 2021; Jiang et al., 2020).

1.1.1.10 Reduction of bias and improved fairness in HR decisions

AI-based systems support objective, data-driven decision-making in recruitment, performance appraisal, and promotion processes, which can help minimize unconscious human bias when algorithms are carefully designed and monitored (Jiang et al., 2020; Vrontis et al., 2021).

1.1.1.11 Personalized learning and development

AI-powered learning platforms assess individual employee skills, learning styles, and career goals to provide customized training programs, thereby improving learning outcomes and supporting continuous employee development (Chen, 2022).

1.1.1.12 Improved performance management

AI technologies enable real-time performance monitoring, predictive performance analysis, and continuous feedback mechanisms, helping organizations identify high-potential employees and improve overall workforce productivity (Vrontis et al., 2021).

1.1.1.13 Effective workforce planning and talent retention

Predictive analytics supported by AI assist organizations in forecasting workforce requirements, identifying attrition risks, and planning succession strategies, contributing to better workforce stability and long-term talent retention (Chowdhury et al., 2023).

1.1.1.14 Enhanced employee engagement and experience

AI-based tools such as chatbots, sentiment analysis systems, and feedback platforms help organizations understand employee needs, address concerns proactively, and improve communication, leading to higher employee satisfaction and engagement (Malik et al., 2021).

1.1.1.15 Strategic transformation of the HR function

The integration of AI transforms HR from a primarily administrative function into a strategic partner by enabling data-driven insights, informed decision-making, and alignment of HR strategies with organizational goals, thereby enhancing organizational effectiveness and competitive advantage (Bersin, 2018; Chowdhury et al., 2023).

1.7 Acceptance of Artificial Intelligence in HR Practices:

The acceptance of Artificial Intelligence (AI) in Human Resource (HR) practices has gained increasing attention as organizations seek innovative ways to improve efficiency, accuracy, and strategic decision-making. Acceptance, in this context, refers to the willingness of organizations, HR professionals, and employees to adopt, trust, and effectively use AI-based tools in HR functions. While technological capability is a critical factor, the successful integration of AI in HR practices largely depends on human acceptance and organizational readiness. (Chatterjee et al., 2021a; Leung, 2015a)

One of the primary drivers of AI acceptance in HR practices is the growing recognition of its potential to enhance operational efficiency and reduce administrative burden. (Raghavan et al., 2020; Sony, Nupur, et al., 2025) AI-powered systems automate repetitive HR tasks such as resume screening, interview scheduling, attendance tracking, and payroll processing. This automation allows HR professionals to redirect their efforts toward value-adding strategic activities, thereby increasing overall acceptance of AI solutions within HR departments.(Bogen & Rieke, 2018)

Perceived usefulness and ease of use play a crucial role in shaping the acceptance of AI in HR practices. When AI applications are user-friendly and demonstrate clear benefits such as faster decision-making, improved accuracy, and reduced bias, HR professionals are more likely to embrace these technologies. The Technology Acceptance Model (TAM) suggests that individuals are more inclined to adopt new technologies when they perceive them as beneficial and easy to use, which is highly relevant in the context of AI adoption in HRM.(Venkatesh & Davis, 2000c)

Employee trust and transparency are also critical factors influencing the acceptance of AI in HR practices. HR decisions related to recruitment, performance appraisal, promotions, and compensation directly affect employees' careers. Concerns regarding data privacy, algorithmic bias, and lack of explainability can create resistance to AI adoption. Therefore, organizations that communicate clearly about how AI systems function and ensure ethical and fair use of AI are more likely to achieve higher acceptance levels among employees.(Bogen & Rieke, 2018)

Organizational culture and leadership support further shape the acceptance of AI in HRM. Organizations that promote a culture of innovation, continuous learning, and digital readiness tend to show higher acceptance of AI technologies. Top management support, adequate training, and change management initiatives help reduce resistance and encourage HR professionals and employees to develop confidence in AI-driven systems.(Minbaeva, 2021)

The level of acceptance of AI in HR practices also varies across industries based on technological maturity, regulatory requirements, and workforce characteristics. For instance, industries such as IT/ITES and Management Consultancy demonstrate higher acceptance due to digital literacy and innovation-driven environments, whereas sectors like healthcare, hospitality, and banking may adopt AI more cautiously due to ethical considerations, data sensitivity, and regulatory constraints. Despite these variations, a gradual increase in acceptance is observed across industries as organizations gain experience and confidence in AI applications.(Vrontis et al., 2022)

In conclusion, the acceptance of Artificial Intelligence in HR practices is a multidimensional process influenced by perceived benefits, ease of use, trust, ethical considerations, organizational culture, and industry context. While challenges related to privacy, bias, and transparency remain, organizations that proactively address these concerns and invest in employee awareness and training are more likely to foster positive acceptance of AI in HRM. As acceptance grows, AI is expected to play an increasingly strategic role in enhancing organizational effectiveness.

1.8 Implementation of AI in HR Practices:

The implementation of Artificial Intelligence (AI) in Human Resource (HR) practices represents a significant shift from traditional, manual HR processes to data-driven and technology-enabled systems. Implementation refers to the systematic adoption, integration, and utilization of AI tools and applications across various HR functions to enhance efficiency, accuracy, and strategic decision-making. While the potential of AI in HRM is widely acknowledged, effective implementation requires careful planning, technological readiness, and organizational alignment.

One of the most important areas of implementing Artificial Intelligence in HR practices is recruitment and selection. Organizations are increasingly using AI-based tools such as applicant tracking systems, resume screening software, and virtual assistants to manage large volumes of job applications efficiently. These tools help in quickly identifying suitable candidates by matching skills, qualifications, and experience with job requirements. By automating repetitive recruitment tasks, AI reduces hiring time, minimizes manual effort, and enhances the overall quality of recruitment decisions. Additionally, AI-enabled systems improve candidate experience by providing timely responses and structured communication throughout the hiring process, allowing HR professionals to focus more on strategic talent acquisition activities. (Nguyen & Le, 2022a; Venkatesh & Davis, 2000a)

Artificial Intelligence has also been increasingly adopted in performance management systems within organizations. Conventional performance appraisal methods are often dependent on subjective judgments and infrequent evaluations, which may fail to capture an employee’s true performance level. AI-enabled performance management systems overcome these limitations by continuously assessing employee-related data such as productivity levels, work patterns, and achievement of assigned goals. These systems offer real-time feedback and forward-looking insights, enabling organizations to recognize high-performing employees, identify areas requiring improvement, and ensure better alignment between individual contributions and organizational objectives.

Training and development are another critical HR function where AI implementation has gained momentum. AI-based learning management systems use employee skill data, learning behavior, and performance outcomes to recommend personalized training programs. These systems support continuous learning by adapting content to individual needs, thereby improving learning effectiveness and employee competence. Such personalized and adaptive learning environments enable organizations to build a future-ready workforce.(Chen, 2022)

In the area of workforce planning and HR analytics, AI plays a vital role by enabling predictive and prescriptive analysis. AI-powered analytics tools assist organizations in forecasting workforce requirements, predicting employee turnover, and identifying factors influencing engagement and retention. By leveraging predictive models, HR managers can proactively design interventions to reduce attrition and enhance employee satisfaction, contributing to long-term organizational sustainability.(J. H. Marler & Boudreau, 2017)

Employee engagement and experience management have also benefited from AI implementation. AI-enabled chatbots and virtual assistants support employees by addressing HR-related queries, facilitating onboarding, and providing real-time assistance. Sentiment analysis tools analyze employee feedback from surveys, emails, and social platforms to assess morale and engagement levels. These insights help organizations design targeted engagement strategies and improve workplace well-being.

Despite its advantages, the implementation of AI in HR practices presents several challenges. Issues related to data quality, privacy, algorithmic bias, and ethical considerations may hinder effective implementation. Additionally, resistance to change, lack of digital skills, and insufficient organizational support can limit the successful adoption of AI technologies. Therefore, organizations must invest in change management initiatives, employee training, and robust governance frameworks to ensure responsible and effective AI implementation in HRM.(Vrontis et al., 2022)

In conclusion, the implementation of Artificial Intelligence in HR practices has transformed traditional HR functions into strategic, data-driven processes. When implemented effectively, AI enhances recruitment efficiency, performance management, learning and development, workforce planning, and employee engagement. However, the success of AI implementation depends on organizational readiness, ethical use, and continuous evaluation. As organizations across industries increasingly embrace digital transformation, AI-driven HR practices are expected to play a crucial role in improving organizational effectiveness.

1.9 Organisational Effectiveness:

Organisational effectiveness refers to the degree to which an organisation successfully achieves its goals and objectives in an efficient, sustainable, and adaptive manner. It is a multidimensional concept that goes beyond financial outcomes to include factors such as productivity, employee satisfaction, innovation, operational efficiency, adaptability to environmental changes, and long-term organizational sustainability. An effective organisation is one that aligns its internal processes, human resources, and strategic objectives to respond effectively to both internal and external challenges.

In the context of Human Resource Management, organisational effectiveness is strongly influenced by the quality of talent, employee performance, engagement levels, and the ability of HR systems to support strategic decision-making. AI-enabled HR practices play a significant role in enhancing organisational effectiveness by enabling data-driven workforce decisions, improving the quality of hiring, and optimizing employee performance management. By automating routine HR activities and providing predictive insights, AI helps reduce operational costs and allows HR professionals to focus on strategic initiatives that add value to the organization.(Davenport & Ronanki, 2018)

Furthermore, AI-driven HR analytics support organisational effectiveness by improving workforce planning, identifying skill gaps, and predicting employee turnover. These capabilities enable organisations to respond proactively to workforce challenges and maintain high levels of productivity and employee satisfaction. The integration of AI into HR practices also enhances innovation and adaptability by supporting continuous learning and agile talent management, which are critical for sustaining competitive advantage in dynamic business environments.(Upadhyay & Khandelwal, 2018b)

Overall, the adoption of AI-enabled HR practices strengthens organisational effectiveness by aligning human capital strategies with business goals, improving decision quality, and fostering a high-performance work environment.

1.10 Relationship between AI-based HR Practices and Organizational Effectiveness:

The relationship between Artificial Intelligence (AI)-based Human Resource (HR) practices and organisational effectiveness has gained growing scholarly and practical attention as organisations increasingly adopt digital technologies to enhance performance and competitiveness. AI-based HR practices refer to the use of intelligent systems such as machine learning algorithms, predictive analytics, chatbots, and automated decision-support tools in HR functions including recruitment, training and development, performance management, employee engagement, and workforce planning. Organisational effectiveness, on the other hand, reflects an organisation's ability to achieve its goals efficiently while ensuring sustainability, adaptability, and stakeholder satisfaction.

AI-based HR practices contribute to organisational effectiveness by improving the quality and efficiency of talent management processes. In recruitment and selection, AI tools enable organisations to screen large volumes of applications, match candidate profiles with job requirements, and predict candidate success more accurately. This leads to improved talent quality, reduced time-to-hire, and lower recruitment costs, all of which positively influence organisational productivity and performance. By ensuring better person–job fit, AI-driven recruitment enhances employee performance and retention, which are key indicators of organisational effectiveness.

Performance management is another critical HR domain where AI strengthens organisational effectiveness. Traditional appraisal systems are often criticised for subjectivity, infrequent feedback, and limited developmental focus. AI-enabled performance management systems continuously monitor performance data, work patterns, and goal achievement, allowing organisations to provide real-time feedback and data-driven evaluations. Such systems support fairer performance assessments, timely identification of skill gaps, and alignment of individual objectives with organisational goals, thereby fostering a high-performance culture and improving overall effectiveness.(Khaled et al., 2023)

AI-based HR practices also enhance organisational effectiveness through personalised training and development initiatives. AI-powered learning systems analyse employee competencies, learning preferences, and performance outcomes to design customised training programs. This targeted approach improves learning effectiveness, accelerates skill development, and supports continuous learning, enabling organisations to adapt quickly to technological and market changes. A skilled and adaptable workforce strengthens innovation capability and long-term organisational sustainability.(Chen, 2022)

From a strategic perspective, AI-driven HR analytics play a crucial role in linking HR practices with organisational outcomes. Predictive analytics enable organisations to forecast workforce needs, identify high-potential employees, and anticipate employee turnover. These insights support proactive decision-making and effective workforce planning, reducing disruptions and enhancing organisational stability. By aligning human capital strategies with business objectives, AI-based HR practices reinforce the strategic contribution of HR to organisational effectiveness.(J. H. Marler & Boudreau, 2017)

Employee engagement and well-being are also positively influenced by AI-based HR practices. AI-enabled chatbots, virtual assistants, and sentiment analysis tools enhance communication, provide timely support, and assess employee morale. Improved engagement and well-being lead to higher job satisfaction, lower absenteeism, and increased commitment, which collectively contribute to improved organisational effectiveness. Moreover, AI facilitates flexible and responsive HR services, strengthening the employee experience in dynamic work environments.(Upadhyay & Khandelwal, 2018b)

Despite these benefits, the relationship between AI-based HR practices and organisational effectiveness is not automatic and depends on several moderating factors such as organisational culture, ethical use of AI, data quality, and employee acceptance. Inadequate transparency, algorithmic bias, and resistance to change can weaken the positive impact of AI on organisational outcomes. Therefore, organisations must ensure responsible AI implementation, effective change management, and continuous monitoring to fully realize the effectiveness gains from AI-enabled HR practices.(Vrontis et al., 2022)

In conclusion, AI-based HR practices have a strong and positive relationship with organisational effectiveness by enhancing talent quality, employee performance, engagement, and strategic decision-making. When implemented ethically and aligned with organisational goals, AI transforms HR into a strategic function that supports sustainable performance, adaptability, and competitive advantage across industries.

1.11 AI adoption constructs (Variables):

1.11.1 Perceived AI acceptance

It shows how positively people view and willing to adopt or use of artificial intelligence. In research on technology adoption and acceptance are affected by multiple factors like perceptual, psychological factors, which influence that whether someone intended to use AI and some are doing show.

1.1.1.16 There are key elements which determine the Perceived AI acceptance

- **Perceived Usefulness (PU):** It is a belief that AI will improve the performance, productivity, and outcomes. Systems seen as valuable and effective as well are more likely to be accepted.
- **Perceived ease of Use (PEOU):** AI technology is believed to be and seen as easier to use and tend to encourage positive attitude towards adoption of AI.
- **Attitude towards AI:** users; always have either positive or Negative attitude towards AI , which is shaped by their experiences, potential benefits and expectation from the technology, which influence the willingness of the users to engage with this.
- **Trust and Perceived Risk:** Reliability, transparency, fairness, and data security are the major factors which increase the confidence in AI. Lack of support acceptance, common errors like errors, privacy loss reduces willingness of adoption of AI technology.
- **Social and contextual influences:** opinions of various groups, culture of the organization, social norms, conditions shape the intentions of the people and comfort them with using AI tools.

Generally, Perceived AI acceptance is the degree of positivity, confidence, and intentions of the individuals or of the organizations hold towards using AI.

1.11.2 Perceived AI Implementation

It refers to how organization and individuals view the process of actually using AI , including benefits, challenges, and overall feasibility. There are multiple factors such as human, organizational which influence willingness and readiness to implementing AI.

1.1.1.17 Key factors influence Perceived AI Implementation:

- **Perceived benefits Vs. Challenges:** People view the AI implementation positively when it is believed will improve the quality, efficiency and less so that high cost, complexity, and technical challenges can be anticipated.
- **Organizational support and readiness:** Back of top management, Availability of resources, skills, clear strategy increase the confidence that AI can be implemented successfully.
- **User experience and technology features:** if the AI solutions are intuitive, compatible with the existing workflows and easy to learn, so perceive AI implementation is more achievable.
- **Trust, Transparency, and Risk perception:** Beliefs about the AI reliability, fairness and the safety always affect the thoughts of the people in implementation of AI systems. When the perceived risk is lower than people are more positive perceptions of implementation.
- **Facilitating conditions and training:** Education regarding AI, Technical support for implementation of AI and enabling environment like government policies and governance, improves perceptions that AI can be integrated effectively.

1.11.3 Technology Readiness

It refers to how a technology prepared, organization or system is to adopt, deploy, scale and benefit from artificial intelligence in a reliable , effective and sustainable way. It includes the technical maturity and the ecosystem readiness around the AI technology. Technology readiness helps the organization to avoid the common pitfalls like deploying AI before data systems are mature or before the teams are trained. failed projects, wasted investments, or unreliable outcomes. A readiness assessment clarifies strengths and gaps, enabling structured planning and risk management prior to full AI adoption.

- **Technical maturity and Infrastructure:** Technology readiness having the fundamental computing resources and platforms like scalable cloud infrastructure, compatible software frameworks, data pipelines, and secure systems. If the infrastructure is not sufficient then, AI tooling, projects can be failed or delayed to successfully launch.
- **Maturity Levels:** Technology Readiness Levels (TRLs) provides a standard way to measure how mature an AI technology is, from early research and proof of concept stages all the way validated, real world deployment. TRLSs application to AI components always

help teams in assessing where models or system stand in their development lifecycle and readiness for operational use.

- Skill and Organisational Preparedness: Readiness goes beyond the hardware and software, it includes the mix of people, skills, governance, and strategic alignment to adopt AI effectively. Trained talent, specified objectives and business processes support and sustain the AI integration.
- **Data Availability and Quality:** AI system depends on the vast amounts of data. Assessing technology readiness includes whether the data of the organisation is accessible, clean, governed and integrated, so that models can be trained and operated reliability at scale.
- **Alignment with the Business Goals:** Technology is mature technically; Successful implementation of the AI system requires the AI initiatives should be tied to strategic business objectives. Readiness presents that AI efforts should be supported by the leadership, aligned with outcomes which are measurable, and also embedded with the goals of the organisations.

1.11.4 Organizational Readiness

Organizational Readiness for AI means, the extent which an organization is prepared to successfully adopt, implement and scale the AI technologies so that organizational goals can be achieved. Multiple dimensions are encompassed, which is go beyond technology alone.

1.1.1.18 Key Dimensions of Organizational readiness for AI:

- **Strategic Readiness:**
  - The extent to which an organization has a clearly defined AI vision aligned with its strategic objectives, supported by strong leadership commitment, a long term AI roadmap, and the identification of high impact AI use cases.
- **Technological Readiness:**
  - The degree to which an organization possesses a robust IT infrastructure and cloud capabilities, ensures the availability, quality and integration of data, and maintains compatibility between AI tools and existing systems.
- **Data Readiness:**
  - The extent to which an organization maintains well structured, accessible, and reliable data, supported by effective data governance and clear ownership, while ensuring compliance with data privacy and security regulations.

- **Human Resource Readiness:**
    - The degree to which an organization has access to AI skilled talent and data experts, fosters employee awareness and openness toward AI adoption, and provides effective training and upskilling programs.
- **Cultural Readiness:**
    - The extent to which an organization promotes an innovation oriented, learning driven culture, encourages openness to change and experimentation, and foster trust in AI driven decision -Making.
- **Financial readiness:**
    - The degree to which an organisation ensures adequate budget allocation for AI initiatives, conducts systematic cost benefit and return on investment evaluation, and plans for sustainable long terms AI investments.

1.1.1.19 Needs of Organizational readiness for AI

Organizational readiness for AI plays a critical role in enabling successful AI implementation and adoption, minimizing resistance to change and associated risks, enhancing decision - making, operational efficiency, and competitiveness and ensuring the responsible and sustainable use of AI technologies.

1.11.5 Environment Readiness

It refers to the extent to which external conditions surrounding an organisation support the adoption, implementation, and effective use of artificial intelligence technologies.

1.1.1.20 Key Dimensions of Environmental readiness for AI:

- **Regulatory and Legal Environment:**
    - The extent to which government policies and AI regulations are supportive, while ensuring robust data protection, privacy and compliance requirements, along with well-defined ethical standards and accountability frameworks.
- **Industry and Competitive Environment:**
    - The degree to which competitive pressures encourage AI adoption, AI technologies are widely implemented across the industry, and organizations engage in benchmarking and the use of best practices within the sector.

- **Technological Ecosystem:**
    - The extent to which organizations have access to a mature technological ecosystem, adding the availability of AI vendors, platforms, and solution, reliable cloud services and digital infrastructure, and opportunities for partnerships with technology providers and startups.
- **Market and Customer Readiness**:
    - The degree to which customers demonstrate acceptance of and trust in AI -enabled services, the market shows demand for AI -driven products and solutions, and stakeholders are aware of the benefits of AI technologies.

1.11.6 Behavioural Intention:

The extent to which individuals or organisations are willing and intend to adopt, use and continue using AI technologies in their tasks and decision-making processes.

1.11.7 Organizational Effectiveness:

The degree to which an organization attains its strategic and operational objectives, enhances performances, and achieves efficiency, innovation, and competitive merits through the adoption and effective utilization of AI technologies.

1.12 AI tools and technologies in Human Resources:

Artificial intelligence provides HR professionals with an advanced range of tools that enhance operational efficiency, support evidence-based decision-making, and enrich the overall employee experience. By enabling automation and intelligent analysis across various HR functions—such as talent acquisition, performance evaluation, and customized employee assistance—AI technologies are reshaping traditional HR operations. These tools facilitate more efficient workflows and enable HR departments to deliver greater value by improving both organizational processes and employee engagement.(*AI in HR: How Is Artificial Intelligence Transforming Human Resources?*, n.d.)

IBM Watson: IBM Watson offers a comprehensive suite of AI-powered solutions that support key HR functions such as talent acquisition, employee engagement, and workforce planning. It assists HR professionals by providing advanced analytics for recruitment, predictive insights into employee engagement, and data-driven support for performance management decisions.

Through capabilities such as resume screening, candidate ranking, and the analysis of engagement metrics, IBM Watson enables HR teams to make more accurate, efficient, and informed human resource decisions.

ChatGPT: ChatGPT, developed by OpenAI, is a conversational artificial intelligence tool capable of interacting with users in a natural and human-like manner, making it well suited for HR-related support functions. In HR practices, it is used to automate responses to employee inquiries, provide real-time assistance during onboarding, and address preliminary questions from candidates during the recruitment process. By efficiently handling frequently asked questions and routine interactions, ChatGPT reduces the administrative workload of HR teams, enabling HR professionals to concentrate on more complex and strategic responsibilities.

HireVue: HireVue is an AI-enabled video interviewing and assessment platform designed to support the screening and evaluation of job candidates. Its artificial intelligence capabilities analyze recorded video interviews to assess candidates' skills, behavioral traits, and potential cultural fit. By identifying suitable candidates at an early stage of the recruitment process, HireVue helps accelerate hiring decisions and allows HR teams to focus their efforts on final interviews with pre-qualified applicants.

Eightfold.ai: Eightfold.ai is an AI-powered talent management platform that supports organizations in attracting, retaining, and developing their workforce. It leverages deep learning algorithms to align candidates with suitable roles based on their skills, experience, and career progression. In addition, the platform identifies existing skill gaps within the organization and recommends relevant upskilling and reskilling opportunities, thereby enhancing workforce planning, internal mobility, and long-term talent development.

Visier: Visier is an AI-enabled people analytics platform designed specifically for human resource functions, offering data-driven insights into workforce planning, employee engagement, and retention. It supports HR leaders by delivering actionable information on employee turnover, productivity, and talent retention, enabling informed decision-making. Through its predictive analytics capabilities, Visier helps HR managers anticipate future workforce requirements and design targeted strategies to address organizational needs effectively.

Pymetrics: Pymetrics is an AI-driven talent assessment platform that combines neuroscience-based methodologies with artificial intelligence to align candidates with roles that match their skills and personality traits. Using game-based assessments, it measures candidates' cognitive and emotional characteristics, enabling a more objective evaluation process. This approach helps reduce bias in hiring decisions and supports HR departments in making data-informed judgments about candidate suitability and long-term potential.

ADP DataCloud: ADP DataCloud is a workforce analytics platform designed to support HR functions such as payroll management, time tracking, and human resource analytics. It assists HR departments by analyzing payroll and workforce data to identify patterns and predict employment trends. By integrating with other HR systems, ADP DataCloud streamlines administrative processes and enhances productivity, while improving accuracy in payroll processing and benefits administration.

Workday: Workday is an integrated human resource management system that incorporates artificial intelligence to support talent management, payroll operations, and workforce analytics. Its AI-powered features facilitate recruitment processes, performance evaluations, and employee development initiatives. By utilizing machine learning–based insights, Workday helps HR departments personalize workforce decisions and align employee growth and development with overall organizational objectives.

HiredScore: HiredScore is an AI-driven recruitment platform that employs natural language processing and machine learning techniques to evaluate and prioritize job applications. It integrates seamlessly with applicant tracking systems to analyze resumes and rank candidates based on their suitability for specific roles. By enhancing the efficiency and accuracy of candidate screening, HiredScore enables HR teams to concentrate their efforts on applicants with the highest potential.

Ultimate Software's UltiPro: UltiPro is a comprehensive HR software platform that leverages AI-powered analytics to manage the entire employee lifecycle, from recruitment to performance management. Its intelligent analytics provide insights into employee turnover, engagement, and performance, offering HR professionals a complete understanding of the workforce. This holistic perspective enables HR leaders to make informed, strategic decisions that enhance the overall employee experience and support organizational objectives.

1.13 Present scenario of acceptance and implementation of Artificial Intelligence (AI) in Human Resource (HR) practices for organizational effectiveness across selected industries:

1.13.1 Level of Acceptance & Adoption in HR Functions:

The acceptance and adoption of artificial intelligence in HR functions are growing rapidly across organizations. Globally, the use of AI tools in HR processes increased from 26% in 2024 to approximately 43% in 2025, reflecting a significant rise in adoption. This trend is particularly pronounced in for-profit sectors, especially among publicly traded companies, where 58% have implemented AI in HR, compared to lower adoption rates in government and non-profit organizations. Many HR leaders now view AI not merely as a tool for automating routine tasks, but as a strategic enabler that enhances competitive advantage and aligns HR initiatives with organizational goals. Industry trends show that technology, finance, and information sectors are early adopters due to their access to resources and data-intensive HR operations, while emerging markets such as India and the GCC are increasingly leveraging predictive analytics to improve talent acquisition, compliance, and employee experience management.(*The Role of AI in HR Continues to Expand*, n.d.)

1.13.2 Key HR Areas Where AI Is Implemented:

Artificial intelligence is transforming multiple aspects of human resource management, significantly enhancing efficiency and strategic decision-making. In talent acquisition and recruitment, AI tools streamline processes by automating job description creation, resume screening, candidate sourcing, and communication, while predictive analytics and AI-driven candidate scoring improve the quality of hire and reduce time-to-hire. For employee engagement and development, AI enables personalized learning and skill gap analysis, allowing tailored development plans, while monitoring employee sentiment and engagement supports retention and performance. Administrative tasks such as payroll, compliance, and handling FAQs are increasingly automated, freeing HR professionals to focus on strategic priorities like workforce planning. Additionally, AI-powered people analytics and predictive models facilitate workforce planning, turnover prediction, and provide insights into diversity, equity, and inclusion (DEI), making HR operations more data-driven and impactful.(*HR Tech Trends 2025 — Global Adoption of AI & Predictive Analytics in HR*, n.d.)

1.13.3 Organizational Effectiveness Outcomes:

The implementation of artificial intelligence in HR has led to significant improvements in efficiency, cost reduction, and overall employee experience. AI tools help shorten HR process times, including recruitment cycles and administrative tasks, with organizations reporting substantial time savings and up to 89% of HR professionals noting reduced effort on routine activities. Additionally, AI provides data-driven insights that enhance forecasting and support more strategic decision-making in talent management. The use of AI-powered chatbots and virtual assistants further improves the candidate and employee experience by offering real-time responses, increasing accessibility, and boosting overall satisfaction (AIHR).(*How AI Transforms HR Management in 2025 | HR Automation*, n.d.)

1.13.4 Challenges in Acceptance and Implementation:

The adoption of AI in HR faces several technical, strategic, and ethical challenges that can hinder its effective implementation. Many HR teams lack formal AI strategies or governance frameworks, while skills gaps and limited AI readiness among professionals further slow adoption. AI systems can also inherit biases from historical data, leading to fairness concerns in recruitment and performance evaluations, and ethical or legal issues related to transparency and data privacy remain significant obstacles Additionally, employees may feel uneasy or distrust AI-driven decisions, such as performance ratings, if the process is not clearly communicated, highlighting the ongoing need to balance human empathy and oversight alongside automated HR functions.(*'Quiet Cracking' At Work: Empathy, Not AI-Driven Rating, To Fill In Void, Say HR Leaders | Nagpur News - The Times of India*, n.d.)

1.13.5 Acceptance Patterns at the Employee and Leadership Levels:

Leaders tend to adopt AI at higher rates than individual contributors, especially within strategic functions, shaping the evolution of HR practices to better align with organizational priorities. Employee acceptance of AI, however, largely depends on factors such as training, clear communication from leadership, and the perceived fairness of AI systems. When organizations provide well-defined AI guidelines and opportunities for upskilling, employees are more likely to feel comfortable with and accept AI technologies in HR processes.

Presently, AI in HR is rapidly moving from early adoption to strategic integration across industries. Its acceptance is strongest in recruitment, analytics, and administrative automation, with clear benefits for organizational effectiveness — including efficiency, improved decision-making, and enhanced employee experiences. However, challenges related to technology readiness, ethical use, bias, and human-centered implementation persist. To realize full potential, organizations must invest in skills, governance, and cultural readiness alongside technological tools.

1.14 The future of Artificial Intelligence in Human Resource Practices:

The future of Artificial Intelligence (AI) in Human Resource (HR) practices is expected to be increasingly transformative, strategic, and human-centric. As organizations continue to adopt AI technologies, HR functions will gradually move beyond administrative efficiency toward a more strategic role focused on talent management, leadership development, employee well-being, and the creation of a positive workplace culture. By automating repetitive and time-consuming tasks, AI allows HR professionals to devote greater attention to high-impact activities that contribute directly to organizational effectiveness and long-term sustainability.

One of the most significant future trends will be the redesign of jobs and HR roles. As AI systems take over routine operational tasks, job roles will evolve to require higher levels of strategic thinking, creativity, problem-solving, and multi-skilled capabilities. HR leaders will be responsible for restructuring job designs by integrating multiple specialized tasks into broader, more flexible roles that effectively leverage AI tools. In addition, the growing use of AI will create demand for new roles that combine human resource expertise with technological and data-driven competencies.

Another important development will be the empowerment of managers through AI-driven insights. AI will enable managers to make more informed decisions related to employee performance, career development, goal setting, and workload distribution. Predictive analytics and real-time data will support proactive talent management and early identification of employee needs. However, the increasing use of AI in managerial decision-making may also raise concerns among employees regarding fairness, transparency, and privacy, particularly in performance evaluation processes.

Therefore, the future success of AI in HR practices will depend on the ability of organizations to balance technological capabilities with human judgment. Managers and HR professionals will need to be trained to use AI responsibly, ethically, and transparently. Establishing clear governance frameworks, ethical guidelines, and continuous upskilling programs will be essential to ensure trust and acceptance among employees.

In conclusion, the future of AI in HR practices lies in its integration as a strategic partner rather than a replacement for human decision-making. When implemented thoughtfully, AI has the potential to enhance workforce productivity, improve employee experience, and strengthen organizational effectiveness while preserving the human values that remain central to human resource management.(*AI for HR: The Future of Human Resources | SAP*, n.d.)

We cannot predict the future entirely, but on the basis of the expert's discussion we can make some educated guesses. In future we can predict that AI will be adopted by the businesses of all sizes.

1.15 Introduction to Selected Industries

The adoption and impact of Artificial Intelligence (AI) in Human Resource (HR) practices do not occur uniformly across industries. Industry characteristics such as technological maturity, regulatory intensity, workforce skill composition, service orientation, and competitive pressure significantly shape how AI is perceived, accepted, and implemented within organizations. Recognizing this contextual diversity, the present study focuses on five selected industries IT/ITES; Healthcare and Hospitality; Consumer Durables and Telecommunications; Banking, Insurance, and Financial Services; and Management Consultancy each of which represents distinct organizational environments and HR challenges. Examining these industries collectively allows for a nuanced understanding of how AI-enabled HR practices operate under varying institutional and operational conditions, thereby enhancing the explanatory power and practical relevance of the study. (Samuel Fosso Wamba et al., 2021; Tornatzky & Fleischer, 1990a)

1.15.1 IT/ITES:

The Information Technology and Information Technology Enabled Services (IT/ITES) sector has been at the forefront of digital innovation and technological adoption in India. Characterized by a knowledge-intensive workforce, global exposure, and rapid skill obsolescence, this industry has historically embraced automation, analytics, and advanced digital tools. AI adoption in HR practices within IT/ITES is relatively mature, with widespread use of algorithmic recruitment, predictive attrition models, learning analytics, and employee engagement platforms. (Prikshat et al., 2021a)

However, despite high technological readiness, HR functions in IT/ITES face challenges related to employee burnout, talent retention, and continuous reskilling. AI systems are often perceived as efficiency-enhancing tools, yet concerns regarding surveillance, fairness, and data privacy persist. Studying this sector provides insight into AI acceptance and implementation in a technologically advanced environment where employees are familiar with digital systems but may also exhibit heightened sensitivity to algorithmic control. (Jöhnk et al., 2021a)

ITES is an Information Technology Enabled Services; it uses information technology to deliver the services. It uses information technology to improve the efficiency and operations of the organisations. ITES also known as web enabled services, remote services and tele working. Nowadays, number of companies depends on ITES for the support to their operations, such as medical transcription, billing and coding, customer support etc. ITES help in smooth functions of business. It includes certain services like Business Process Outsourcing (BPO), Knowledge Process Outsourcing (KPO), customer development, and customer services. The good example of ITES is customer support center in India handles various queries for a company which is based out at USA. Nowadays various sectors like Banking, Healthcare, retail are using the ITES to support their regular operations.

Real Life Example of ITES:

1. Data Entry and Data Processing

2. Customer care & Call center Operations
3. Telecommunication Services
4. Accounting & Financial Services
5. Animation & Content Development
6. Legal Work and Documentations.

Today, ITES provides various benefits to the users, like It is cost effective so that the expenses can be reduced to large extent. It can excess skilled & diverse workforce. It makes the processes more flexible and scalable so that the demand of business can be meet up.

Apart from the merits of ITES it has some demerits also like, data security is the major challenge which is difficult to handle. It becomes difficult for ITES to maintain the consistent services quality across the time zones and regions and. It consumed lot of time to deploy the trained and skilled workforce.

1.15.2 Hospitality and Healthcare

The Healthcare and Hospitality sectors are highly people-centric, service-intensive, and emotionally demanding industries where HR practices directly affect service quality and patient or customer satisfaction. These industries operate under strict regulatory frameworks, ethical constraints, and heightened expectations of human empathy and judgment. As a result, AI adoption in HR practices within these sectors tends to be cautious and selective (Raghavan et al., 2020)

In healthcare, AI is increasingly used for workforce scheduling, credential verification, and training analytics, while in hospitality, AI-enabled HR tools support recruitment, employee engagement, and service workforce optimization. However, employee acceptance of AI in these sectors is often shaped by concerns regarding job displacement, erosion of human interaction, and ethical accountability. Therefore, studying AI in HR practices in healthcare and hospitality provides critical insights into how trust, perceived risk, and professional identity influence acceptance and implementation outcomes. (Kellogg et al., 2020; Sony, Amin, et al., 2025)

AI in hospitality tailors guest experience through chatbots, smart rooms, and personalized recommendations, while optimizing operations with automated check-ins, dynamic pricing, and predictive maintenance: in healthcare, AI reshapes diagnostics, drug discovery, and patient care by leveraging machine learning for image analysis, robotic surgery, and administrative automation to boost efficiency, accuracy, and focus on well-being. Both sectors harness AI for data analysis, cost reduction, and service enhancement, though hospitality prioritizes guest satisfaction and healthcare emphasizes clinical outcomes, with shared challenges in data security, privacy, and ethical use.

1.15.3 Consumer Durables and Telecommunications

The Consumer Durables and Telecommunications sector operate at the intersection of manufacturing, service delivery, and large-scale customer interaction. Organizations in this sector typically employ a diverse workforce comprising technical staff, sales personnel, customer service employees, and managerial professionals. HR practices must therefore balance standardization with flexibility across geographically dispersed operations. (Chatterjee et al., 2022)

AI adoption in HR within this sector is often driven by the need for efficiency, scalability, and cost optimization. AI-enabled tools are used for mass recruitment, performance tracking, training personalization, and workforce planning. However, variability in employee digital literacy and organizational readiness can influence how AI is perceived and implemented. This sector offers a valuable context for examining how technology characteristics, facilitating conditions, and external support shape employee acceptance and organizational effectiveness. (Nguyen & Le, 2022a)

AI is extensively used in telecommunication as well as in consumer durables industries, so that the user experience and efficiency of these industries can be enhanced.

1.1.1.21 In Telecommunications

In the telecom industry, AI is used extensively for managing the networks which are complex and deliver the personalized services.

1.1.1.21.1 Key applications include:

- AI driven network optimization uses real time data analysis to forecast congestion, dynamically route traffic and allocate bandwidth, enabling networks to adjust automatically for performance and reliability; such intelligent systems form self – optimizing networks that can configure themselves, respond to faults, and recover from issues with minimal human intervention, which reduces downtime and enhance overall network stability.
- AI based predictive maintenance continuously monitors network hardware, such as cell towers and routers -using sensors and data analytics to identify early warning signs of failure, enabling planned, proactive servicing before problems arise rather than waiting to react to breakdowns.
- AI powered chatbots and virtual assistance deliver instant, around the clock support for routine questions like billing or basic trouble shooting, easing pressure on call centres and speeding up service, which helps reduce workloads and boosts overall customer satisfaction.
- AI powered fraud detection and security systems continuously analyse network traffic and usage patterns in real time to spot unusual behaviour, such as SIM card cloning, identity theft, subscription fraud, or other anomalies, flagging and blocking suspicious activity to protect customer data and preserve company profit.
- AI-powered fraud detection and security systems continuously analyze network traffic and usage patterns in real time to spot unusual behavior such as SIM card cloning, identity theft,

subscription fraud, or other anomalies—flagging and blocking suspicious activity to protect customer data and preserve company revenue

- Machine Learning models analyse the behaviour of the customers, preferences, and the demographic data to the segmented audiences. It enables the companies to deliver hyper personalized service plans, tailor targeted marketing campaigns and recommend the next best offers which help in improving the engagement and also reduces the customer churn.
- AI support network planning by analysing user density, demand forecasts, geographic factors, and infrastructure data to point out best sites for the new cell towers and the other network infrastructure, helps in decision of expansion, improve the coverage and investment strategies guide properly.

1.1.1.22 In Consumer Durables:

In Consumer Durable Sectors, AI is mainly focus on creating intelligent, automated, and personalized experience within the products and also improve the lifecycle of overall product.

- AI enables smart home integration by allowing different connected devices, such as thermostats, lights and security system, to work together intelligently. It coordinates the actions and responses across the ecosystem for more intuitive control and automation.
- AI enhance functions of consumer technology and user experience across multiple devices.

Smartphones, AI is used for the advanced image processing, facial recognition, and personalized interface that adapt to user behaviour. Smart TV, deliver content which are tailored and intuitive voice-controlled navigation, thus make the entertainment more accessible and engaging. Wearable, such as smartwatches, fitness trackers use the AI, so that health metrics can be monitored. It monitors heart rate and patterns of sleep and then give great insights. smart appliances use AI automation and efficiency optimisation, which include the recognition of object in devices like refrigerators and alerts related to the maintenance issues.

- AI continuously analyse real time operational data from the devices, so that potential malfunctions can be anticipated before the occurrence. It enables the proactive maintenance which can extends the life span of the products and also prevents the breakdown, which is unexpected rather than fixing the reactively issues.
- AI powered user interface uses the technologies like speech recognition, natural language Processing, and also the recognition of various gesture so that the interactions with the devices feel intuitive and human like, allow the users to control the systems with the voice, movements and the other natural actions rather than the traditional inputs such as keyboards and the buttons.
- AI-powered Natural User Interfaces (NUIs) use technologies such as natural language processing (NLP), speech recognition, and gesture recognition to make interactions with devices feel intuitive and human-like, allowing users to control systems with voice, movements, or other natural actions rather than traditional inputs like keyboards or buttons.

- Manufactures uses AI across the supply chain and the productions process, which uses machine learning so that the forecasting of demand can be improved, optimize production planning, enhance the quality control and also manage the inventory levels.

1.15.4 Banking, Insurance and Financial Services

The Banking, Insurance, and Financial Services (BIFS) sector is characterized by high regulatory oversight, data sensitivity, and risk aversion. HR practices in this sector play a critical role in ensuring compliance, ethical conduct, and customer trust. AI adoption in HR has gained momentum in areas such as recruitment analytics, fraud detection training, performance monitoring, and leadership development. (Vasiljeva et al., 2021a)

Despite strong institutional pressure to adopt AI, employee acceptance in this sector is often moderated by concerns related to data privacy, algorithmic bias, and job security. The BIFS sector therefore presents a unique setting to study how organizational readiness, top management support, and governance mechanisms influence perceived AI implementation and its eventual contribution to organizational effectiveness. (Amankwah-Amoah et al., 2021a)

Table 1-2: Major applications of AI

Sectors	***Applications***
BANKING & FINANCE	• **Fraud Detection:** Major amount of Real time transactions data is analyzed by AI algorithms, It identifies and prevent the money laundering and the susceptive activities effectively and efficiently. Thus, AI is very useful in fraud detection • **Customer Services:** AI- powered chatbots provide virtual assistants, address routine inquiries, provide 24/7 support, provide customized financial advice. • **Credit Scoring & Loans:** Wider range of data is analyzed by machine learning models to assess the creditworthiness. It also helps in faster approval of loan and in assessment of risk also. • **Investment Management:** Nowadays AI tools are used to know the preferences of the investors, in analyzing the trends of market, provide cost effective portfolio recommendation and management. They also take help of Robo advisors. • **Process Automation:** Documents Processing and data entry are time consuming. And human errors happen. AI, which automates the time-consuming tasks and helps in reducing the human error and improve the operational efficiency.
INSURANCE	• **Claims Processing:** AI and machine learning helps in expedite the claims management, for this it analyses the images. documents and the data. It assesses the data

validity and also automates the payouts; it also reduces the processing time.

- **Personalized Pricing & Underwriting:** AI analyses the data such as health history, records etc. Its helps in assessing the risk accurately. It allows the insurers to provide competitive and customized policy premiums.
- **Risk Assessment:** There are different types of risk, which should be analyzed to manage the risk. AI helps the insurers to understand the and in managing exposure of different types of risk.

AI transform the entire banking sector. It has transformed the banking, financial services and the Insurance (BFSI) sector. As compared to earlier, after the use of AI, it has enhanced the efficiency of the sectors, personalized the customer services and managed the risk more effectively. Uses of AI ranges from the customer facing chatbots to complex back-office operations, such as detection of fraud and algorithmic trading.

1.1.1.23 Benefits to the BFSI Sector:

- **Cost Efficient & Increased Efficiency:** AI helps in automation of the repetitive work, so that employees can concentrate on other work and more strategic activities. It also helps in reducing the overall cost.
- **Enhanced Customer Experience:** Customized services, provide 24/7 support through AI tools and improve the customer loyalty and satisfaction.
- **Improved Decision -Making:** AI algorithms process and interpret the vast data and provide the insights which is useful in decision making. These data help in making more informed and data driven decisions in the different areas such as investment strategies and in risk management.
- **Enhanced Security & Compliance:** AI helps in monitoring the transactions for anti-money laundering compliances. It helps in continuously responding to the threats in real time.

1.1.1.24 Challenges and Future Considerations

- **Data Privacy & Security:** Handling the sensitive datasets always raises the concerns, needed the security measures and compliance with the regulations.
- **Bias & Ethics:** AI systems can unintentionally mirror and amplify biases embedded in the past data due to which result produced is unfair, like discriminatory loan approval decisions. Therefore, the financial institutions must act to address and reduce these biases, so that the fair result can be produced. AI systems can unintentionally mirror and amplify biases embedded in their historical training data, which may produce unfair results—such as discriminatory loan approval decisions—so financial institutions must proactively address and mitigate these biases to ensure fair and equitable outcomes.

- **Regulatory uncertainty:** Institutions and governing bodies Collaboratory evolve the regulatory landscapes for AI financial services. It will help in establishing effective and transparent frameworks.
- **Talent and Skills Gap:** The demand for a workforce adaption is increasing in data science and AI related skills, the organisation should work on upskilling and reskilling programmes of their employees.

1.15.5 Management Consultancy

Management consultancy firms are knowledge-driven organizations where human capital constitutes the primary source of competitive advantage. These firms operate in dynamic environments requiring rapid problem-solving, innovation, and continuous learning. AI adoption in HR practices within consultancy firms is often strategic, aimed at enhancing talent analytics, competency mapping, knowledge management, and leadership development. (J. Marler et al., 2017)

Employees in consultancy firms typically possess high levels of digital competence and autonomy, which can foster favourable attitudes toward AI adoption. However, concerns related to professional judgment, intellectual ownership, and role redefinition remain relevant. Studying AI in HR practices in management consultancy firms enables an examination of how creativity, self-efficacy, and performance expectancy shape acceptance and implementation outcomes, as well as their impact on organizational effectiveness. (Pan et al., 2021a)

Management Consulting uses AI in multiple tasks, like data analysis, scheduling and reporting and boosts strategic work so that the work can be done faster and provide the deeper insights. It helps the consultants in focusing on the higher value activities, such as innovation, complex problem solving and guidance, competitive advantages, transforming workflows for efficiency, and accuracy. Consultants use the AI tools, Generative tools are used to accelerate research synthesis, in drafting high quality content. Machine leaning help in data analysis, visualization, and potential insights to make informative strategic decision.

1.1.1.25 Key Applications:

- AI can analyze the vast datasets to uncover the patterns, trends, and insights, empowering the organizations so that it helps in generating faster, accurate and recommendations that helps in making inform strategic decision making.
- AI automates the routine tasks such as summarize the reports and the meeting notes, entering & organizing data, drafting the reports such as workplans, proposals, and keep the consultant free from the administrative work so that more focus can be done on high value and strategic activities.
- Use predictive modeling for the analysis of past and the current data and predict the future market trends, financial results, and project timelines, thus enable informed planning and strategic decision making.

- AI is very useful in generations of idea and help in developing new frameworks, and the purposive solutions and create strategies that helps in expansion of possibilities.
- AI is useful in enhancing the knowledge management and workflow by optimizing the project processes, improve the allocation of limited resources and streamline the knowledge sharing. It helps in reduction of bottlenecks and in making better use of organizational expertise.

1.15.6 Rationale for Industry Selection

The selected industries collectively represent varying degrees of technological maturity, regulatory pressure, workforce composition, and service orientation. This diversity allows the study to capture both common patterns and context-specific differences in AI acceptance and implementation in HR practices. By examining these industries together, the research moves beyond sector-specific insights and contributes to a more comprehensive understanding of AI-driven HR transformation in the Indian organizational context.

1.16 The future of Artificial Intelligence in Human Resource Practices:

The future of Artificial Intelligence (AI) in Human Resource (HR) practices is expected to be increasingly transformative, strategic, and human-centric. As organizations continue to adopt AI technologies, HR functions will gradually move beyond administrative efficiency toward a more strategic role focused on talent management, leadership development, employee well-being, and the creation of a positive workplace culture. By automating repetitive and time-consuming tasks, AI allows HR professionals to devote greater attention to high-impact activities that contribute directly to organizational effectiveness and long-term sustainability.

One of the most significant future trends will be the redesign of jobs and HR roles. As AI systems take over routine operational tasks, job roles will evolve to require higher levels of strategic thinking, creativity, problem-solving, and multi-skilled capabilities. HR leaders will be responsible for restructuring job designs by integrating multiple specialized tasks into broader, more flexible roles that effectively leverage AI tools. In addition, the growing use of AI will create demand for new roles that combine human resource expertise with technological and data-driven competencies.

Another important development will be the empowerment of managers through AI-driven insights. AI will enable managers to make more informed decisions related to employee performance, career development, goal setting, and workload distribution. Predictive analytics and real-time data will support proactive talent management and early identification of employee needs. However, the increasing use of AI in managerial decision-making may also raise concerns among employees regarding fairness, transparency, and privacy, particularly in performance evaluation processes.

Therefore, the future success of AI in HR practices will depend on the ability of organizations to balance technological capabilities with human judgment. Managers and HR professionals will need to be trained to use AI responsibly, ethically, and transparently. Establishing clear governance frameworks, ethical guidelines, and continuous upskilling programs will be essential to ensure trust and acceptance among employees.

In conclusion, the future of AI in HR practices lies in its integration as a strategic partner rather than a replacement for human decision-making. When implemented thoughtfully, AI has the potential to enhance workforce productivity, improve employee experience, and strengthen organizational effectiveness while preserving the human values that remain central to human resource management.(*AI for HR: The Future of Human Resources | SAP*, n.d.)

1.16.1 Critical Drivers of AI Acceptance:

- **Performance Expectancy:** HR professional is more likely to accept AI when it enhances decision making accuracy and improves efficiency in handling routine administrative tasks.
- **Organizational Support:** The successful adoption of AI relies on strong leadership backing and investment in AI Centres of Excellence (CoEs), which facilitate collaboration between HR and IT to ensure AI tools align with people focused objectives.
- **User Competence:** Employees demonstrate greater acceptance of AI when they have received training in digital literacy, data ethics, and prompt engineering.

1.16.2 Implementation Trends by industry:

The adoption of AI in HR is not even across the sectors:

- Information technology (IT): IT leads AI adoption, with nearly 70% of Indian IT professionals activity using AI in 2026. Primarily leveraging predictive analytics for talent retentions and automating recruitment processes.
- Services Based industries: These industries heavily rely on conversational AI chatbots for round the clock employee support, with catboats managing up to 80% of routine queries.

- Manufacturing & Engineering: AI adoption is rising in manufacturing and engineering sectors, where sensors and predictive modelling are used to enhance workplace safety, identify health risks, and reduce accidents.
- Adoption is rising in manufacturing and engineering sectors, where sensors and predictive modelling are used to enhance workplace safety, identify health risks, and reduce accidents.

1.16.3 Impact on Organizational effectiveness:

Few key channels are used to improve the effectiveness by AI driven Practices.

- **Recruitment Precision:** Hybrid approaches that integrate machine learning with genetic algorithms achieve over 95% accuracy in candidate shortlisting and performance prediction.
- **Operational Efficiency:** Automating data intensive workflows like payroll and compliance has enabled many organizations to reduce labour costs by approximately 26.2%.
- **Enhanced Employee Experience:** Personalization engines deliver 'Netflix Style' curated learning paths and career development opportunities, tailored to employees' real time skills gaps.
- Personalization engines deliver "Netflix-style" curated learning paths and career development opportunities, tailored to employees' real-time skills gaps.

1.16.4 Critical Challenges:

- **Ethical Concerns:** Challenges like data privacy, lack of transparency in 'Black Box' algorithms, and potential algorithmic biases continue to be major obstacles to building trust.
- **Psychological impact:** Increasing employees concerns about 'Fear of being Obsolete' and technostress highlight the need for proactive HR strategies to sustain engagement.
- **Regulatory Compliance:** The EU AI act significantly affects employment related AI applications, classifying many as 'high risk' and mandating rigorous audits and human oversight.

While it is impossible to predict the future with complete certainty, insights from expert discussions allow us to make informed projections. Based on this analysis, it is anticipated that, over time, businesses of all sizes will increasingly adopt Artificial Intelligence, integrating it into various functions to improve efficiency, decision making, and overall organizational performance.

Artificial Intelligence has proven to be highly effective in employee development by providing personalized learning experience, enhancing productivity, and offering more precise insights into

Learning outcomes compared to traditional methods. When implemented successfully in HR practices, AI can lead to increased learning retention, higher productivity, reduced training costs, and most effective career management.

However, organizations face few problems in realizing these benefits, involving concerns over data privacy, potential biases, system compatibility, and employee acceptance. Looking ahead, the continued evolution of AI promises even greater opportunities for personalized and ethical development initiatives, supporting proactive organizational growth, improved employee satisfaction, and flexible career advancement pathways.

To fully leverage the opportunities, HR professional must address current challenges while preparing to integrate future AI -driven solutions, therefore enhancing organizational development programs and fostering a skilled motivated, and future ready workforce.

1.17Structure of the Thesis

The thesis is organized as follows:

- **Chapter 1: Introduction to Topic**

  Introduces the research context, background, rationale, and purpose of the study.

- **Chapter 2: Review of Literature**

  Reviews relevant literature and develops the conceptual framework and hypotheses.

- **Chapter 3: Research Methodology**

  Details the research methodology, including design, sampling, instruments, and analytical techniques.

- **Chapter 4: Data Analysis**

  presents data analysis and empirical results.

- **Chapter 5**: **Findings and Discussions**

Discusses findings in relation to objectives, hypotheses, and existing literature.

- **Chapter 6: Conclusions, Recommendations, and Implications**

  Outlines conclusions, implications, and recommendations.

- **Chapter 7: Limitations and Future Scope**

  Discusses limitations and future research directions.

CHAPTER - 2 REVIEW OF LITERATURE

2.1 Introduction

This chapter is a comprehensive, theory-driven evaluation of research associated with the thesis "Acceptance & Implementation of Artificial Intelligence in HR Practices for Organisational Effectiveness in Selected Industries." A literature review in doctoral research is not a descriptive catalogue of prior studies; rather, it is a structured synthesis that traces how ideas have evolved, clarifies key concepts and topic boundaries, evaluates what is known with methodological and contextual sensitivity, and identifies inconsistencies and under-explored relationships that justify the current analysis(Lim et al., 2022; Okoli, 2015; Snyder, 2019). In line with this goal, the chapter integrates evidence from technology & information-systems adoption theories and HRM to explain why organisations and HR professionals accept (or resist) AI, how AI-enabled HR practices integrate in processes and management, and under what conditions such implementation contributes to organisational effectiveness (Al-Suqri et al., n.d.; F. Davis et al., 1989; *Diffusion of Innovations*, 2014; Everett Roge, 1995; quarterly & 1989, n.d.; Tornatzky & Fleischer, 1990b; Venkatesh et al., 2003a; Venkatesh & Davis, 2000a) The review also highlights the Indian organisational context, where scale, workforce heterogeneity, digital maturity, and evolving data-protection obligations influence both adoption decisions and responsible deployment, laying the groundwork for the conceptual gaps and research opportunities addressed in subsequent chapters (*Deloitte's Global Human Capital Trends Workday Differentiators*, 2024; Digital Personal Data Protection Act 2023, 2023; *Nasscom Technology & Leadership Forum 2024*, 2024)

2.2 Artificial Intelligence (AI)

The combination of hardware, software & network technologies that allows information systems to implement the tasks traditionally associated with human reasoning abilities, which includes but not limited to learning, reasoning, pattern recognition, and decision-making. Previously, AI research was focused on verbal reasoning and rule-based algorithms, but the modern AI applications are dependent on Machine Learning (ML), neural networks, Natural Language Processing (NLP) and data-driven self-learning algorithms which has an ability to learn and develop over time (Alsheibani & Messom, 2018; Russell & Norvig, 2010). This transition from static programming to adaptive learning systems has greatly expanded the possible acceptance & implementation of AI in organisational contexts. An innovative technology that enhances machine's capabilities rather than merely automating task and application extends far beyond operational efficiency navigating the strategic decision-making, knowledge management, and organizational learning. As a transformative organizational resource, AI has the potential to reshape traditional functions, managerial roles, workflows, and structures of an organization. (Erik Brynjolfsson and Andrew McAfee, 2017)

The acceptance of AI is impacted by industry and geographical location; it is being utilised and influenced by technological readiness, organisational culture, leadership commitment, and environmental pressures. In earlier times, artificial intelligence applications were rather primitive. Experimental systems like expert systems (ES) and knowledge management systems

(KMS) were used with limited knowledge, scalability, and only structured data usage. (F. Davis et al., 1989; Y. Lee et al., 2003a; Venkatesh et al., 2003a) Whereas the current AI systems are very capable of processing high volumes, high speed, and different variety of data with processing capability of both structured and unstructured data which facilitates in descriptive, predictive, and prescriptive analytics and helps in data-driven real-time decision support to the organizations. (Go et al., 2020a; Peisl & Edlmann, 2020) Current AI systems are capable of processing large volumes, high speeds, and a variety of data types, including both structured and unstructured data. This capability enables the processing of descriptive, predictive, and prescriptive analytics, thereby facilitating data-driven real-time decision support for organisations. Any technology implementation, including artificial intelligence, requires a huge monetary investment, but more than that, it requires a continuously learning organisation that is ready to restructure processes, develop new competencies, and adopt new governance structures. (Davenport, 2018; Erik Brynjolfsson and Andrew McAfee, 2017) The organisations that adopt artificial intelligence as a part of their strategic goals are more likely to improve their organisational performance, but it is impacted by employees' resistance towards change due to fear of the unknown, lack of trust in machine learning (ML) tools and algorithms, and fear of losing jobs due to the adoption of AI in organisational practices. In Indian context AI adoption is largely impacted by factors like availability of labours, cost-effectiveness, complex regulatory compliances, unreliable technology infrastructure, ethical considerations, socio-economic & cultural norms. (Tayal & Upadhyay, 2019; Upadhyay & Khandelwal, 2018a)

2.3 Artificial Intelligence in HR Practices

Artificial intelligence in HRM is a system that carries out tasks typically associated with human intelligence, like recognizing patterns, making predictions, and providing data-driven decision support. It utilizes various techniques, including machine learning, natural language processing, and generative AI. In HR environments, AI should be seen not just as a tool for automation, but also as a means of enhancement, where human insight and algorithmic power work together to influence decisions and outcomes (Davenport, 2018; Jarrahi, 2018) This distinction is important for HR practices because many HR decisions—like sourcing, hiring, performance evaluation, promotion, disciplinary actions, succession planning, and employee engagement are closely tied to the social contexts, values, and culture of an organization. AI tools can really change the game when it comes to privacy, transparency, and how we view fairness, all while boosting efficiency. (Kellogg et al., 2020; Meijerink et al., n.d.; Schafheitle et al., n.d.) Recent systematic reviews indicate a significant increase in AI–HRM research, highlighting common themes such as talent acquisition, HR analytics, personalization of employee experience, and ethics/governance. However, there is lack of evidence regarding the timing and way organization will benefit from same. (Basu et al., 2025; Úbeda-García et al., n.d.; Venugopal et al., 2024)

The integration of artificial intelligence into human resource practices is changing how companies handle their workforce, presenting a mix of opportunities and challenges. Many organizations are now using AI-powered HR tools to improve decision-making, simplify processes, and increase overall efficiency in their HR functions. AI algorithms assist in talent acquisition by swiftly analyzing vast amounts of candidate data, allowing recruiters to more effectively find the best matches. AI also enhances performance management by increasing efficiency and transparency, as well as providing personalized employee engagement through real-time insights that were not possible before. Earlier research has demonstrated that these developments in AI not only enhance operational efficiency but also help HR take on a more strategic position within organizations. (Gulliford & Parker Dixon, 2019; Hogg, 2019; Jatoba et al., 2019) The successful adoption of AI in HR requires planning and efforts and the outcomes depend on factors such as organizational culture, mindset of employee, technological readiness, and management support. Many researchers have developed conceptual framework to study change readiness to understand the enablers and challenges of acceptance and implementation of AI in HR Practices. (Holt et al., 2007; Rafferty et al., 2013) For technology driven transformation in an organization it is important to communicate the same to employees clearly and transparently to gain their trust, and train them for the upcoming change as well as the technology part. (J. Jha et al., 2023; M. Jha et al., 2025; Soni, 2022) The employees should also be aware about the ethical and privacy concerns related to the adoption of the system which is being integrated. Insights form these theories of change management and technology acceptance will help the researcher the human side of AI implementation which is also very important to understand as understanding the technology itself. (Brougham & Haar, 2018; Jöhnk et al., 2021a; Lazanyi, 2018; J. Marler et al., 2017; Rafferty et al., 2013; Rusly et al., 2015; Virajanand Varma, 2012)

The acceptance of AI systems by HR professionals and employees plays a crucial role in ensuring successful implementation. Based on technology acceptance models, earlier research shows that factors like perceived usefulness, ease of use, trust, and fairness play a crucial role in influencing attitudes toward artificial intelligence-powered HR systems. (Venkatesh et al., 2012) Concerns regarding the transparency of algorithms, possible biases, and the reduced influence of human perception significantly impact how individuals embrace them in HR Practices.

Majority of organizations face data quality issues, human resource Information systems which are fragmented and do not possess enough analytical capabilities. Major multinational organizations have started using artificial intelligence for recruitment analytics, chatbots and prediction of attrition, but small and medium sized organizations are not able to adopt the same due to limited resources and lack of skilled employees to manage the same. The differences highlight the importance of tailored implementation frameworks that consider the unique characteristics of various organizations.

Based on the insights shared by previous researchers, this study focuses on the critical factors that influence the readiness of employees to acceptance and implement artificial intelligence in HR practices. This thesis not only address the gap in current literatures but also offers valuable insights to organizations willing to utilize AI in HR practices effectively while ensuring a positive experience for their employees.

2.4 Application of AI in HR Practices

The use of Artificial Intelligence (AI) in Human Resource (HR) practices marks a significant change in how organizations handle their workforce, allowing for more informed, efficient, and strategic decision-making. The concept of Artificial Intelligence was developed by John McCarthy a professor at Massachusetts Institute of Technology (MIT) in the year 1956 but it has gained popularity in very recent times, its incorporation into HR functions has really picked up speed in the last few years. Technological changes in HR started with the launch of Human Resource Information Systems (HRIS) in the 1970s, which helped automate tasks like payroll processing and recordkeeping. By 1990s, we saw the rise of Electronic Human Resource Management (E-HRM), which used internet technologies to make HR functions more efficient at any time from any place. (Bondarouk et al., 2016; Leong, 2018)

The integration of artificial intelligence requires not only the adoption of new technologies but also significant transformations within structure of organization and cultural frameworks emphasizing strategic partnership and employee development, alongside with digital transformation initiatives. (Claus, 2019; DiRomualdo et al., 2018; Pillai & Sivathanu, 2020; Sivathanu & Pillai, 2018) The application of AI in human resources is especially prominent in recruitment and selection. Artificial intelligence technologies enhance the hiring process by predicting job openings, refining job descriptions to attract suitable candidates, automating job advertisements across various recruitment platforms, and effectively sourcing and screening applicants from extensive talent pools. (Dickson & Nusair, 2010; Upadhyay & Khandelwal, 2018a) Automated scheduling of interviews, calls, and meetings reduces administrative burden, allowing HR professionals to focus on higher-value tasks. However, Artificial intelligence also improves the processes of candidate evaluation by implementing automated background checks and psychometric assessments. Additionally, chatbots and AI-driven customer relationship tools facilitate continuous engagement and communication with candidates (Meijerink et al., 2020). Nonetheless, many companies hesitate to make substantial investments in AI technologies due to high upfront costs and concerns over return on investment (ROI) (Berhil et al., 2020). Organizations that have adopted artificial intelligence frequently observe benefits such as reductions in operational costs, enhanced productivity, increased employee satisfaction, and better service delivery. (Gikopoulos, 2019; Papageorgiou, 2018; Pillai, 2021)

Irrespective of the advantage that adoption of AI has, many organizations have significant hurdles while implementing the same. The technology is a very small aspect of adoption the challenges are more when it comes to employee's resistance to change, fear of job replacement, lack of skills to work with new technology, data privacy issues, fairness, ethical and legal challenges. (Chakma, 2021; Hashmi & Baig, 2020; Pillai, 2021; Ranjitha S & Usha K, 2021; Tambe et al., 2019) In addition to human and organizational aspects of adoption there are financial constraints, Complex AI programming customized for various HR functions, cyber security risks, failure of AI to understand human emotions, give empathetic feedback during performance evaluations, engagement activities, and interviews. (Ahmed, 2018) Furthermore, the swift integration of AI in response to crises such as the COVID-19 pandemic has led to employee concerns regarding job security, trust, the sufficiency of training, and uncertainties related to the changing nature of their roles. (Cabrera et al., 2023; Makarius et al., 2020)

To address the above-mentioned challenges, continuous employee training & development both in terms of change management and technology skills is required. HR staff is required to develop advanced digital literacy, data analysis skills, critical thinking, cognitive decision-making, and leadership skills that align with AI-enabled environments. (Burgess, 2021; Jaiswal et al., 2021; Johansson et al., 2019; Sakka et al., 2022)

Artificial intelligence systems acquire knowledge from pre-existing data, which may unintentionally integrate and continue historical biases if not meticulously overseen. For instance, Amazon's hiring algorithm was discovered to have a bias against female candidates due to the training data being largely composed of male resumes, highlighting the ethical concerns associated with AI-driven human resources decisions. (Alfons & Alfons Kodiyan, 2019; Dastin, 2022; Lavanchy, 2006; Martin, 2022) This highlights the importance of extensive supervision, transparency, and strategies to mitigate bias in order to achieve impartial results.

Artificial intelligence demonstrates remarkable capabilities in speedy data analysis and the recognition of patterns, it fails to replicate the complex judgment, empathy, and negotiation skills that human HR professionals use for precise decision-making processes. Rather, artificial intelligence functions most effectively as a supplementary tool for enhancing human judgment rather than replacing it.(Jarrahi, 2018; Prikshat et al., 2021a) Emerging technologies, such as Internet of Things (IoT) and artificial intelligence, significantly impact human resource development by influencing customer satisfaction, recruitment processes, training methodologies, and strategies for global competition.(Al Mamun et al., 2025) Equipping HR professionals to effectively utilize these technologies necessitates innovation, adaptability, and a commitment to continuous learning. (Álvarez-Gutiérrez et al., 2022; Balas, n.d.; Carter et al., 2025; J. Marler et al., 2017; M. Stone et al., 2020; P. Stone et al., 2016)

AI applications cluster into several practice areas:

The processes of talent acquisition and selection have increasingly incorporated artificial intelligence, which is utilized for résumé processing candidate ranking, the deployment of chatbots for screening and engagement, as well as the analysis of video interviews. Those in favour argue that algorithmic screening has the potential to improve both efficiency and consistency; yet, studies suggest that models developed using historical data may reinforce existing discrimination, and claims made by vendors about the reduction of bias often exceed what can be substantiated through empirical evidence. (Fui-Hoon Nah et al., 2023; Raghavan et al., 2020; Soleimani et al., 2025) The examination of facial and biometric inference in the hiring process has drawn significant public attention, emphasizing the associated ethical and legal consequences. This situation has intensified demands for transparent validation methods and the incorporation of human supervision in management of such tools. (Charlwood & Guenole, 2022; Eubanks, 2025; Pandey et al., 2023) Artificial Intelligence is useful in the recruitment process by not only be beneficial to organizations but also to candidates by a reformation of the application process by designing user-friendly and meaningful application forms, which will improve application completion rates. AI also maintains a database of past candidates, which helps in identifying candidates from an existing pool of candidates, reducing the time and resources lost in searching for fresh talent. The onboarding process begins once the recruitment part is finished, AI helps in conducting induction processes beyond the regular working hours. AI helps the new employee to finish the onboarding process at their own pace which results in faster integration and reduces the administrative burden on HR personnel. AI also provides remote support applications like chatbots to employees at any place and time of the day.

For Training and development (T&D) of employees artificial Intelligence helps in skills development, personalized gap analysis and learning pathways and internal succession planning. Industry evidences shows that Indian organizations lack the skills required to use AI in HR Practices, hence the implementation is negligible. Implementation of AI enabled T&D relay heavily on the data readiness of organization and empowerment of employees. (Agarwal, 2024; Deloitte's Global Human Capital Trends Workday Differentiators, 2024; Nasscom Technology & Leadership Forum 2024, 2024)

AI enabled Performance Management Systems (PMS) automates the process of performance by real time data collection, tracking of KPI, performance mapping based on KPI, providing personalized feedback on improvisation, base for continuous improvement rather than improvisation after annual or bi-annual reviews, predict trends, support data driven unbiased decisions form performance appraisals. It helps in determining the employee engagement levels, future performance issues, and risk of attrition so that organizations are able to act proactively. It is also very useful in work from home setup as it can monitor the employees, collect the data from multiple sources, tracks output based results and very flexible to use. (Alekseeva et al., 2020; Nyathani, 2023; Smith, 2019) Research on algorithmic management indicates that increased monitoring can impact autonomy and trust, potentially reducing effectiveness in the absence of strong governance and transparency. (Keegan & Farwa, 1 C.E.; Kellogg et al., 2020) With the help of AI tailored feedback and a talent recognition system can be developed which will understand the need of employees and leads to employee engagement and job satisfaction very precisely along with many other benefits of having this information. AI is also able to evaluate key success factors of employees to identify the employees to be promoted, which energies succession planning or internal mobility leading to a reduction in talent acquisition costs and boost employee retention rates. Along with identifying the opportunities to promote the employees within the organizations AI also provides predicted information regarding the person who will quit from the organization, which allows the HR Personnel to deploy the retention efforts and strategically reduce attrition.

AI in Human Resource Analytics uses Predictive analytics models and machine learning algorithms to manage huge amount of HR data which is majorly unstructured in nature and increasing day by day, if this big data is approached in appropriate way then it can be used for workforce planning, engagement, gap analysis, training & development and productivity, measure attrition risk, employee sentiment analysis, performance management, reduces bias in decision making, Career planning & succession planning and many other HR tasks. (Angrave et al., 2016; Kakulapati et al., 2020; Levenson, 2005; Quddus Mohammed, 2019; Saxena et al., 2022) Owing to HR Analytics, companies have access to data regarding what's happening in an organization and how employees are perceiving it. When organizations are equipped with data it allows to fix the problems and improve future practices. It comes to the notice of employees as the changes are implemented the processes are improved, they can suggest valuable feedback to management and management can act on it. This helps in building and maintaining the trust of employees which further leads to employee engagement, success, and improves employee retention percentages. By tracking employee engagement at every level, organizations will gain an enhanced understanding of employee metrics, HR Analytics along with employee wellbeing will assist organizations to create an atmosphere where employees feel engaged and empowered. Compensation Analytics is a novel part of HR Analytics focus on the effectiveness and optimization of employment cost; it helps organizations to make data-driven decisions regarding fair compensation. The compensation contributes to the largest element in the organization's annual budget; it is also one of the largest sources of data, consisting of precise and varied information, which can be used to develop a strategic and tactical plan in addition to guide business objectives. Whether an organization is hiring a new employee or addressing salary concerns of existing employees or developing a competitive reimbursement strategy to attract good talent, depending on data(facts) eliminates the decisions based on assumptions and gut feeling. (Alam, n.d.; Bose et al., 2021; Fermin Diez, 2019; Kranthi Kumar Routhu, 2020; Technology & 2025, 2025; Verma, 2025)

The employee experience and the delivery of HR services are being significantly influenced by the integration of HR chatbots, automation in case management, and tailored communication strategies, all of which enhance the quality and responsiveness of services provided. Nonetheless, achieving “implementation success” generally necessitates the integration with Human Resource Information Systems (HRIS), the transformation of processes, and effective change management, rather than simply the deployment of tools. (Basu et al., 2025; Davenport, 2018)

In conclusion, while AI holds transformative promise for HR practices, its effective adoption demands addressing technological, ethical, and human challenges through integrated efforts spanning training, organizational change, and ethical governance.

2.5 Factors Affecting Acceptance of AI

The readiness for organizational change is shaped by various individual and structural factors. Key influences include employee commitment, self-efficacy, organizational and leadership readiness, as supported by multiple studies. (Errida & Lotfi, 2020; Hidayati et al., 2019; Jöhnk et al., 2021a; Soomro et al., 2021) Furthermore, the organization's learning culture, Knowledge exchange systems, transformation commitment, change readiness, (P. Malik & Garg, 2017; Prikshat et al., 2021a) top management leadership style, intention of employees to use technology. (Esen & Özbağ, 2014) Technological and educational competencies significantly influence the capacity to adapt to change. (Mahendrati & Mangundjaya, 2020; Ranawaka et al., 2020; Virajanand Varma, 2012) Building trust among employees and enhancing their capability to support change initiatives are essential. (Rafferty & Minbashian, 2019; Thakur & Srivastava, 2017) Furthermore, the level of technological proficiency, variations among professional groups regarding technology adoption, and demographic factors significantly influence their readiness for change. (Rusly et al., 2015)

The acceptance of change is influenced by psychological factors, including positive attitude and creativity, as well as perceptions regarding the user-friendliness of technologies. (Esen & Erdoğmuş, 2014; Phoolka, 2018) The readiness of an organization to integrate artificial intelligence (AI) into its decision-making processes has the potential to improve service delivery and decrease costs. Still, motivating decision-makers to implement these changes remains to be a significant challenge. Consequently, it is essential to incorporate change readiness that is specifically designed for AI applications in order avoid failures and prevent expensive errors. (Alami et al., 2021)

The implementation of AI presents numerous advantages, such as enhancements in candidate experiences, increased recruitment efficiency, enhanced motivation, strategic compensation planning, tailored learning opportunities, professional development, and comprehensive employee support. (Guenole & Feinzig, 2018) HR managers' beliefs positively correlate with their readiness for change, whereas anxiety related to AI adoption negatively impacts this readiness. The presence of high-perform33333333ance work systems may reduce this anxiety and influence HR managers' readiness for AI-related changes. (Suseno et al., 2021)

The Younger generations showcase reluctance to accept Artificial Intelligence or robots as their colleagues as they do not trust the social and emotional competencies of machines, despite of the potential they have to offer. (Lazanyi, 2018) The successful integration of Artificial Intelligence requires a Socio-technical approach that considers both its novelty and its scope within the organization. This framework promotes a simpler integration of AI technologies and enhances the efficiency and effectiveness of change management processes. (Kim et al., 2022; Makarius et al., 2020)

The acceptance and implementation of artificial intelligence (AI) in human resource (HR) practices are shaped by a variety of interconnected factors that encompass individual, organizational, and technological dimensions. The acceptance by employees is largely influenced by their beliefs, trust, and fear regarding artificial intelligence. Factors such as employee's trust on technology, perception of ease-of-use, beliefs of employees towards actual utility of AI affect positively towards acceptance. (Esen & Erdoğmuş, 2014; Suseno et al., 2021) But employees are more concerned regarding them being replaced by technology such as AI, human machine interaction, AI having no emotions and empathy creates obstacles for AI adoption. (Suseno et al., 2021)

The successful implementation of AI within an organization is significantly influenced by the active participation from senior executives and the support from top management, as they are crucial in offering strategic direction and ensuring the appropriate allocation of resources. Leadership styles that display transformational qualities, including vision, empathy, and adaptability, have a favourable influence on the adoption of AI. (Hermawan & Suharnomo, 2020) Moreover, fostering a culture that emphasizes learning and encourages the sharing of knowledge, along with continuous development of skills is essential for cultivating the competencies required for the effective utilization of AI. (Mahendrati & Mangundjaya, 2020; P. Malik & Garg, 2017) Building trust in technology, achieved through clear communication regarding the capabilities and limitations of AI, is essential for addressing employee resistance. (Insights to Impact: Inside Perceptyx's Award-Winning AI Solution, 2025.; Omar Ashurbayev, 2025)

The acceptance of AI systems in human resources is significantly influenced by various technological factors, such as the ease of use, reliability, and the ability to integrate smoothly with existing HR systems. The ease of use and the perceived usefulness, in alignment with the Technology Acceptance Model (TAM), serve as significant indicators of the intention to work with AI in HR activities. (Esen & Özbağ, 2014) Furthermore, the effectiveness of employees' technological skills and the availability of specialized training significantly impact the successful integration of AI. (Ranawaka et al., 2020) This demonstrates the significance of developing supportive environments that address skills deficiencies and promote confidence in engaging with AI.

The socio-technical dimension serves as a holistic framework that highlights the interaction between social elements, such as employee readiness and organizational culture, and technical components, including the novelty of artificial intelligence and the scope of the system. The successful integration of AI is dependent upon the management of this dynamic, ensuring that technological advancements are in balance with organizational objectives and that employees are adequately prepared both emotionally and in terms of skills. (Kim et al., 2022; Makarius et al., 2020) Addressing shifts in interprofessional dynamics and demographic factors can improve acceptance rates and facilitate a more seamless implementation process. The complexity of AI acceptance in HR requires integrating psychological, organizational, and technological strategies. Cultivating positive beliefs, reducing anxiety, investing in leadership readiness, fostering a learning culture, and ensuring user-friendly technology are all critical for successful AI-driven HR transformations. (Luciano Floridi, 2018; Taddeo & Floridi, 2018)

Considerations of ethics are becoming increasingly important in conversations surrounding artificial intelligence in human resources, especially concerning data privacy, algorithmic bias, and the monitoring of employees. The changing regulatory environment in India, particularly with respect to data protection laws, has increased organizational awareness regarding the importance of responsible AI practices. (Floridi et al., 2018) The perceptions of employees regarding fairness and transparency are fundamental in influencing their trust and acceptance of AI systems.

The adoption of AI in Indian organizations is further shaped by environmental factors, including competitive pressure, technological instability, and institutional norms. The Technology–Organization–Environment (TOE) framework has been extensively utilized to explain the ways in which these multilevel factors collaboratively influence adoption decisions in emerging markets. (Baker, 2012; Tornatzky & Fleischer, 1990a) The integration of these frameworks facilitates a comprehensive understanding of the acceptance and implementation of AI within human resource practices.

2.6 Existing models on Acceptance & Implementation of Technology

This study explores employee perspectives for the integration of artificial intelligence in HR Practices, the previous researchers have been employing a framework that combines the Technology, Organisation, and Environment Model with Transaction Cost Theory. The adoption of artificial intelligence is positively influenced by technological proficiency and legislative support; however, factors such as the relative advantages of AI, industry characteristics, and organizational size do not have an impact on its adoption. The governance of artificial intelligence is influenced by transaction costs and the expertise of organizational technology. (Pan et al., 2021a)

Although the criteria related to technology readiness and competitive pressure moderately predict the acceptance of AI applications in HR recruitment, the characteristics of innovation, specifically relative advantage, and complexity, show a considerable capacity to predict such adoption. (Hmoud, 2021) Researchers utilized the Technology-Organization-Environment (TOE) framework alongside the Diffusion of Innovation Theory (DOI) to promote further exploration of AI adoption readiness within organizations. The combination of the Technology Acceptance Model (TAM) with the Technology, Organisational, and Environment Model (TOE) indicates a negative correlation among organisational readiness, compatibility, and perceived ease of use. (Alsheibani & Messom, 2018) The TOE-TAM integration indicates that technology adoption in organizations is affected by various factors, including perceived usefulness, perceived ease of use, relative advantage, compatibility, complexity, organizational readiness, educational and training purposes, support from top management, competitive pressure, and assistance from vendors. (Chatterjee et al., 2021a) The TOE model indicates that the adoption of AI by employees is affected by the support of top management, a competitive environment, and legal regulations. (Gangwar et al., 2015a) The Technology Acceptance Model (TAM), a framework established three decades ago, remains relevant in the study of technology acceptance. (Vasiljeva et al., 2021a) The framework defines three essential components: system attributes and functionalities, which include perceived usefulness and ease of use; user motivation, characterized by attitudes towards utilization; and actual use of the system. In light of the model's saturation, as indicated by current studies, it may be essential to explore alternative models to examine the deployment of predictive systems. (F. Davis, 1985; F. D. Davis, 1989a)

The Technology Acceptance Model (TAM) indicates that employees exhibit a negative attitude towards the adoption of AI voice assistants. (Balakrishnan et al., 2021a; Chuttur, 2009b; Gianina Lala, 2014) Moreover, the perceived collaboration of technology has gained significant importance in contemporary models for the acceptance of advanced robotics. This trend illustrates the progression of technology acceptance models in conjunction with highly interactive systems, enhanced functionalities, and more intuitive user interfaces. (Go et al., 2020a) The adoption of technology is significantly influenced by voluntary acceptance by user, favourable perceptions of technology, expectations regarding performance, perceived advantages, groundbreaking innovations, and user experiences. These factors play a crucial role in shaping technology acceptance, psychological influences, and perceptions of risk.(Park et al., 2022a) The Technology Acceptance Model (TAM) is presently under investigation regarding its applicability in the field of artificial intelligence. This framework encompasses factors such as perceived ease of use, perceived innovativeness, employee perceptions, and user intentions to buy. (Y. Lee et al., 2003a) Furthermore, the growing integration of artificial intelligence within the workplace enhances the effectiveness of human resource management. (Iyer et al., 2020a; Money & Turner, 2004a; Singh et al., 2020a)

2.6.1 Technology–Organization–Environment (TOE) Framework

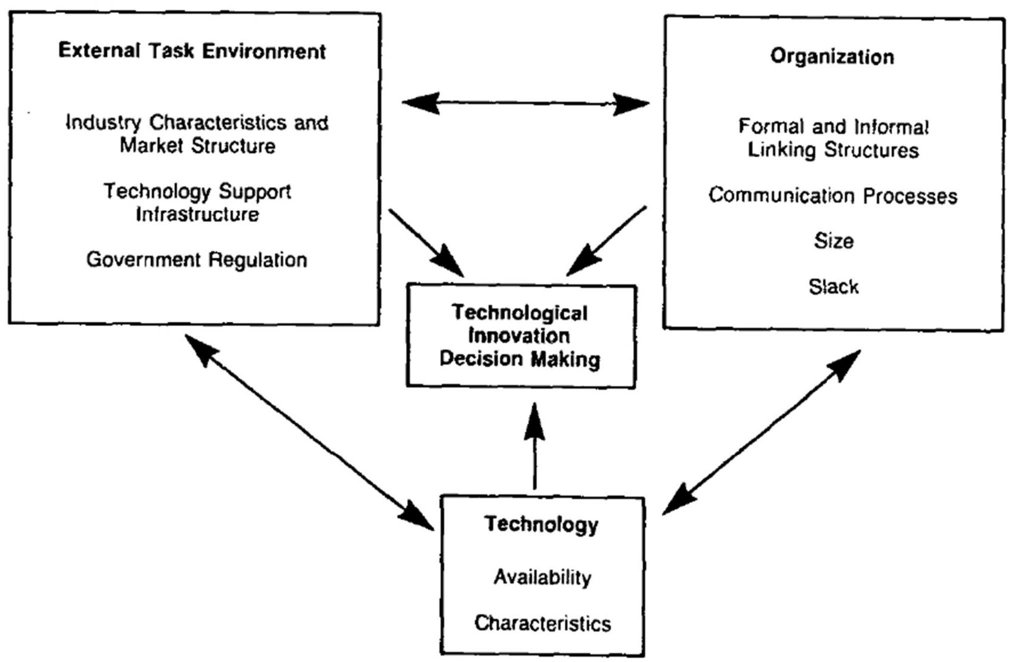

Figure 2-1: Technology-Environment-Organization (TOE) Framework

originally known as The Context of Technological Innovation (Source: Book on The Process of Technological Innovation by (LOUIS G TORNATZKY & MITCHELL FLEISCHER, 1990))

The Technology–Organization–Environment (TOE) framework is one of the most widely adopted theoretical models for examining how organizations perceive, adopt, and implement technological innovations. The framework provides a concise yet adaptable structure for examining the motivations and factors that lead organizations to analyse, adopt, and integrate new technologies. It categorizes the influencing factors into three interdependent areas: technological, organizational, and environmental. (Tornatzky & Fleischer, 1990a) The TOE framework has been widely utilized in research concerning the adoption of artificial intelligence (AI) across various organizational contexts, including human resource management (HRM), owing to its adaptation across different sectors and technologies. In the field of AI-enabled HR practices, the significance of the TOE framework has increased by the concurrent rise of advanced technological attributes—such as algorithmic decision-making, data-driven systems, and automation—which require considerable organizational change. The transformations include the development of new skills, the establishment of governance mechanisms, the implementation of ethical considerations, and the allocation of financial expenditures. Furthermore, the external environment, defined by competitive pressures, vendor ecosystems, and regulatory compliance, significantly influences the processes of acceptance and implementation. As a result, the TOE framework offers a thorough, evidence-based perspective for analyzing the implementation of AI within HR practices. (Del Barone et al., 2025; LOUIS G TORNATZKY & MITCHELL FLEISCHER, 1990; Pillai & Sivathanu, 2020)

In the technological components of the TOE framework, research findings consistently highlight perceived relative advantage and cost-effectiveness as key factors influencing the adoption of AI in human resource management. Studies indicate that organizations are motivated to implement AI when they recognize tangible benefits, including simpler recruitment processes, improved decision-making quality, scalability, and refined analytical abilities. Consequently, tools powered by artificial intelligence—like résumé screening systems, recruitment chatbots, and candidate ranking algorithms—have become more integrated into talent acquisition processes, resulting in improved efficiency over conventional human resources practices. (Chiu, 2017; Li, 2020a; Nguyen & Le, 2022a; Shakeel & Siddiqui, 2021a) The existing literature advises that these technological benefits could be neutralized by ongoing challenges as the concerns surrounding data security, privacy safeguards, algorithmic bias, and insufficient transparency continue to pose substantial obstacles that may damage trust and reduce the potential benefits of AI systems. The significance of these risks is particularly prominent in human resources contexts, as the decisions made have a direct impact on the performance of employees and the integrity of the organization.

The organizational aspect of the Technology-Organization-Environment (TOE) framework emphasizes the essential importance of change readiness, governance, and internal capabilities in successfully integrating AI into human resource practices. Substantial empirical research indicates that support from top management is a significant for both the adoption and ongoing utilization of AI technologies. The commitment of management plays a crucial role as they allow the allocation of resources, validation of the process of exploration, and minimizing resistance to change, particularly in areas of human resources that are traditional focus is on employees. (Pillai, 2021; Shakeel & Siddiqui, 2021a)

Organizational readiness includes the presence of technological infrastructure, the proficiency in digital and analytical skills, the development of data governance capabilities, and the level of process development. Research indicates that organizations with advanced HR digitalization and robust analytics capabilities are more inclined to move beyond the initial assessments towards the effective integration and routine application of AI tools. The size of an organization and its financial resources play a significant role in the acceptance and implementation of AI technologies. Organizations with plenty of resources are generally more equipped to manage the costs, risks, and uncertainties that come with deploying AI solutions. (Guillaume REVILLOD, 2024; Guillaume Revillod, 2024; Management & 2024, 2024; Pillai & Sivathanu, 2020; Science & 2025, 2025; society & 2025, 2025) Qualitative analysis shows that public sector and large organizational contexts, highlights the significance of managerial capabilities including strategic thinking, change management, and emotional intelligence. These capabilities serve as essential intermediaries between the implementation of AI and the overall objectives of the organization, which involve resilience, adaptability, and effectiveness. (Del Barone et al., 2025)

The environmental aspect of the TOE framework covers external factors that both facilitate and limit the adoption of AI in human resource management. Competitive pressure is frequently recognized as a significant factor, as organizations perceive investments in AI as crucial for maintaining talent pipelines, improving employer branding, and attaining strategic agility in unpredictable labour markets. (Pillai & Sivathanu, 2020; Shakeel & Siddiqui, 2021a) Vendor availability and external expertise further facilitate adoption, particularly for organizations lacking in-house AI capabilities. At the same time, dependence on external vendors may present difficulties concerning long-term dependability, governance control, and the strategic ownership of HR data and algorithms. Regulatory uncertainty and ethical concerns, particularly those related to fairness, accountability, and privacy, are often identified as significant barriers that hinder adoption, especially in public sector organizations. (Del Barone et al., 2025; G Revillod, 2025)

Recent empirical evidence suggests that integrating TOE with complementary models such as the Technology Acceptance Model (TAM) or Task–Technology Fit (TTF) substantially enhances explanatory power by capturing both organizational-level determinants and individual acceptance dynamics.

Process-oriented analyses further reveal that the influence of TOE dimensions varies across stages of adoption. The impact of environmental factors becomes more apparent in the early stages of evaluation, while the significance of organizational competencies and leadership support increases during the phases of ongoing use and institutional integration. This structured understanding highlights the evolving characteristics of AI integration within human resource practices.

Despite significant advancements, the existing literature highlights multiple crucial gaps, indicating that consistent findings are present concerning key determinants such as perceived technological advantage, top management support, organizational readiness, and competitive pressure. A rigorous modelling of the interrelationships among these factors is still lacking. There is a noteworthy lack of long-term studies that investigate the integration of AI into standard HR practices and the ways in which organizational change maintains value over time. Furthermore, the viewpoints of employees—encompassing aspects like perceived fairness, trust, and behavioural reactions have not been thoroughly examined, even though they are crucial for ethical governance and sustained effectiveness.

Overall, the TOE framework provides a robust and well-established foundation for analysing AI integration in HRM. Empirical evidence consistently highlights technological benefits, leadership support, organizational preparedness, and environmental pressures as key drivers, while ethical, privacy, and security concerns persist as enduring challenges. Advancing scholarship in this domain requires more comprehensive empirical frameworks that integrate micro-level acceptance perspectives with organizational performance outcomes and governance structures. Such an approach would move the literature beyond adoption-centric explanations toward a deeper understanding of responsible AI implementation and its sustained contribution to organizational effectiveness. (Best et al., 2017; Chiu, 2017; Li, 2020a; Nguyen & Le, 2022a; Tornatzky & Fleischer, 1990a)

2.6.2 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), originally proposed by (F. D. Davis, 1989a), is one of the most influential theoretical frameworks for explaining individuals' acceptance and use of information systems. Rooted in the Theory of Reasoned Action (TRA), The Technology Acceptance Model (TAM) suggests that a person's intention to utilize a technology, along with their actual usage, is mainly influenced by two cognitive beliefs: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). Perceived usefulness denotes the level to which a person believes that utilizing a system will improve job performance, whereas perceived ease of use indicates the extent to which the system is regarded as requiring little effort to use.

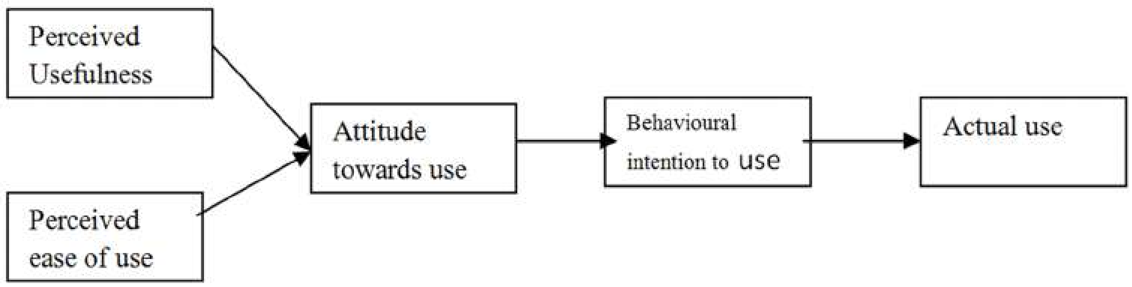

Figure 2-2: Technology Acceptance Model (TAM)

Source: (F. D. Davis, 1989a; Fred Davis, 1987)

Throughout its development, the Technology Acceptance Model has undergone rigorous validation and has been broadened to incorporate a variety of technological environments, such as enterprise systems, analytics, and digital platforms. The simplicity, ability to predict outcomes, and flexibility of this approach have rendered it especially effective for examining the acceptance of new technologies like artificial intelligence. (Filomena Buonocore et al., 2026; Khan et al., n.d.; Venkatesh et al., 2003a; Venkatesh & Davis, 2000a; Viswanath Venkatesh, 2003)

The application of the Technology Acceptance Model to artificial intelligence presents distinct differences from traditional information systems, primarily due to the autonomous, learning-oriented, and translucent nature of AI. In contrast to traditional IT systems, AI technologies frequently function as agents that support or make decisions, thereby introducing elements of uncertainty, ethical dilemmas, and trust-related challenges into the process of acceptance. (Brougham & Haar, 2018; Jarrahi, 2018) As a result, researchers believe that the perceived usefulness of AI extends beyond mere efficiency improvements to encompass aspects such as decision quality, predictive accuracy, and strategic value.

Research findings indicate that perceived usefulness is a key factor influencing the acceptance of AI, especially when AI systems clearly enhance task performance or eliminate mental load. (Davenport, 2018; J. Jha et al., 2023; Raisch & Krakowski, 2021a; Scott W. O'Connor, 2020) Nonetheless, the concept of perceived ease of use takes on greater complexity in the context of artificial intelligence, as users often engage not directly with algorithms, but with AI-integrated interfaces that are incorporated within organizational frameworks. This indirect interaction redirects attention from operational convenience to aspects such as interpretability, transparency, and clarity.

Human resource management represents a particularly sensitive domain for applying TAM, as HR decisions directly affect employees' careers, fairness perceptions, and organizational trust. AI-enabled HR tools are increasingly used in recruitment, performance appraisal, learning and development, and workforce analytics. In these contexts, TAM constructs have been widely employed to examine HR professionals' and managers' acceptance of AI systems.

Research utilizing the Technology Acceptance Model in Human Resource Management consistently identifies perceived usefulness as a significant predictor of acceptance, particularly when AI systems showcase their effectiveness in enhancing recruitment efficiency, decreasing time-to-hire, and facilitating data-driven decision-making. (Pillai & Sivathanu, 2020; Shakeel & Siddiqui, 2021a) Human resources professionals are more inclined to embrace AI tools when they perceive that these systems improve accuracy, consistency, and scalability in comparison to conventional HR methods.

The perception of ease of use plays a significant role in acceptance, although its impact is frequently moderated by factors such as training, system support, and previous technological experience. The presence of intricate interfaces, insufficient transparency, and restricted clarity could reduce the perceived ease of use, consequently hindering acceptance despite clear performance advantages. This issue is especially significant in AI-driven recruitment and performance evaluation systems, as the lack of transparency in algorithms can lead to resistance among HR professionals.

Given the limitations of the original TAM in capturing social, ethical, and organizational factors, several extensions have been proposed. TAM2 and UTAUT incorporate constructs such as social influence, facilitating conditions, and experience, which are particularly relevant in organizational HR settings where technology use may be mandated or norm-driven. (Venkatesh et al., 2003b; Venkatesh & Davis, 2000a)

In AI-enabled HR practices, researchers have further extended TAM by incorporating variables such as trust in AI, perceived fairness, risk perception, and ethical concerns. Empirical evidence suggests that trust acts as a critical mediator between perceived usefulness and behavioural intention, especially in high-stakes HR decisions such as candidate screening and promotion. (Raghavan et al., 2020; Venugopal et al., 2024) Similarly, perceptions of algorithmic bias and privacy risks can weaken acceptance even when systems are easy to use and functionally effective.

Recent studies that combine the Technology Acceptance Model with organizational-level frameworks, such as the Technology-Organization-Environment model, illustrate that while the Technology Acceptance Model accounts for individual acceptance, factors like organizational readiness and environmental pressures influence the successful implementation and institutionalization of accepted systems. (Chatterjee et al., 2021; Gangwar et al., 2015; M. PANIMALAR, 2013.; Shakeel & Siddiqui, 2021)

From a managerial perspective, the acceptance of AI by HR professionals and line managers is essential, yet it alone does not guarantee organizational effectiveness. Research based in the Technology Acceptance Model indicates that when AI systems are regarded as both beneficial and user-friendly, there is a greater likelihood of their integration into HR processes. This integration can result in enhanced operational efficiency, consistent decision-making, and improved workforce planning. However, literature also highlights that acceptance does not automatically translate into positive organizational outcomes. Overreliance on AI systems without adequate human intervention may undermine employee trust and procedural justice, negatively affecting engagement and performance. Therefore, the relationship between TAM constructs and organizational effectiveness is often indirect, mediated by implementation quality, governance mechanisms, and human–AI collaboration practices. (Jarrahi, 2018; Raisch & Krakowski, 2021a)

Despite its widespread use, TAM has been critiqued for its narrow focus on cognitive beliefs and its limited consideration of contextual and ethical dimensions. In AI–HR contexts, TAM alone cannot adequately explain resistance arising from moral concerns, professional identity threats, or institutional constraints. Moreover, most TAM-based studies adopt cross-sectional designs, limiting insights into how acceptance evolves over time as AI systems learn and change. Scholars therefore advocate for integrative approaches that combine TAM with frameworks such as TOE or Task–Technology Fit (TTF) to capture both individual acceptance and organizational implementation dynamics. (Abbas et al., 2018a; Basu et al., 2025)

In the context of the present thesis, TAM provides a robust theoretical foundation for examining acceptance of AI among HR professionals and managers. Constructs such as perceived usefulness and perceived ease of use are essential for understanding attitudes toward AI-enabled HR tools. However, to comprehensively explain implementation and organizational effectiveness, TAM is best applied in conjunction with TOE, enabling a multilevel analysis that links individual acceptance with organizational and environmental conditions.

2.6.3 Unified Theory of Acceptance and Use of Technology (UTAUT) Model

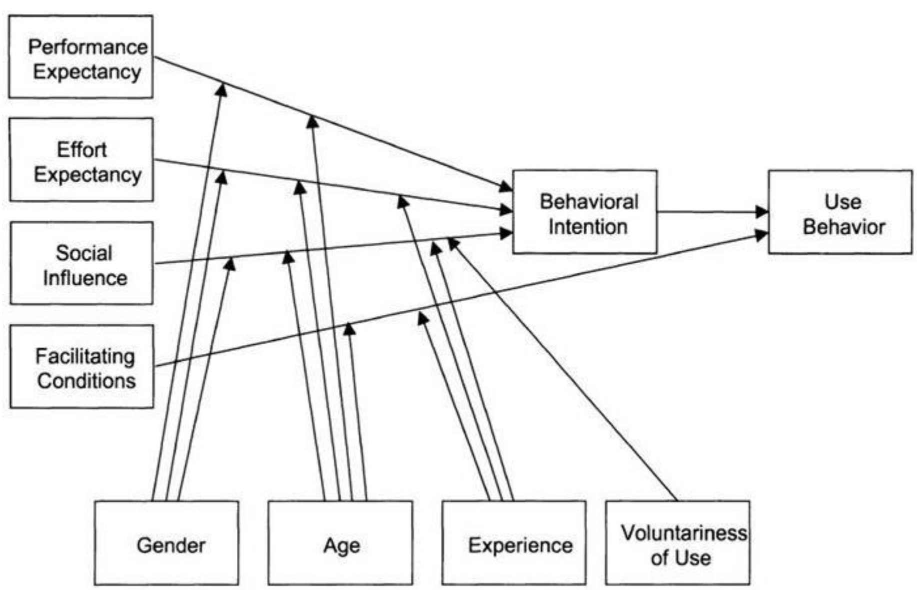

Figure 2-3: Unified Theory of Acceptance and Use of Technology (UTAUT)

Source: (Venkatesh et al., 2003b)

The Unified Theory of Acceptance and Use of Technology (UTAUT) was introduced to integrate previous technology acceptance models into a cohesive and streamlined framework that effectively discusses technology adoption and usage behaviours within organizations. UTAUT integrates constructs from eight prominent theories, including the Technology Acceptance Model (TAM), Theory of Planned Behaviour (TPB), and Innovation Diffusion Theory (IDT). The model suggests that behavioural intention and actual use of technology are primarily influenced by four core determinants: Performance Expectancy**,** Effort Expectancy**,** Social Influence**,** and Facilitating Conditions, with effects moderated by age, gender, experience, and voluntariness of use. (Venkatesh et al., 2003a)(Venkatesh et al., 2003).

due to its strong explanatory capabilities and emphasis on organization, UTAUT has found extensive application in research exploring organization technologies, digital platforms, analytics systems, and, more recently, applications of artificial intelligence. Applying UTAUT to artificial intelligence calls for an examination of the unique features of AI, such as its autonomy, learning ability, transparency, and its capacity to impact critical decision-making processes. In the field of artificial intelligence, the concept of performance expectancy encompasses not only enhancements in productivity but also advancements in decision-making quality, predictive accuracy, and strategic understanding. Research findings suggest that the perceived benefits in performance are the most significant factor influencing the intention to adopt AI-enabled systems within various types of organizations. (Raisch & Krakowski, 2021a)

Effort expectancy, traditionally associated with ease of use, takes on a broader meaning in AI-based systems. Users may not interact directly with algorithms; instead, effort relates to system interpretability, quality of interfaces, training adequacy, and cognitive burden associated with understanding AI outputs. Studies suggest that when AI systems are perceived as complex or opaque, effort expectancy negatively affects acceptance even when performance benefits are evident.

Social influence is particularly salient in organizational HR contexts where technology use may be shaped by managerial expectations, professional norms, and institutional pressures. Acceptance of AI in HR is often influenced by senior leadership endorsement, peer usage, and perceived rightfulness of algorithm-supported decisions.

Facilitating conditions reflect the degree to which organizational and technical infrastructure supports AI use. In AI-HR contexts, this includes availability of quality data, analytics expertise, vendor support, training programs, and governance mechanisms. Empirical evidence consistently shows that facilitating conditions are more predictive of actual use and sustained implementation than of initial intention.

Human resource management represents a socially embedded and ethically sensitive domain, making UTAUT particularly suitable for examining AI acceptance. AI-enabled HR practices such as recruitment automation, performance analytics, learning personalization, and attrition prediction require acceptance not only by HR professionals but also by line managers and employees affected by data-driven decisions.

Studies applying UTAUT in HR-related technology adoption demonstrate that performance expectancy significantly influences acceptance when AI systems reduce time-to-hire, enhance candidate quality, or support evidence-based workforce decisions. In contrast to administrative HR technologies, AI systems employed in analytical and judgment-based HR practices frequently encounter resistance due to concerns regarding fairness, accountability, and the potential loss of human autonomy.

Social influence plays a stronger role in HR AI adoption than in many other organizational technologies. Leadership support, organizational communication, and alignment with HR professional values significantly shape acceptance, particularly in collectivist and hierarchical organizational cultures.

Facilitating conditions are critical in HR contexts due to the dependence of AI systems on reliable employee data and HRIS integration. Research indicates that insufficient infrastructure or weak data governance can hinder effective implementation even when users exhibit positive intentions.

In developing economies like India, UTAUT offers a significant perspective for understanding the contextual factors that affect AI adoption. Indian organizations frequently demonstrate significant diversity within their workforce, different levels of digital advancement, and pronounced hierarchical frameworks for decision-making. The characteristics enhance the significance of social influence and enabling conditions in determining the acceptance of AI. Research findings from India and similar settings indicate that support from management and the organization significantly influence the intention to adopt AI-driven HR systems. The presence of limited analytics skills, decentralized data systems, and resource constraints highlights the significance of creating favourable circumstances for influencing actual usage. Furthermore, advancements in regulations concerning employee data protection and the ethical use of artificial intelligence create new contextual pressures that affect the processes of acceptance and implementation. (Raza et al., 2021a; Tan, 2013; Venkatesh et al., n.d., 2003a; Venkatesh & Davis, 2000a; Venkateswaran et al., 2019)

From an organizational effectiveness perspective, UTAUT explains the micro-level mechanisms through which AI acceptance translates into use. When HR professionals and managers perceive AI systems as performance-enhancing, supported by adequate infrastructure, and socially legitimate, they are more likely to integrate these systems into routine HR workflows. This integration can improve operational efficiency, decision consistency, and strategic workforce planning.

Nevertheless, existing literature advises that a strong behavioural intention by itself does not ensure favourable outcomes for organizations. Insufficient governance, excessive automation, or a disconnect between AI results and the core values of the organization may weaken trust and reduce employee engagement, ultimately leading to a decline in overall effectiveness. Consequently, UTAUT provides insight into the reasons behind the utilization of AI systems, whereas complementary frameworks, like TOE, clarify the extent to which the use of AI contributes to sustainable organizational value. Despite its strengths, UTAUT has limitations when applied to AI in HR practices. The model does not explicitly account for ethical considerations, perceived fairness, or algorithmic transparency factors that are critical in HR decision-making. Additionally, UTAUT assumes relative stability in technology features, whereas AI systems evolve dynamically over time. Scholars therefore recommend extending UTAUT by incorporating constructs such as trust in AI, perceived risk, and ethical concern, or integrating it with organizational-level frameworks like TOE to capture both acceptance and implementation dynamics.

For the present thesis, UTAUT provides a robust theoretical foundation for examining individual-level acceptance and use of AI among HR professionals and managers. Constructs such as performance expectancy, effort expectancy, social influence, and facilitating conditions are particularly relevant for understanding AI adoption in HR practices. When integrated with

TOE, UTAUT enables a multilevel analysis that links individual acceptance to organizational readiness, environmental pressures, and ultimately organizational effectiveness.

2.6.4 Diffusion of Innovation (DOI) Theory

The Diffusion of Innovation (DOI) theory, proposed by Rogers 1962 as shown in figure 2-1, explains how, why, and at what rate new ideas and technologies spread within a social system. DOI conceptualizes diffusion as a process through which an innovation is communicated over time among members of a social system. The theory identifies five key attributes of an innovation—relative advantage, compatibility, complexity, trialability, and observability—that significantly influence the rate and extent of adoption known as Perceived attributes of Innovations. (Rogers, 1962)

In contrast to models that focus on individual acceptance, the Diffusion of Innovations framework offers a process-oriented and social viewpoint regarding the adoption of technology. This is especially significant for organizational innovations that demand collective acceptance, behavioural change, and institutionalization. As a result, DOI has been extensively utilized to examine the adoption and implementation of information technologies, enterprise systems, and emerging digital innovations, such as artificial intelligence. (EVERETT M. ROGERS, 2014)

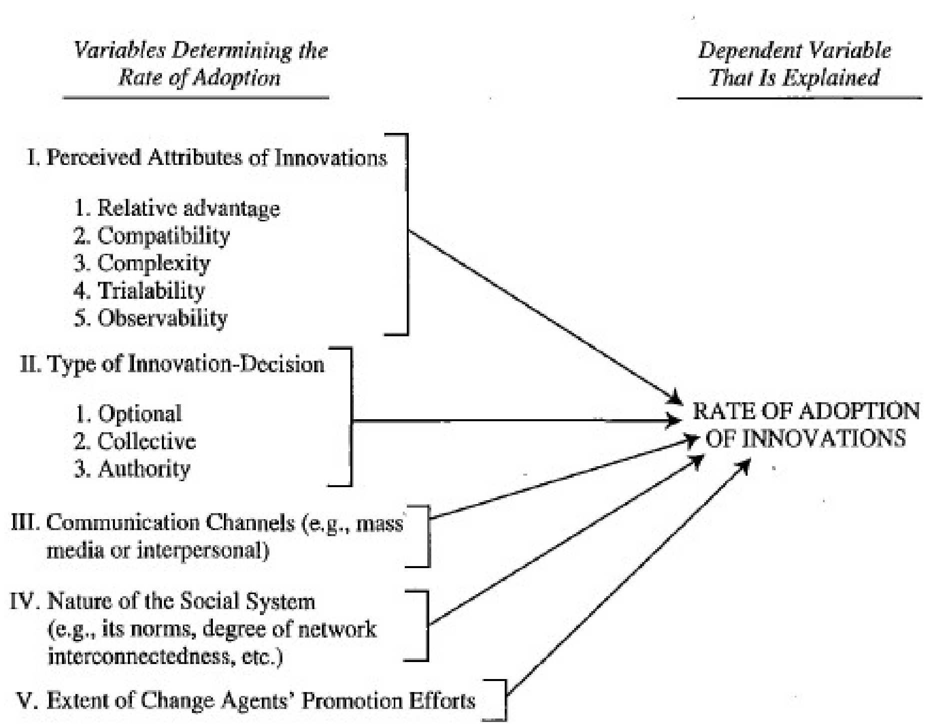

Figure 2-4 : Diffusion of Innovation by Everett M Rogers

Source: (EVERETT M. ROGERS, 2014; Rogers, 1962)

The integration of AI into organizations is significantly influenced by the perceived characteristics of AI technologies. The concept of relative advantage refers to the degree to which AI is viewed as more effective than current HR practices, particularly in enhancing recruitment efficiency, predictive accuracy, or consistency in decision-making. Research findings consistently indicate that relative advantage serves as a key factor influencing the adoption of AI in human resource management (Pillai & Sivathanu, 2020)

Compatibility refers to the degree to which AI aligns with existing organizational values, HR practices, workflows, and ethical norms. In HR contexts, compatibility is particularly critical because AI systems may challenge long-established people-centric practices, professional judgment, and fairness expectations. Research indicates that differences between AI tools and organizational culture can significantly slow implementation, even when technological benefits are evidently visible. Complexity, refers to the perceived challenges associated with understanding and using innovation, serves as a significant obstacle in the diffusion of artificial intelligence. AI systems are frequently perceived as transparent or "black-box" technologies, which could decrease acceptance among HR professionals and employees. The perception of high complexity may foster suspicion and resistance, especially in critical HR decision-making situations. Trialability refers to the extent to which AI systems can be experimented with on a limited basis before full-scale adoption. Organizations that experiment with AI tools in recruitment or HR analytics tend to progress toward wider adoption, as the ability to trial these tools diminishes uncertainty and perceived risk. Observability reflects the visibility of AI's benefits within and across organizations. The presence of success stories, comparative analysis with competitors, and observable enhancements in performance serve to expedite the adoption of AI by validating its application and reducing uncertainty.

The DOI theory highlights that the process of adoption develops in distinct stages, which generally encompass knowledge, influence, decision, implementation, and confirmation. This structured approach offers important perspectives on the development that organizations experience as they transition from initial awareness to ongoing implementation of AI-enabled HR practices. In the knowledge stage, organizations gain awareness of AI applications through various channels such as vendors, industry forums, or peer organizations. The persuasion stage encompasses the formation of attitudes, during which HR leaders evaluate the perceived benefits, potential risks, and ethical considerations involved. The decision-making phase finishes in either the adoption or rejection of a proposal, frequently initiated through pilot projects. The implementation phase encompasses the incorporation of AI into human resources systems and workflows, whereas the confirmation phase assesses whether the use of AI will be sustained, broadened, or terminated based on the outcomes observed.

Empirical evidence suggests that many organizations stall between the decision and implementation stages due to organizational readiness gaps, data limitations, or resistance from HR professionals. DOI thus helps explain why AI diffusion in HR is often uneven and incremental rather than rapid and uniform. DOI highlights the role of communication channels and social systems in shaping adoption. In organizational settings, diffusion is influenced by leadership communication, professional networks, HR communities of practice, and institutional norms. Organizations that are early adopters, particularly those that are large, resource-rich, or focused on technology, play a vital role in justifying the use of AI in human resources by showcasing its feasibility and advantages.

In human resources applications, the process of diffusion is influenced by the professional identity of individuals and the ethical considerations that accompany their roles. Human resource professionals might exhibit reluctance towards innovations that could challenge their decision-making or jeopardize the trust established with employees. Consequently, the integration of AI in human resources is influenced not solely by technological characteristics but also by societal acceptance and alignment with established norms.

From an organizational effectiveness perspective, DOI suggests that the benefits of AI-enabled HR practices are realized progressively as the innovation diffuses and becomes institutionalized. Early stages may yield limited gains, while sustained diffusion and routinization can lead to improvements in efficiency, decision quality, and strategic workforce management.

In developing economies like India, DOI offers a valuable perspective for analyzing diverse adoption patterns. There is significant variation among Indian organizations regarding their digital maturity, human resources capabilities, and availability of skilled talent. Consequently, the diffusion of AI is frequently directed by multinational corporations and major domestic firms, whereas small and medium enterprises tend to adopt a more cautious approach. The diffusion trajectories are further influenced by cultural factors, hierarchical decision-making processes, and the presence of regulatory uncertainty. The influence of observability through industry leaders and trialability via vendor-led pilots plays a significant role in the acceleration of AI diffusion within HR practices in India. DOI complements TOE by clarifying the ways in which external visibility and social learning impact adoption decisions.

Despite its strengths, DOI has limitations when applied to AI in HR practices. The theory does not explicitly address power dynamics, ethical risks, or employee perceptions, which are critical in HR contexts. Additionally, DOI focuses on adoption and diffusion but offers limited insight into micro-level acceptance or post-adoption governance challenges.

Researchers therefore recommend integrating DOI with models such as TAM, UTAUT, or TOE to capture individual acceptance, organizational readiness, and environmental pressures alongside diffusion processes.

For the present thesis, DOI offers a valuable process-oriented lens to examine how AI-enabled HR practices spread within organizations over time. By focusing on innovation attributes and adoption stages, DOI helps explain variation in acceptance, implementation, and sustained use of AI in HR. When combined with TOE and acceptance models, DOI strengthens the theoretical foundation for analyzing how AI adoption translates into organizational effectiveness.

2.7 Organizational Effectiveness

Organizational effectiveness has been a fundamental concept in the fields of management and organizational studies, illustrating an organization's capacity to meet its goals while ensuring internal stability and the ability to adapt to changes in the environment. Initial studies defined effectiveness mainly through the perspective of achieving goals and enhancing productivity. In contrast, modern research highlights that effectiveness is a complex and evolving concept, especially within organizations that prioritize knowledge and human interaction. Researchers suggest that the effectiveness of an organization cannot be fully understood through financial or operational metrics alone, as these indicators do not encompass the human, social, and adaptive aspects that are crucial for enduring sustainability. This viewpoint holds particular significance within the realm of human resource management, as employee attitudes, motivation, autonomy, and commitment have a direct impact on organizational results. (Mahoney & Weitzel, 1969; *What Is Organizational Effectiveness? - SixSigma.Us*, n.d.)

The literature identifies multiple theoretical approaches to understanding organizational effectiveness. The goal attainment approach views effectiveness as the extent to which an organization achieves predefined objectives. While useful, this approach has been criticized for overlooking internal processes and employee well-being. The systems approach conceptualizes organizations as open systems interacting with their environments, emphasizing adaptability, resource acquisition, and internal integration. This approach highlights the importance of coordination, communication, and flexibility—dimensions that become increasingly critical with the introduction of advanced technologies such as artificial intelligence (AI). The human relations approach emphasizes employee satisfaction, morale, and motivation as key indicators of effectiveness. From this perspective, organizations that foster autonomy, participation, and value congruence are more likely to achieve sustained performance. This approach provides a strong theoretical foundation for examining effectiveness outcomes of AI-enabled HR practices, as such technologies directly influence employee experiences and perceptions of fairness and control. (Daft, 2016; Kim S. Cameron, 1986; Quinn & Rohrbaugh, 1983)

Within the Indian organizational and HRM literature, D. M. Pestonjee's framework offers a comprehensive and people-oriented conceptualization of organizational effectiveness. Dr. Pestonjee conceptualizes effectiveness as a function of both organizational processes and employee-related outcomes, emphasizing that long-term effectiveness emerges when organizations balance productivity with human satisfaction and growth. Pestonjee's framework includes dimensions such as goal clarity, planning and foresight, communication quality, autonomy, initiative, commitment, value congruence, and organizational pride. Unlike purely economic models, this framework captures the psychological and social dimensions of effectiveness, making it particularly suitable for studies examining technology-driven transformation in HR practices. Considering the impact of AI adoption in HR on decision-making, control mechanisms, and the dynamics between employees and organizations, Pestonjee's model serves as a valuable framework for evaluating whether the implementation of AI contributes positively or negatively to organizational effectiveness. (Pareek & Rao, 2015; Pestonjee, 1988a)

Existing research consistently shows that HR practices are crucial in influencing organizational effectiveness. Research on strategic human resource management indicates that effective HR practices improve employee capabilities, motivation, and opportunities for performance, which in turn supports organizational performance and adaptability. Human resource systems that foster autonomy, encourage participation, and facilitate skill development are linked to increased employee engagement, commitment, and discretionary effort. On the other hand, HR practices that are viewed as controlling, unclear, or unjust can diminish morale and undermine the sense of belonging within the organization. (Becker, 1998; management & 1997, 1997)The effectiveness of HR practices is influenced not only by their technical efficiency but also by the way employees perceive and experience them. This understanding is essential when analyzing AI-enabled HR practices, as AI systems can enhance efficiency while also raising concerns about surveillance, bias, or the erosion of human judgment. Recent literature on AI in HRM suggests that AI-enabled HR practices have the potential to enhance organizational effectiveness by improving process efficiency, decision accuracy, and strategic workforce planning. AI-driven recruitment tools, for example, can reduce time-to-hire and enhance candidate matching, while predictive analytics can support proactive talent management and retention strategies. Nonetheless, empirical research suggests the adoption of AI does not naturally result in enhanced effectiveness. The achievement of effective outcomes is dependent upon the acceptance, implementation, and governance of AI within organizations. Poorly executed AI systems may reduce trust, diminish perceived autonomy, and adversely impact employee morale, ultimately compromising organizational effectiveness even in the face of efficiency improvements. Researchers suggests that AI improves effectiveness by supporting human judgment instead of replacing it. This viewpoint is consistent with theories of human relations and systems effectiveness, highlighting the significance of employee acceptance and the ethical execution of practices. (W. DeLone et al., 2003; W. H. DeLone & McLean, 1992; Raisch & Krakowski, 2021b) Constructs such as autonomy, initiative, commitment, and value congruence core dimensions in Pestonjee's framework are strongly associated with sustained organizational performance. AI-enabled HR practices influence these dimensions in complex ways. On one hand, automation of routine tasks may increase autonomy and allow employees to focus on higher-value activities. On the other hand, algorithmic decision-making may reduce perceived control and increase feelings of surveillance. The net effect on organizational effectiveness therefore depends on employees' perceptions of fairness, transparency, and alignment with organizational values. (Pestonjee, 1988a)

Organizational effectiveness is commonly understood as an organization's ability to achieve desired outcomes such as productivity, adaptability, employee satisfaction, and sustained performance. The literature suggests that AI-enabled HR practices can enhance organizational effectiveness by improving talent acquisition accuracy, optimizing workforce deployment, and supporting proactive decision-making. (Samuel Fosso Wamba et al., 2021)

From a resource-based perspective, the integration of AI capabilities within HR systems can function as strategic assets when they are aligned with human expertise and established organizational practices. (Barney, 1991). Nonetheless, research indicates that the implementation of AI does not naturally lead to enhanced effectiveness. In organizations within India, the effectiveness of outcomes frequently depends on the alignment of AI initiatives with the prevailing organizational culture and the intentions of leadership. (Raisch & Krakowski, 2021a) This underscores the importance of investigating the mediating and moderating factors that influence the relationship between AI and effectiveness.

Research indicates that organizations that engage employees in AI-related change initiatives and offer transparent communication and training tend to experience more favourable effectiveness outcomes. The literature on technology adoption emphasizes that the effectiveness of organizations during periods of technological change relies on the harmonious alignment of technology, organizational structure, and personnel. Change initiatives that focus solely on technical deployment while neglecting human and cultural aspects frequently lead to superficial adoption and minimal performance improvements. Within the framework of AI integration in human resources, organizational effectiveness is most accurately perceived as a long-term result that arises following the phases of acceptance and implementation. The effectiveness of initiatives is enhanced by ongoing learning, flexible governance, and the alignment of AI projects with the overarching objectives of the organization. The literature reviewed indicates that organizational effectiveness is a complex construct influenced by human resource practices, employee experiences, and the adaptability of the organization. The potential of AI-enabled HR practices to improve effectiveness is substantial; however, their impact is influenced by factors such as acceptance, ethical governance, and the quality of implementation. (Hermawan & Suharnomo, 2020; Information & Information, 2014a; Kukafka et al., 2003a; Mahoney & Weitzel, 1969)

By adopting the D. M. Pestonjee framework, the present study contributes to the literature by offering a people-centric assessment of organizational effectiveness in the context of AI adoption in HR practices. This approach responds directly to identified gaps and provides a robust theoretical foundation for examining the relationship between AI acceptance, implementation, and organizational effectiveness.

2.8 Artificial Intelligence in HR Practices and Organizational Effectiveness

The literature on artificial intelligence (AI) in human resource (HR) practices and the literature on organizational effectiveness have largely evolved as parallel yet interdependent research streams. While AI–HR research focuses on technological adoption, efficiency, and decision enhancement, organizational effectiveness literature emphasizes goal attainment, employee commitment, adaptability, and long-term sustainability. A comparative examination of these two bodies of literature reveals both convergence and tension, particularly in relation to human outcomes, governance, and sustained performance.

The literature on AI in HR practices predominantly conceptualizes AI as a strategic enabler that enhances efficiency, accuracy, and scalability of HR functions. Empirical studies consistently report that AI improves recruitment speed, candidate matching, workforce analytics, and administrative efficiency. (Pillai & Sivathanu, 2020; Prikshat et al., 2021a; Sivathanu & Pillai, 2018) AI-based tools such as résumé screening algorithms, chatbots, and predictive analytics are shown to reduce time-to-hire and support data-driven decision-making. Recent studies indicate that the adoption of AI in HR goes beyond just technical efficiency, including significant organizational and human implications. Researchers have observed increasing concerns regarding algorithmic bias, transparency, data privacy, and the diminishing role of human judgment in human resources decisions. (Jöhnk et al., 2021a; Raghavan et al., 2020) Consequently, acceptance, trust, and ethical governance have surfaced as essential moderators within the AI–HR literature.

Organizational effectiveness literature adopts a multidimensional perspective, emphasizing not only performance outcomes but also internal health and adaptability. Researchers argue that effectiveness encompasses goal achievement, coordination, employee satisfaction, autonomy, commitment, and alignment between individual and organizational values. (Daft, 2016; Pestonjee, 1988a) Human-centric models, particularly Pestonjee's framework, stress that long-term effectiveness depends on employee initiative, morale, and value congruence rather than short-term efficiency alone. This stream of literature consistently demonstrates that organizational effectiveness is shaped by HR practices that foster trust, participation, and discretionary effort. Empirical evidence suggests that AI-enabled HR practices contribute to effectiveness by streamlining operations and enabling faster decision cycles. (Meet Bhatt & Dr. Priyanka Shah, 2025a; Samuel Fosso Wamba et al., 2021) However, effectiveness literature suggests that efficiency gains must translate into meaningful organizational outcomes rather than isolated process improvements.

The application of AI in human resources is often regarded as a means to improve the quality of decision-making by utilizing predictive analytics and insights derived from data. The literature on organizational effectiveness underscores the significance of making informed decisions and ensuring strategic alignment. Comparative studies indicate that the effectiveness of organizations can be enhanced through the alignment of HR decisions with strategic objectives, particularly when there is human oversight involved. (Raisch & Krakowski, 2021a) In the absence of alignment, decisions made by AI could weaken trust and diminish effectiveness, even when they are technically accurate.

The literature on AI in human resources increasingly links the adoption of AI to enhanced organizational flexibility and adaptability, especially in dynamic labour markets. Research on organizational effectiveness also recognizes adaptability as a fundamental measure of success in changing environments. The convergence is found in the understanding that workforce analytics powered by AI improve adaptability through proactive talent planning and scenario analysis. (Prikshat et al., 2021a) The effectiveness of outcomes is dependent upon the extent to which organizations incorporate AI insights into their adaptive HR policies. A significant difference can be observed in how employee experience is addressed. Although the literature on organizational effectiveness highlights the importance of employee morale, autonomy, and commitment as crucial for achieving effectiveness, early studies on AI in human resources frequently overlooked these aspects, prioritizing efficiency metrics instead. Recent research has started to address this issue by exploring the impact of AI on employee trust, perceived fairness, and psychological safety. (Brougham & Haar, 2018; Jarrahi, 2018; Meet Bhatt & Dr. Priyanka Shah, 2024a) Comparative analysis reveals that the effectiveness of AI is significantly heightened when it bolsters employee well-being, rather than detracts from it.

Theories of organizational effectiveness highlight the importance of autonomy and initiative as key factors influencing commitment and performance. On the other hand, the literature on AI in human resources frequently shows AI as a tool for control that standardizes and oversees HR decision-making processes. This tension is apparent in research indicating that excessive algorithmic control may reduce perceived autonomy and heighten resistance, which in turn adversely impacts effectiveness outcomes. (Raghavan et al., 2020) Consequently, the two bodies of literature differ in their underlying assumptions regarding control and privacy. Research in the intersection of AI and human resources frequently assesses success by examining immediate performance metrics, including efficiency, precision, and financial savings. The literature on organizational effectiveness highlights the importance of long-term sustainability, alignment of values, and fostering a sense of pride within the organization. Comparative evidence indicates that AI-driven HR practices achieve sustainable effectiveness primarily when integrated within ethical governance frameworks and bolstered by ongoing learning. (Del Barone et al., 2025) Immediate benefits lacking human integration could undermine long-term efficacy. Recent integrative studies support a perspective of complementarity between humans and AI, suggesting that AI improves organizational effectiveness by augmenting human capabilities instead of replacing human judgment. (Bhatt & Shah, 2023; Raisch & Krakowski, 2021a) This viewpoint connects AI–HR practices with human relations and systems methodologies to enhance effectiveness.

Frameworks such as TOE, TAM, and UTAUT further suggest that acceptance and implementation mediate the relationship between AI adoption and effectiveness outcomes. Organizational effectiveness, therefore, emerges as a consequential outcome, not a direct result, of AI adoption in HR practices. The comparative literature demonstrates that while AI in HR practices holds significant potential to enhance organizational effectiveness, this potential is realized only under specific conditions. Effectiveness outcomes depend on acceptance, ethical implementation, leadership support, and alignment with human values. By integrating AI–HR literature with organizational effectiveness theory, particularly the Pestonjee framework, the present study addresses a critical gap and offers a holistic, people-centric understanding of how AI-enabled HR practices influence organizational effectiveness.

Literature Review Conclusion

Recent global study has expanded the understanding of AI in HR beyond acceptance and behavioural intention to implementation and organisational value creation. AI-enabled HR practices are increasingly seen as socio-technical systems, where outcomes depend on employee perceptions, leadership support and organisational readiness as well as technological capabilities (Jarrahi et al., 2023; Rai et al., 2024; Tarafdar et al., 2023; Stahl et al., 2024). In the context of HR, studies focus on the need for AI-powered functions such as recruitment, performance analytics, and people analytics to be accepted by employees and performed effectively to generate value (Budhwar et al., 2023; Minbaeva, 2023).

Further emerging evidence suggests that acceptance alone is not sufficient and implementation – through integration and routinisation of AI in HR processes – is the key driver of organisational effectiveness (Wamba et al., 2023; Mikalef et al., 2024; Venkatesh et al., 2023; Dwivedi et al., 2023). Meanwhile, models such as TOE and DOI stress the importance of contextual readiness and post-adoption assimilation, particularly in accounting for industry-specific differences in AI results (Baker, 2024; Oliveira & Martins, 2023; Chowdhury et al., 2023; Zhu et al., 2023).

Despite these advancements, there is a lack of research on the acceptance and implementation of AI in HR practices and the combined effect of these in organisational effectiveness across industries, especially in emerging economies. To fill this gap, the present study extends the recent global literature by developing a process-oriented framework connecting perception, behavioural intention, acceptance, implementation, and organisational effectiveness. It is argued that implementation, not acceptance, is the crucial route to achieving AI-driven HR outcomes.

2.9 Research Gap

The rapid diffusion of artificial intelligence (AI) across organizational functions has generated a substantial body of literature examining its adoption and use. Within the domain of human resource (HR) practices, existing studies have predominantly focused on identifying adoption determinants, such as perceived usefulness, perceived ease of use, technological readiness, and organizational support. While this stream of research has contributed valuable insights into why organizations and individuals consider adopting AI-enabled HR systems, several critical conceptual, empirical, and contextual gaps remain unresolved.

A notable limitation in the current body of research is the focus on initial adoption or intention to utilize AI, with relatively fewer investigations examining how AI becomes integrated into standard HR practices and becomes established over time. Recent reviews indicate that although the factors influencing adoption are thoroughly documented, the shift from acceptance to sustained implementation—and its connection to organizational effectiveness has not been sufficiently examined. (Basu et al., 2025; Venugopal et al., 2024; Venumuddala & Kamath, 2020)

Many studies look at adoption of artificial intelligence as a single occurrence, failing to recognize it as a process that involves the evolution of organizational routines, governance structures, and employee practices as AI systems develop over time. As a result, the ways in which AI-enabled HR practices foster long-term organizational effectiveness remain studied and lack empirical investigation.

A significant gap exists in the fragmented strategy for acceptance, implementation, and organizational outcomes. Models of acceptance, including the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), are commonly utilized in order to clarify behavioral intentions and usage patterns. In contrast, frameworks at the organizational level, such as the Technology–Organization–Environment (TOE) model, concentrate on the conditions necessary for adoption. Nevertheless, current studies infrequently combine these viewpoints into an integrated explanatory framework that encompasses: Employee's willingness to accept AI in HR practices, perceived ease of use and usefulness as components of technology readiness, organizational and environmental readiness for implementation, and the resultant impact on organizational effectiveness.

Although TAM, UTAUT, and TOE have been widely utilized in distinct ways, there is a notable lack of comprehensive empirical research that integrates all three frameworks to investigate perceived acceptance and implementation of AI in HR practices at the same time, especially from the viewpoint of employees across various industries. This conceptual division restricts a comprehensive understanding of the organizational implications of AI.

Although organizational effectiveness frequently appears as a result of digital transformation, numerous studies on AI and HR tend to define effectiveness in a limited manner, focusing primarily on indicators such as productivity, efficiency, or cost reduction. Conversely, the literature on organizational effectiveness highlights that effectiveness—particularly within HR contexts—should encompass employee experience, trust, legitimacy, autonomy, and procedural justice. (Kellogg et al., 2020; Pestonjee, 1988a)

Recent studies indicate that the productivity benefits generated by AI can be enhanced or reduced based on employees' views regarding fairness, transparency, and ethical governance. (W. DeLone et al., 2003; Kellogg et al., 2020) Nonetheless, there is a scarcity of empirical research that directly connects the acceptance and implementation of AI in HR practices to comprehensive, people-focused indicators of organizational effectiveness, resulting in a notable conceptual gap.

Recent HR–AI literature increasingly recognizes fairness, bias mitigation, transparency, and accountability as capabilities that condition acceptance and implementations, rather than as secondary ethical concerns. ((M.M. Abdullah Al Mamun Sony a b, 2025; Raghavan et al., 2020; Sony, Nupur, et al., 2025); Raghavan et al., 2020). Despite this recognition, the governance capabilities within HR settings remains developing and inconsistent.

Most studies discuss ethical risks at a conceptual level, without empirically examining how governance-related perceptions influence employee acceptance, perceived implementation quality, and organizational effectiveness. This gap is particularly salient in HR practices, where algorithmic decisions directly affect careers, pay, and job security.

Existing research on AI in HR often provides a broad overview across organizations, with limited differentiation across industries. However, HR functions, regulatory environments, and workforce characteristics vary significantly across sectors. The lack of industry-specific analysis constrains understanding of how AI-enabled HR practices should be tailored to different organizational contexts.

Furthermore, much of the available empirical evidence is concentrated in technology-intensive industries and large-scale organizations, while sectors such as manufacturing, services, public sector organizations, and micro, small, and medium enterprises (MSMEs) remain unexplored.

Although there are significant evidence at the industry level suggesting a swift integration of AI within Indian organizations, there is a notable shortage of peer-reviewed empirical research focused on organizational dynamics in the Indian HR landscape. The existing body of research predominantly focuses on metropolitan technology hubs and large multinational corporations or Global Capability Centres (GCCs), while there is a noticeable lack of representation from public sector organizations, micro, small, and medium enterprises (MSMEs), and non-IT industries. (Deloitte's Global Human Capital Trends Workday Differentiators, 2024; Nasscom Technology & Leadership Forum 2024, 2024)

Moreover, there exists a notable lack of quantitative research at the employee level that examines the acceptance and implementation of AI in human resource practices within organizations in India. The current findings are limited by this contextual gap, emphasizing the need for research that is both empirically based on circumstances. A significant portion of AI research continues to be founded in the technical realm, emphasizing algorithm development, system architecture, and computational efficiency. There has been relatively limited focus on the acceptance by individuals, their behavioural responses, and the implementation of AI in organizational HR practices. This imbalance highlights the need for management-focused research that shifts attention from "how AI is built" to "how AI is accepted, implemented, and experienced" by employees and HR professionals.

In summary, the literature reveals a multi-layered research gap encompassing conceptual fragmentation, limited process-oriented analysis, underdeveloped effectiveness measurement, and contextual insufficiencies—particularly within the Indian organizational landscape. An integrated, empirical investigation is essential that combines TAM, UTAUT, and TOE to comprehensively examine AI acceptance and implementation. Examines the journey from acceptance to perceived implementation, assesses organizational effectiveness through human-centred, multidimensional frameworks, and offers industry- and context-specific evidence from organizations in India.

By addressing these gaps, we can enhance our theoretical understanding of AI in HR practices while providing practical insights for organizations aiming to adopt AI in a responsible and effective manner. This approach will ultimately improve both organizational performance and the employee experience.

Table 2-1: The conceptual gaps identified through a comparative review of literature on Artificial Intelligence (AI) in HR practices and organizational effectiveness.

Thematic Area	***Key Insights from Existing Literature***	***Limitations / Gaps Identified***	***How the Present Study Addresses the Gap***
Focus of AI in HR Practices	The study of AI primarily focuses on its role in enhancing efficiency, accuracy, speed, and scalability within HR functions. (Pillai & Sivathanu, 2020; Prikshat et al., 2021a)	The focus is placed on technical and operational results, while there is a lack of consideration for wider organizational and human effects.	This study explores the role of AI in human resources, moving beyond just efficiency by connecting its acceptance and implementation with multiple dimensions of organizational effectiveness.
Conceptualization of Organizational Effectiveness	Organizational effectiveness is widely recognized as multidimensional variable which includes goal achievement, adaptability, employee morale, autonomy, and commitment (Pestonjee, 1988a)	Studies on AI in human resources rarely embrace comprehensive or human-centred frameworks for effectiveness; instead, effectiveness is frequently assessed in a restricted manner through specific performance indicators.	The study uses the D. M. Pestonjee's framework to integrate human-centric and long-term effectiveness outcomes for AI-enabled HR practices.
Link between AI Adoption and Effectiveness	Research indicates that the adoption of AI has the potential to improve organizational performance and agility. (Samuel Fosso Wamba et al., 2021)	The absence of a direct empirical connection between the acceptance and implementation of AI and organizational effectiveness is ambiguous as there is no theoretical evidence to prove the same.	The research develops a structured model linking readiness → acceptance → implementation → organizational effectiveness.

Role of Acceptance in AI Outcomes	Acceptance models (TAM/UTAUT) explain intention and use of AI technologies at the individual level.	Acceptance is often studied independently without implementation & organizational outcomes	Perceived AI acceptance is shows that employees accept the change before implementing the technology and then the organizational effectiveness will follow.
Implementation versus Acceptance	Technology adoption research, particularly TAM and UTAUT, emphasizes *perceived usefulness, ease of use, effort expectancy,* and *performance expectancy* as drivers of behavioural intention and acceptance. Similarly, DOI theory highlights stages of innovation adoption but does not sufficiently capture post-adoption depth in organizational contexts such as HR.	Existing studies largely remain confined to acceptance or behavioural intention, often assuming that these lead directly to effective usage. There is limited examination of post-adoption behaviour, particularly the extent of implementation, process integration, and routinization of AI in HR practices.	The present study extends TAM and UTAUT beyond incorporating AI Implementation as a distinct post-adoption construct, informed by DOI theory's emphasis on innovation integration. Perceived AI Acceptance is conceptualized as an *attitudinal that is* shaped by perceived usefulness, ease of use, and social influence, whereas Perceived AI Implementation captures the *behavioural aspect* of AI through actual system usage, integration into HR functions, and routinization over time. By positioning implementation as a mediating mechanism, the study explains how acceptance is translated into organizational effectiveness, thereby bridging the gap between intention and realized outcomes.
Perception vs Behavioural Intention	TAM and UTAUT distinguish between Perception (e.g., perceived usefulness, ease of use, effort expectancy, social influence) and behavioural intention as predictors of technology adoption. The TOE framework further emphasizes that acceptance is influenced by	Prior studies fail to differentiate between perceptions and behavioural intention, leading to conceptual overlap. Additionally, the integration of contextual (TOE) factors with individual-level perceptions remains underdeveloped, particularly in AI–HR research.	The present study integrates TOE with TAM and UTAUT to provide a multi-level explanation of AI adoption. Perception is conceptualized as a *cognitive evaluation* shaped by: Technological factors (perceived usefulness, ease of use) – TAM, Organizational factors (management support, facilitating conditions) – TOE/UTAUT & Environmental factors (social influence, competitive pressure) – TOE/UTAUT. Behavioural Intention is defined as a *construct* reflecting

	technological, organizational, and environmental contexts.		willingness or attitude towards the use AI. The study further distinguishes Perceived AI Acceptance as a construct the employees' readiness to use AI and Perceived AI Implementation as the construct of actual system usage, thereby establishing a sequential progression: AI Perception → Behavioural Intention → Perceived AI Acceptance → Perceived AI Implementation → Organizational Effectiveness. This integrated approach enhances conceptual clarity and captures both individual cognition and contextual influences in explaining AI-enabled HR outcomes.
Ethics, Trust, and Risk Considerations	Recent research highlights the ethical concerns, biases, and privacy risks associated with AI-enabled practices in human resources.	Discussions surrounding ethical concerns frequently take place in a conceptual framework, rather than being empirically connected to outcomes of effectiveness.	Integrates acceptance and risk perceptions to evaluate their indirect influence on organizational effectiveness.
Temporal Perspective	Organizational effectiveness is understood as a long-term outcome.	AI–HR studies are largely cross-sectional and short-term in orientation.	Conceptually positions organizational effectiveness as a post-implementation outcome rather than an immediate result of adoption.
Contextual Focus (Emerging Economies)	Most empirical AI–HR studies are conducted in developed countries or large multinational firms.	There is very limited evidence available from emerging economy and Indian organizational contexts.	Examines AI in HR practices within an Indian organizational setting using contextually relevant effectiveness measures.
Theoretical Integration	Studies typically rely on any of the single framework – TAM or UTAUT or TOE, or DOI).	Fragmented theoretical explanations fail to capture multi-level dynamics.	This study integrates DOI, TAM, UTAUT, and TOE to provide a comprehensive, multi-stage explanation of AI-driven effectiveness.

Table 2-2 Gap-Conceptual Framework Variables Analysis

Research Gap Identified	***Explanation of the Gap***	***Conceptual Framework Variables Addressing the Gap***	***How the Present Study Fills the Gap***
Gap 1: Lack of understanding of how AI becomes embedded into HR routines over time	Existing studies focus on adoption intention, but rarely examine routine and sustained implementation of AI in HR practices.	Perceived AI Implementation, Organizational readiness for AI, Strategic alignment, Training & technical support, Governance & evaluation mechanisms	Explicitly models Perceived AI Implementation as a distinct construct beyond acceptance, capturing routinization, alignment, and sustainability of AI in HR practices.
Gap 2: Fragmented treatment of acceptance, implementation, and organizational outcomes	TAM, UTAUT, and TOE are used independently; few studies integrate acceptance and implementation to explain organizational effectiveness.	Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation & Organizational Effectiveness	Integrates TAM + UTAUT + TOE into a single causal pathway linking intention → acceptance → implementation → effectiveness.
Gap 3: Limited focus on employee willingness to accept AI in HR practices	Employee perceptions, trust, and willingness are underexplored, especially in HR contexts.	Technology Readiness, Perceived usefulness (relative advantage), Perceived ease of use (complexity), Self-efficacy & Attitude toward change	Examines employee-level acceptance drivers rather than only managerial or organizational perspectives.
Gap 4: Narrow conceptualization of organizational effectiveness	Most AI–HR studies measure effectiveness through efficiency or productivity, ignoring human outcomes.	Organizational Effectiveness (Pestonjee Framework)	Uses a multidimensional, people-centric effectiveness measure, capturing both performance and employee experience outcomes.

Gap 5: Underdeveloped empirical operationalization of fairness, trust, and legitimacy	Ethics and governance are discussed conceptually but rarely linked to acceptance or effectiveness empirically.	Perceived AI Acceptance, Compatibility, Uncertainty/Risk (privacy, security, trust)	Operationalizes trust, risk, and compatibility as measurable acceptance dimensions influencing implementation and effectiveness.
Gap 6: Limited industry-specific and sectoral insights	Most studies provide generalized findings without sectoral differentiation.	Technology Readiness, Organizational Readiness, Environment Readiness	Data collected across selected industries, allowing comparative understanding of how AI acceptance and implementation vary by sector.
Gap 7: Scarcity of Indian, employee-level quantitative studies	Existing Indian studies are limited, location-specific, and largely qualitative or conceptual.	Entire Framework (all variables measured quantitatively)	Provides large-sample, employee-level quantitative evidence from Indian organizations including and beyond major IT hubs.
Gap 8: Overemphasis on AI development rather than HR implementation	AI research is dominated by technical design rather than organizational usage and outcomes.	Perceived AI Acceptance, Perceived AI Implementation, & Organizational Effectiveness	Shifts focus from AI as a technology to AI as an organizational and HR system shaping work and effectiveness.

2.10Conceptual Framework

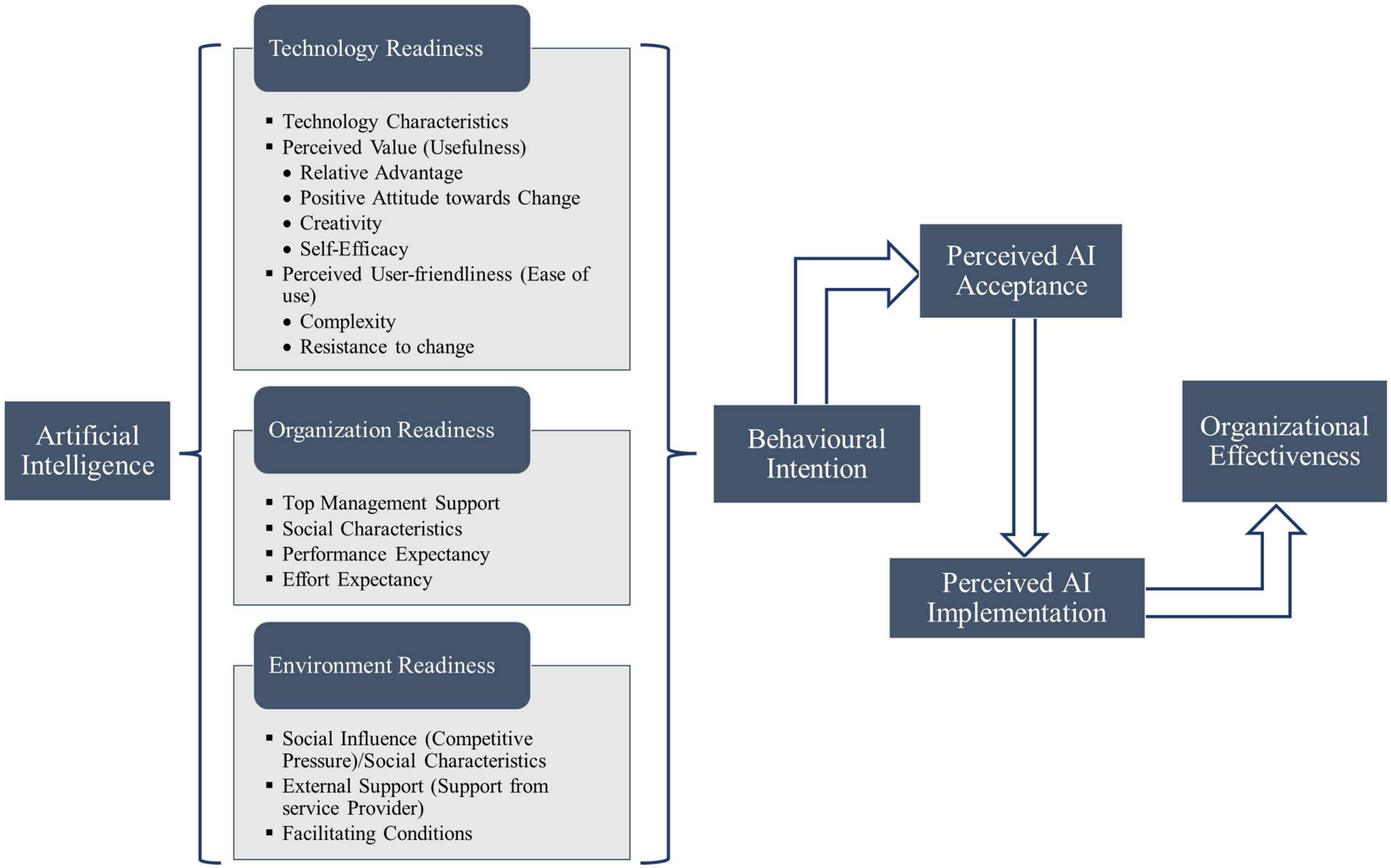

Figure 2-5 Conceptual Framework showing relationship between Artificial Intelligence in HR Practices and Organizational Effectiveness (Developed by researcher using TOE, TAM & UTAUT Model and few variables added by researcher)

Table 2-3 Synthesis of Theoretical Frameworks Supporting the Study

Framework Component (as per model)	***DOI (Diffusion of Innovation)***	***TAM (Technology Acceptance Model)***	***UTAUT (Unified Theory of Acceptance and Use of Technology)***	***TOE (Technology–Organization–Environment)***
Technology Readiness (Technology characteristics, perceived usefulness, relative advantage, ease of use, complexity, resistance to change)	Relative advantage, complexity, and compatibility are core innovation attributes influencing adoption (Rogers, 2003; Pillai & Sivathanu, 2020)	Core focus via perceived usefulness and perceived ease of use (Davis, 1989)	Performance expectancy and effort expectancy explain perceived technological value (Venkatesh et al., 2003)	Addressed as technological context including technology characteristics and readiness (Tornatzky & Fleischer, 1990; Baker, 2012)
Organization Readiness (Top management support, social characteristics, performance expectancy, effort expectancy)	Organizational norms and leadership influence diffusion indirectly (Rogers, 2003)	Not addressed	Explicitly captured through social influence and facilitating conditions (Venkatesh et al., 2003; Venkatesh et al., 2012)	Central focus via organizational readiness, leadership support, skills, and governance (Pillai & Sivathanu, 2020; Barone et al., 2025)
Environment Readiness (Competitive pressure, vendor support, facilitating conditions)	Observability and peer adoption within social systems accelerate diffusion (Rogers, 2003)	Not addressed	Facilitating conditions partially capture environmental support (Venkatesh et al., 2003)	Core component including competitive pressure, regulation, and vendor ecosystem (Tornatzky & Fleischer, 1990; Shakeel & Siddiqui, 2021)

Behavioural Intention	Attitude formation during persuasion stage precedes adoption decisions (Rogers, 2003)	Primary dependent variable influenced by PU and PEOU (Davis, 1989)	Primary outcome influenced by PE, EE, and SI (Venkatesh et al., 2003)	Not directly modelled
Perceived AI Acceptance	Acceptance develops gradually through social validation and diffusion (Rogers, 2003)	Strong explanatory power for individual acceptance of AI systems (Pillai & Sivathanu, 2020)	Strong explanatory power in organizational settings with managerial influence (Shakeel & Siddiqui, 2021)	Indirectly addressed through organizational alignment
Perceived AI Implementation	Explains transition from adoption to diffusion, limited on routinization (Rogers, 2003)	Weak explanatory power	Moderate through facilitating conditions and use behaviour (Venkatesh et al., 2003)	Strong explanatory power for implementation, integration, and sustained use (Tornatzky & Fleischer, 1990; Barone et al., 2025)
Organizational Effectiveness	Indirect outcomes emerge post-diffusion (Rogers, 2003)	Not addressed	Indirect via use behaviour and performance expectancy (Venkatesh et al., 2003)	Directly addresses performance, effectiveness, and sustainability (Wamba et al., 2021; Barone et al., 2025)
Overall Contribution to Present Study	Explains how AI diffuses across HR functions	Explains why HR professionals accept AI	Explains usage behaviour under organizational influence	Explains implementation and organizational effectiveness

2.11 Theoretical Foundation for framework of Constructs Based on DOI, TAM, UTAUT, and TOE

2.11.1 Artificial Intelligence (AI) in HR Practices (Independent Variable)

The use of Artificial Intelligence in human resource practices involves the implementation of algorithmic, data-driven, and automated systems capable of learning, reasoning, and decision support designed to improve various HR functions, including recruitment, selection, performance management, learning and development, and workforce analytics. Unlike traditional HR information systems, AI systems are adaptive, data-intensive, and capable of autonomous or semi-autonomous decision-making. The implications of HR decisions on fairness, career paths, and trust render the integration of AI within HR more complicated and ethically challenging compared to other organizational functions. (Amankwah-Amoah et al., 2021a) From a theoretical Studies found, the integration of AI in human resources signifies organizational development that transforms decision-making power, information management, and the relationship of human-technology engagement. The implementation of AI in human resources has gained popularity because of its self-governing and flexible characteristics, which requires not only a foundation of technical readiness but also a willingness to embrace change, coherence within the organization, and recognition within the broader context. (Basu et al., 2025; Jöhnk et al., 2021a; Nguyen & Le, 2022a; Prikshat et al., 2021a; Raisch & Krakowski, 2021a)

In contrast to traditional information systems, AI systems demonstrate a level of autonomy, adaptability, and predictive ability that enhances their strategic importance while additionally increasing the associated risks. Thus, understanding that adoption of AI in human resources is necessary for exploration of not only technological characteristics but also cognitive processes, organizational readiness, and external factors. (Gangwar et al., 2015a; Jöhnk et al., 2021a; Kukafka et al., 2003b; Prikshat et al., 2021a) The adoption of AI in human resources has a profound impact on individuals, their careers, and the values of fairness within organizations. Therefore, its successful acceptance and implementation require not just technical readiness, but also a harmonious alignment of intellectual, organizational, and environmental factors., organizational, and environmental factors.

Theoretically the variable is taken from Diffusion of Innovation (DOI) theory and Technology-Organization-Environment (TOE) Model where AI represents technology adopted. DOI represents AI as a complex organizational innovation and in TOE it is AI represented as a technology requiring multi-level readiness.

2.11.2 Technology Readiness (Technological Context)

The concept of technology readiness reflects the extent to which an organization considers AI technologies as useful, practical, and harmonious with its current HR processes. This construct is supported by the DOI and TAM frameworks, that includes elements such as perceived relative advantage, perceived usefulness, ease of use, and complexity. The DOI framework suggests that innovations characterized by a greater relative advantage and reduced complexity tend to spread more quickly, whereas the TAM model highlights that an individual's acceptance is influenced by their perception of usefulness and ease of use.

The proposed framework suggests that technology readiness refers to the beliefs of HR professionals about AI's potential to enhance the efficiency, accuracy, and scalability of HR practices. despite this, a high perception of complexity, insufficient transparency, or reluctance to embrace change could reduce readiness and lower the intention to work with AI. (Al-Suqri et al., n.d.; *Diffusion of Innovations*, 2014; EVERETT M. ROGERS, 2014; Everett Roge, 1995; Pillai & Sivathanu, 2020; Sivathanu & Pillai, 2018)

2.11.2.1 Technology Characteristics

The technology characteristics represents the functional attributes of AI systems that influence decisions regarding their adoption. Previous studies shows that organizations are more willing to implement AI when it provides reliable, scalable, and task-compatible HR services. (Gangwar et al., 2015a; Gutierrez et al., 2017a; Pan et al., 2021a) In human resources contexts, the capacity of AI to provide widespread services, such as chatbots and automated screening, along with its potential to enhance HR workflows and adapt features to meet organizational requirements, significantly boosts its perceived compatibility. AI systems are viewed as prevalent and reliable when they deliver uninterrupted HR services regardless of time, location, or the presence of human personnel. This widespread presence reduces the need for human intervention and improves the consistency of services. The dependability of AI-driven HR outputs plays a crucial role in fostering trust, especially in areas that involve sensitive data, like recruitment screening and workforce analytics. (Davenport, 2018)

The alignment with current HR functions and systems is of the highest priority. The DOI theory suggests that innovations that align with established values and workflows are likely to spread more rapidly. (EVERETT M. ROGERS, 2014) When AI applications are in balance with HR functional requirements—such as recruitment analytics or workforce planning—the perceived risk associated with implementation reduces. (Nguyen & Le, 2022a; Prikshat et al., 2021a) From a DOI perspective, these characteristics together influence relative advantage, compatibility, and complexity, which in turn decide the pace and scope of diffusion. (Chatterjee et al., 2021a, 2022; Gangwar et al., 2015a; Gutierrez et al., 2017a; Jatobá et al., 2019)

2.11.2.2 Perceived Usefulness

Based on the Technology Acceptance Model, perceived usefulness refers to the extent to which HR professionals perceive that AI improves HR performance, decision-making accuracy, and overall efficiency. Research findings consistently highlight perceived usefulness as the most significant factor influencing the acceptance of AI in human resource management. (Pillai & Sivathanu, 2020) The perceived value reflects how AI is considered in terms of delivering better results than current manual or automated HR systems. This concept is based on the perceived usefulness of the Technology Acceptance Model and the relative advantage outlined in the Diffusion of Innovations theory. Research consistently shows that the adoption of AI is accelerated when organizations perceive it as an opportunity to gain a competitive edge, lower operational expenses, and improve human resource efficiency. (Abdekhoda et al., 2018a; Cai et al., 2020; Li, 2020a; Vasiljeva et al., 2021a)

In human resources practices, the concept of relative advantage is through quicker hiring processes, enhanced alignment of candidates with job requirements, the utilization of predictive analytics, and data-driven workforce decisions. (Chatterjee et al., 2021a; Dodel & Mesch, 2020; Matias, 2021a) According to DOI theory, relative advantage referred to benefits of AI-enabled HR practices as compared to traditional methods, including aspects like reduced bias, expedited hiring processes, and enhanced talent matching (EVERETT M. ROGERS, 2014). The ease of use indicates the perceived simplicity of AI systems. In the realm of artificial intelligence, this encompasses the ease of interface use and the clarity of output interpretation, as opposed to direct engagement with the algorithms themselves. (Venkatesh et al., 2003a)

2.11.2.2.1 Perceived Usefulness - Relative Advantage

Perceived value refers to the belief that AI-enabled HR practices deliver superior outcomes compared to existing manual or automated systems. This construct integrates TAM's perceived usefulness with DOI's relative advantage. The integration of AI in human resources is regarded as beneficial when it contributes to operational efficiency, enhances the precision of decision-making, lowers administrative expenses, and strengthens competitive advantage. Organizations view AI as a valuable resource, particularly when it facilitates quicker talent acquisition, enhances predictive workforce planning, and supports evidence-based decision-making. The reduction of costs stands out as a significant aspect of perceived value, as artificial intelligence reduces repetitive human resources tasks and minimizes the likelihood of errors linked to manual processing. The perception of AI by HR professionals as a catalyst for measurable performance enhancements notably bolsters their intentions to adopt such technologies. (Abdekhoda et al., 2018a; Amankwah-Amoah et al., 2021a; Pan et al., 2021a; Prikshat et al., 2021a)

2.11.2.2.2 Perceived Usefulness - Positive Attitude towards Change

Positive attitude toward change reflects individuals' openness, optimism, and readiness accept AI-driven transformation. Change readiness literature suggests that positive attitudes reduce uncertainty, anxiety, and resistance during technological transformation. Individuals who believe that AI enhances convenience, autonomy, learning opportunities, and work efficiency are more likely to support its adoption. The assurance in the reliability of AI enhances its acceptance significantly. This concept serves as a psychological link connecting perceived value with behavioural intention. (Gutierrez et al., 2017a; Leung, 2015a; Matias, 2021a; Nguyen & Le, 2022a)

2.11.2.2.3 Perceived Usefulness - Creativity

Creativity represents individual innovativeness and curiosity toward new technologies. Creative individuals are more willing to explore AI systems, experiment with new functionalities, and overcome initial technical challenges. From a DOI perspective, creative individuals resemble early adopters who facilitate diffusion by demonstrating feasibility and benefits to others. Creativity reduces perceived complexity and enhances exploratory learning, strengthening technology readiness. (Abdekhoda et al., 2018a; Gholami et al., 2018; Li, 2020a; Matias, 2021a)

2.11.2.2.4 Perceived Usefulness - Self-Efficacy

Self-efficacy is individual's belief in their ability to successfully use AI-enabled HR systems. Rooted in social cognitive theory, self-efficacy strongly influences perceived ease of use and behavioural intention. Employees with high self-efficacy feel confident handling AI-related changes, especially when supported by training and organizational resources. The availability of training enhances self-efficacy, thereby lowering anxiety and resistance. The factor is part of UTAUT model. (Y. Lee et al., 2003a; Park et al., 2022b; Sohn & Kwon, 2020a; Xu & Wang, 2021a)

2.11.2.3 Perceived User-Friendliness

Perceived user-friendliness derived from TAM & DOI is a variable that captures the extent to which AI systems are viewed as understandable, transparent, and manageable. AI systems are often perceived as "black boxes," increasing perceived complexity and resistance. High complexity negatively influences acceptance, especially in HR decisions requiring explainability. (Raghavan et al., 2020)

2.11.2.3.1 Perceived User-Friendliness - Complexity

The perception of high complexity tends to raise doubts, enhance perceived risk, and develop resistance. The issues surrounding technology errors, decreased human interaction, potential data misuse, and ambiguous advantages contribute to an increased perception of complexity. The DOI framework identifies complexity as a negative variable influencing adoption, whereas the TAM framework directly associates it with perceived ease of use. (Nguyen & Le, 2022a; Vasiljeva et al., 2021a)

2.11.2.3.2 Perceived Iser-Friendliness - Resistance to Change

Resistance to change reflects emotional, ethical, and job-related concerns arising from AI adoption. Fear of losing job, surveillance, system failure, and decrease in human relationships are common factors that affects resistance. Resistance is particularly salient in HR contexts, where AI directly affects employment security, privacy, and trust. Resistance controls the relationship between readiness and behavioural intention. (Cao et al., 2021a; Rahman et al., 2016a; Shakeel & Siddiqui, 2021a)

2.11.3 Organization Readiness (Organizational Context)

Organization readiness is the internal capability of the organization to adopt and implement AI-enabled HR practices. Based on the TOE framework and supported by UTAUT, this construct includes top management support, organizational culture, HR digital maturity, performance expectancy, and effort expectancy. (Pillai & Sivathanu, 2020; Tornatzky & Fleischer, 1990a; Venkatesh et al., 2003a)

2.11.3.1 Top Management Support

Top management support is the extent to which senior leadership actively endorses and invests in artificial intelligence (AI) within HR practices. Within the Technology–Organization–Environment (TOE) framework, it is a key organizational factor that validate AI adoption and shapes strategic decisions.

The commitment of top management plays a crucial role in the adoption of AI by ensuring the allocation of financial and technological resources, development of necessary infrastructure, and facilitating employee training. A strong support from senior management decreases uncertainty and resistance by indicating that the adoption of AI is in integration with the organization's long-term objectives. Furthermore, senior leadership implements governance structures, performance benchmarks, and ethical frameworks for the application of AI in human resources. The adoption of AI has the potential to transform usual decision-making structures. Therefore, it is essential for leadership to provide strong support and maintain transparent communication about the objectives and advantages of AI. This approach enables employees to view the transition as both trustworthy and advantageous, ultimately promoting acceptance and promoting innovation. (Chiu, 2017; Gangwar et al., 2015a; Nguyen & Le, 2022a; Prikshat et al., 2021a)

2.11.3.2 Social Characteristics

Social characteristics refer to the influence of societal norms and encouragement from peers. People are more inclined to embrace AI when it is supported by supervisors, colleagues, and influential peers. When important people in organization such as managers or experienced coworkers support and actively use AI-based HR systems, others are more likely to follow. This normative pressure reduces uncertainty and accelerates acceptance, particularly in hierarchical organizational cultures. Within HR practices, social influence is especially salient because AI tools often require coordination across functions (HR, IT, operations) and collective compliance. Peer support also facilitates informal learning and problem-solving, reducing perceived complexity and enhancing confidence in system use. This construct is based on established theories such as TAM, and UTAUT, each of which identifies social influence as a key factor in shaping behavioural intention. (A. Agarwal, 2022a; F. D. Davis, 1989a, 1993; Fred D. Davis, 1989; Tam & Oliveira, 2016a; Viswanath Venkatesh, 2003)

2.11.3.3 Performance Expectancy

Performance expectancy is the extent to which individuals believe that using AI-enabled HR practices will enhance their job performance, productivity, and flexibility. Derived from UTAUT, performance expectancy is conceptually similar to perceived usefulness in TAM but places stronger emphasis on productivity, efficiency, and quality outcomes.

In the field of human resources, performance expectancy refers to the belief that artificial intelligence will reduce administrative burdens, enhance the accuracy in recruitment and evaluation processes, and facilitate quicker access to information regarding staff performance.

When HR professionals recognize that AI tools enhance their ability to perform tasks more efficiently—such as identifying appropriate candidates, forecasting attrition, or tailoring learning interventions—their willingness to adopt these systems grows. The significance of performance expectancy in the context of AI adoption is noteworthy, as artificial intelligence (AI) systems frequently serve as tools that support decision-making processes. (Shakeel & Siddiqui, 2021a; Venkatesh & Davis, 2000b)

2.11.3.4 Effort Expectancy

Effort expectancy indicates the level of simplicity involved in learning and using AI-enabled HR systems. This construct is based on UTAUT, covers cognitive and operational effort, along with interface simplicity to include clarity of outputs, interpretability of recommendations, and availability of learning support. AI systems are misunderstood as complex and difficult to understand and unfamiliar but it comes with lots of potential performance benefits. Training programs, user-friendly dashboards, and responsive support services significantly enhance effort expectancy by lowering perceived barriers to use. (Del Giudice et al., 2021a; Im et al., 2011a)

2.11.4 Environment Readiness (Environmental Context)

Environment readiness refers to external pressures and supports that influence AI adoption in HR practices. Based on TOE and DOI, this construct includes competitive pressure, vendor support, regulatory environment, and facilitating conditions. DOI theory highlights the role of observability and peer adoption in accelerating diffusion, while TOE emphasizes that regulatory compliance and market competition significantly shape organizational technology decisions. In HR contexts, access to external expertise and vendor ecosystems reduces implementation uncertainty, whereas regulatory ambiguity and ethical concerns may slow adoption. (Best et al., 2017; EVERETT M. ROGERS, 2014; LOUIS G TORNATZKY & MITCHELL FLEISCHER, 1990; Shakeel & Siddiqui, 2021a; Tornatzky & Fleischer, 1990a)

2.11.4.1 Social Influence (Competitive Pressure)

Competitive pressure represents the extent to which organizations perceive AI adoption in HR practices as necessary to maintain or enhance market position. From both TOE and DOI perspectives, competitive pressure accelerates adoption by increasing the perceived cost if AI is not adopted. Organizations often adopt AI in HR to remain competitive in talent acquisition, employer branding, and workforce optimization. When competitors leverage AI to attract talent or improve efficiency, firms that delay adoption risk losing market share or strategic relevance. This perceived threat strengthens organizational commitment to AI adoption, even when internal readiness is moderate.

2.11.4.2 External Support (Vendor Support)

The expertise of vendors plays a significant role in minimizing both the complexity and risk associated with implementation processes. External support encompasses the support offered by AI vendors, consultants, and technology partners. In the literature on TOE, vendor support emerges as a vital environmental facilitator, especially for organizations that do not possess in-house AI expertise. The assistance provided by vendors plays a crucial role in mitigating implementation risks through the provision of technical guidance, system customization, training, and ongoing maintenance after the implementation phase. Reliable external assistance enhances an organization's assurance in adopting AI and alleviates concerns associated with system failures or challenges in scalability. In human resources settings, the expertise of vendors holds significant importance, particularly in light of the regulatory, ethical, and data privacy issues related to employee information.

2.11.4.3 Facilitating Conditions

The conditions that facilitate progress are indicative of the availability of infrastructure, resources, and the compatibility of systems. The conditions that facilitate AI usage encompass the organizational and technical resources necessary for effective implementation. This framework connects the Technology-Organization-Environment (TOE) model and the Unified Theory of Acceptance and Use of Technology (UTAUT), incorporating elements such as infrastructure readiness, system compatibility, and decision-making autonomy. Facilitating conditions allow employees to effectively engage with AI systems without facing structural limitations. Having sufficient resources, compatible human resources information systems, and the autonomy to make decisions contribute to a greater sense of control and diminish frustration, thereby facilitating the continued use of AI.

2.11.5 Behavioural Intention to Use AI

Behavioural intention represents the individual-level willingness of HR professionals and managers to use AI-enabled HR systems. TAM and UTAUT identify behavioural intention as the most immediate antecedent of technology use. Within the field of AI in human resources, behavioural intention covers cognitive evaluations regarding the utility of AI, the simplicity of interaction, and potential results, alongside the impact of social influences from both leadership and colleagues. The behavioural intention acts as an essential intermediary that connects readiness factors to acceptance. (F. Davis, 1985; F. D. Davis, 1989a; Venkatesh et al., 2003a; Venkatesh & Davis, 2000b)

2.11.6 Perceived AI Acceptance

The perception of AI acceptance indicates the degree to which individuals recognize, feel, and ethically endorse AI as a suitable tool for making decisions in human resources. Acceptance goes beyond mere intention, as it encompasses elements of trust, legitimacy, and alignment of values. The Technology Acceptance Model discusses acceptance by focusing on perceptions of usefulness and user-friendliness, whereas the Unified Theory of Acceptance and Use of

Technology broaden this perspective by integrating factors such as social influence and enabling conditions. From a DOI perspective, acceptance develops through social validation and collective experience as time progresses. Acceptance reflects compatibility perceptions and risk assessment. (F. D. Davis, 1989a; EVERETT M. ROGERS, 2014; Rogers, 1962; Shakeel & Siddiqui, 2021a)

2.11.6.1 Compatibility

Compatibility refers to the degree to which AI-enabled HR practices align with organizational values, managerial norms, and existing systems. Based on DOI, compatibility reduces disturbance and resistance by ensuring continuity with established practices. The acceptance of AI systems tends to rise when they enhance managerial flexibility and uphold professional values, rather than replacing them. The alignment with current HR systems minimizes technical challenges and improves overall integration.

2.11.6.2 Uncertainty/Risk

Uncertainty and perceived risk relate to concerns regarding data privacy, security, algorithmic bias, and system reliability. Trust plays a crucial role in mitigating these risks. In human resources applications the processing of sensitive employee information can lead to a considerable reduction in acceptance due to perceived risks. The assurance of confidentiality, secure transactions, and ethical safeguards fosters trust and promotes acceptance.

2.11.7 Perceived AI Implementation

The concept of perceived AI implementation relates to the extent to which AI systems are integrated into human resource workflows, routines, and decision-making processes. The TOE theory offers a robust framework for understanding implementation, highlighting the importance of organizational capability, governance, and alignment with the environment. The DOI framework offers a process-oriented view, clarifying the journey of AI from its initial adoption to its eventual integration into routine practices. Successful implementation necessitates a harmonious relationship among technological readiness, organizational support, and the reliability of the surrounding environment. A deficiency in any aspect may lead to a mere superficial or symbolic implementation. The implementation process includes not only ongoing system maintenance but also continuous learning and alignment with organizational objectives, highlighting that the adoption of AI is an evolving journey rather than one-time event. Implementation signifies the organizational-level realization of AI adoption, in contrast to only acceptance. (Del Barone et al., 2025; EVERETT M. ROGERS, 2014; Tornatzky & Fleischer, 1990a)

2.11.8 Organizational Effectiveness

Organizational effectiveness means to the capacity of an organization to meet its objectives efficiently, all the while maintaining employee well-being, fostering internal health, and demonstrating adaptability to changes in the environment. Current management literature acknowledges that effectiveness is a multidimensional construct, especially in relation to the adoption of artificial intelligence (AI) in human resource (HR) practices. In this context, it is essential for technological advantages to align with employee acceptance, ethical governance, and long-term sustainability.

From a Technology–Organization–Environment (TOE) perspective, AI is capable to enhance organizational effectiveness only when combined with complementary organizational processes, skills, and governance structures. The Literatures consistently highlights that effectiveness arises from the ongoing implementation of AI, rather than simply its adoption. The mere acceptance of a concept, without its effective implementation, can lead to limited or even negative results. This highlights the significance of collaboration between humans and AI, as well as the need for institutional support. (Del Barone et al., 2025; LOUIS G TORNATZKY & MITCHELL FLEISCHER, 1990; Samuel Fosso Wamba et al., 2021)

This study aims to provide a comprehensive perspective by utilizing the D. M. Pestonjee Organizational Effectiveness framework, a well-recognized model in Indian organizational research that aligns closely with human resource-focused and people-centred viewpoints. Pestonjee defined effectiveness as a combination of organizational processes and human outcomes, highlighting that sustained effectiveness relies on achieving a balance between productivity and factors such as employee satisfaction, autonomy, and adaptability—elements that are especially important in the context of AI-enabled human resources. In this context, the effectiveness of an organization is demonstrated by its ability to achieve goals, adapt to changes, ensure employee satisfaction, maintain efficient internal processes, encourage organizational integration, and maintain its sustainability over time. The integration of AI in HR practices enhances various dimensions by improving the quality of recruitment, facilitating data-informed decision-making, promoting workforce adaptability, and reinforcing interdepartmental coordination. Nonetheless, these advantages emerge solely when AI systems are in harmony with organizational objectives, regarded as fair and transparent, and supported by sufficient training and governance frameworks. The existing literature indicates that AI contributes to organizational effectiveness not merely by automating tasks or improving efficiency, but through its responsible application, which strengthens employee engagement, enhances organizational resilience, and promotes sustainable performance. (Ashraf & Abd Kadir, 2012; Georgopoulos, 1957; Hermawan & Suharnomo, 2020; Mahoney & Weitzel, 1969; Pestonjee, 1988a; Reetu et al., 2019; Tayal & Upadhyay, 2019)

2.11.9 Conclusion of Literature Review

Artificial intelligence in HR practices has the potential to significantly improve organizational success by increasing efficiency, decision quality, and adaptability, according to the studied research. Existing research, however, mostly focuses on adoption factors or academic results, providing little understanding of how AI is embraced by employees, integrated into HR practices, and converted into long-term organizational success. The literature also shows a lack of empirical, employee-level research in the Indian organizational setting and displays theoretical fragmentation, with acceptance, implementation, and effectiveness frequently researched in isolation.

Furthermore, while recent studies acknowledge the importance of fairness, transparency, and governance in AI-enabled HR practices, their implementation is still not very popular. These gaps underscore the need for an integrated, human-centric framework that examines AI acceptance and implementation through combined theoretical framework and evaluates their impact on multidimensional organizational effectiveness. Addressing these gaps provides the foundation for the present study and develop the conceptual framework, research objectives, and hypotheses that follow.

CHAPTER - 3 RESEARCH METHODOLOGY

3.1 Introduction

This chapter outlines the research methodology adopted to examine the perceived acceptance and perceived implementation of Artificial Intelligence (AI) in Human Resource (HR) practices and its impact on organizational effectiveness. The chapter presents the problem statement, objectives, scope of the study, original contribution of the research, research design, data collection procedures, sampling design, research instrument, and data analysis tools. The methodological choices are carefully aligned with the nature of the research problem and the conceptual framework developed for the study. The methodological framework is aligned with the study's objectives and the integrated conceptual framework grounded in TOE, TAM, and UTAUT.

3.2 Problem Statement

The rapid advancement of Artificial Intelligence (AI) presents a transformative opportunity for Human Resources (HR) practices. AI tools, encompassing machine learning, natural language processing, and predictive analytics, promise to revolutionize traditional HR functions such as talent acquisition, performance management, employee engagement, and workforce planning. By automating repetitive tasks, enhancing data-driven decision-making, and personalizing employee experiences, AI has the potential to significantly improve HR effectiveness. However, despite the clear potential benefits, the widespread acceptance and successful implementation of AI in HR practices across various industries face significant challenges. These challenges are not solely technical but also deeply rooted in human factors, organizational culture, and ethical considerations. The research is aimed at examining the pivotal role of factors that influence that perceived acceptance and perceived implementation of Artificial Intelligence in HR Practices and its impact on Organizational Effectiveness. This study aims to investigate the factors influencing the acceptance and Perceived implementation of AI in HR practices within selected industries (e.g., IT/ITES, Consumer Durables/Telecommunication, Financial Services, Healthcare, Management Consultancy), and subsequently, analyze the discernible impact of this integration on the overall organizational effectiveness of firms operating within these sectors. It seeks to identify common enablers, barriers, explore the ethical considerations, assess employee perceptions, and provide actionable insights for organizations looking to leverage AI for a more efficient, effective, and human-centric HR function.

3.3 Objectives of the Study

- To analyze the factors influencing the Acceptance and Perceived Implementation of Artificial Intelligence (AI) in Human Resources (HR) practices across selected industries.
- To develop conceptual framework for Acceptance and Implementation of Artificial Intelligence in HR Practices and organisational Effectiveness.
- To measure the impact of Artificial Intelligence in HR Practices on Organizational Effectiveness
- To study difference between Selected Industries and Variables of Artificial Intelligence.
- To study difference between Selected Industries and Organizational Effectiveness.
- To study the difference Between variable of Artificial Intelligence and demographic factors.
- To study the difference Between Organisational Effectiveness and demographic factors.

3.4 Hypothesis

Hypothesis 1: Distribution is not Normal

Hypothesis 2: Correlation Matrix is not an identity matrix

Hypothesis 3: Observed variables load significantly on their respective latent factors

Hypothesis 4: Observed indicators significantly represent their latent constructs

Hypothesis 5: The proposed measurement model fits the observed data adequately

Hypothesis 6: Constructs demonstrate adequate reliability and convergent validity

Hypothesis 7: Constructs exhibit discriminant validity. (Fornell–Larcker Criterion)

Hypothesis 8: Construct pairs demonstrate discriminant validity. (HTMT Ratio)

Hypothesis 9: Artificial Intelligence has a significant effect on Behavioural Intention

Hypothesis 10: Behavioural Intention has a significant effect on Perceived AI Acceptance

Hypothesis 11: Perceived AI Acceptance has a significant effect on Perceived AI Implementation

Hypothesis 12: Perceived AI Implementation has a significant effect on Organizational Effectiveness

Hypothesis 13: No multicollinearity exists among predictor constructs

Hypothesis 14: The structural model adequately fits the data

Hypothesis 15: There is a Significant difference among Variables of Study (Technology Characteristics, Positive Attitude Towards Change, Creativity, Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Social Characteristics & Performance Expectancy, Effort Expectancy, Social Influence, External Support & Facilitating Conditions, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation & Organizational Effectiveness) and different age groups

Hypothesis 16: There is a Significant difference among Variables of Study (Technology Characteristics, Positive Attitude Towards Change, Creativity, Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Social Characteristics & Performance Expectancy, Effort Expectancy, Social Influence, External Support & Facilitating Conditions, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation & Organizational Effectiveness) and different Experience groups

Hypothesis 17: There is a Significant difference among Variables of Study (Technology Characteristics, Positive Attitude Towards Change, Creativity, Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Social Characteristics & Performance Expectancy, Effort Expectancy, Social Influence, External Support & Facilitating Conditions, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation & Organizational Effectiveness) and different Education

Hypothesis 18: There is a Significant difference among Variables of Study (Technology Characteristics, Positive Attitude Towards Change, Creativity, Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Social Characteristics & Performance Expectancy, Effort Expectancy, Social Influence, External Support & Facilitating Conditions, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation & Organizational Effectiveness) and different Income groups

Hypothesis 19: There is no Significant difference among Variables of Study (Technology Characteristics, Positive Attitude Towards Change, Creativity, Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Social Characteristics & Performance Expectancy, Effort Expectancy, Social Influence, External Support & Facilitating Conditions, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation & Organizational Effectiveness) and different Industry

Hypothesis 20: There is no Significant difference among Variables of Study (Technology Characteristics, Positive Attitude Towards Change, Creativity, Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Social Characteristics & Performance Expectancy, Effort Expectancy, Social Influence, External Support & Facilitating Conditions, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation) and different Industry Groups

Hypothesis 21: There is no Significant difference among Organisational Effectiveness and different Industry Groups

Hypothesis 22: There is a Significant difference among Variables of Study (Technology Characteristics, Positive Attitude Towards Change, Creativity, Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Social Characteristics & Performance Expectancy, Effort Expectancy, Social Influence, External Support & Facilitating Conditions, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation & Organizational Effectiveness) and different Size of Organization

Hypothesis 23: There is a Significant difference among Variables of Study (Technology Characteristics, Positive Attitude Towards Change, Creativity, Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Social Characteristics & Performance Expectancy, Effort Expectancy, Social Influence, External Support & Facilitating Conditions, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation & Organizational Effectiveness) and different Level of Management

Hypothesis 24: There is a Significant difference among Variables of Study (Technology Characteristics, Positive Attitude Towards Change, Creativity, Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Social Characteristics & Performance Expectancy, Effort Expectancy, Social Influence, External Support & Facilitating Conditions, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation & Organizational Effectiveness) and different Location

Hypothesis 25: There is a Significant difference among Variables of Study (Technology Characteristics, Positive Attitude Towards Change, Creativity, Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Social Characteristics & Performance Expectancy, Effort Expectancy, Social Influence, External Support & Facilitating Conditions, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation & Organizational Effectiveness) and different Gender groups

3.5 Scope of the study

- This research focuses on Employee Perception based study of Acceptance and Implementation of Artificial Intelligence in HR Practices. As at the time of data collection there was not much integration of Artificial Intelligence in HR Practices.
- The scope of the study is only limited to service sector firms like IT/ITES, Healthcare, Consumer Durables, Telecommunication, Finance & Financial Services & Management Consultancy. This allows for in-depth analysis and comparative insights while making the study manageable.
- The geographical scope of the study is limited to the state of Gujarat, India.
- The study relies on quantitative primary data, collected through a structured questionnaire administered to employees working in the selected sectors.

3.6 Research Design

Research design provides the overall framework that guides the systematic collection, analysis, and interpretation of data in order to address the research problem in a rigorous and logical manner. It ensures coherence between research objectives, theoretical foundations, and empirical procedures. (Creswell & Creswell, 2018) Given the complex and evolving nature of Artificial Intelligence (AI) adoption in Human Resource (HR) practices, the present study adopts a descriptive and explanatory research design, supported by a quantitative, cross-sectional approach.

Descriptive Research Design

A descriptive research design is suitable when the goal is to precisely demonstrate the characteristics, perceptions, and attitudes of a population regarding a particular phenomenon. (Kothari & Garg, 2025; Sekaran & Bougie, 2016) This study employs a descriptive design to methodically evaluate employees' perceptions of AI acceptance, perceived implementation, and organizational effectiveness within selected service sector industries. In numerous Indian organizations, the adoption of AI in HR is still in its early stages. Descriptive analysis serves to identify current patterns, levels of readiness, and differences in perception without changing the research context. (Joseph F. Hair, William C. Black, Barry J. Babin, Ralph E. Anderson, 2018).

Quantitative Research Approach

The study adopts a quantitative research approach, which is well suited for testing relationships among latent constructs and validating theoretical models through statistical analysis Quantitative methods allow for objective measurement of perceptions, enable comparison across industries and demographic groups, and facilitate generalizable conclusions within the defined population. The use of standardized scales further enhances consistency and reliability in measurement. (Alan Bryman, 2016)

Cross-Sectional Survey Design

A cross-sectional survey design is employed, wherein data are collected from respondents at a single point in time. This design is widely used in technology adoption and HR research to assess perceptions and behavioural intentions in dynamic organizational settings (Venkatesh et al., 2012). Given the practical constraints and evolving nature of AI adoption, cross-sectional data provide a realistic snapshot of current acceptance and implementation levels while allowing for robust statistical testing of the proposed conceptual framework.

Theory-Driven Design Justification

The research design is explicitly theory-driven, integrating constructs from multiple adoption and implementation theories to address limitations of single-model approaches. While TAM and UTAUT explain individual-level acceptance and usage intentions, TOE captures organizational and environmental readiness, and DOI provides insight into innovation diffusion processes. By combining these perspectives within a descriptive–explanatory design, the study offers a comprehensive understanding of AI adoption in HR that moves beyond intention to actual perceived implementation and organizational outcomes.

Human-Centric Orientation

Importantly, the research design acknowledges that AI adoption in HR is not purely a technological phenomenon but a socio-technical process involving human perceptions, trust, resistance, and ethical considerations. By focusing on employee perceptions and organizational effectiveness outcomes, the design aligns with contemporary calls for human-centred AI research in management studies. (Kellogg et al., 2020; Raisch & Krakowski, 2021a)

Suitability to Indian Organizational Context

The chosen research design is particularly appropriate for the Indian service sector context, where AI integration in HR varies widely across industries and organizational maturity levels. The design allows for comparative analysis across sectors while remaining sensitive to contextual and cultural factors influencing acceptance and implementation.

Furthermore, the design supports multivariate statistical analysis, allowing the study to test complex relationships and mediation effects among constructs. This is particularly important in understanding AI adoption in HR practices, where acceptance does not automatically translate into effective implementation or improved organizational effectiveness.

Overall, the chosen research design is well suited to address the objectives of the study, providing a robust methodological foundation for empirically examining AI acceptance, implementation, and organizational effectiveness within the Indian service sector context.

3.7 Population and Sampling Design

3.7.1 Population and Sampling Design

3.7.1.1 Target Population

The target population comprises employees and HR professionals working in selected industries namely Information Technology / Information Technology Enabled Servies (IT/ITES), Hospitality & Healthcare, Consumer Durables and Telecommunications, Banking Insurance and Financial Services (BFSI) and Management Consultancy firms where AI-enabled HR practices are in use or under consideration. The study focuses on the Indian organizational context focusing on state of Gujarat, including both private and public sector organizations.

3.7.1.2 Sampling Technique

Sampling refers to the process of selecting a subset of individuals from a larger population to draw conclusions about the population. In social science and management research, sampling is essential because studying the entire population is often impractical due to constraints related to time, cost, accessibility, and availability of respondents. A carefully chosen sampling technique ensures that the collected data are relevant, reliable, and appropriate for addressing the research objectives.

Sampling techniques are classified into probability sampling and non-probability sampling, depending on whether each unit of the population has a known and equal chance of selection.

Probability Sampling

Probability sampling is a method in which every element of the population has a known, non-zero, and equal chance of being selected. Common probability sampling techniques include simple random sampling, stratified sampling, systematic sampling, and cluster sampling. The primary advantage of probability sampling lies in its ability to support statistical generalization and reduce selection bias.

However, probability sampling requires a clearly defined sampling frame and complete access to the population. In studies involving emerging technologies such as Artificial Intelligence (AI) in HR practices, these conditions are often difficult to meet. Employees with adequate exposure or awareness of AI-enabled HR systems may not be easily identifiable in advance, making probability sampling less feasible for the present study.

Non-Probability Sampling

Non-probability sampling refers to sampling techniques where the probability of selection of each population element is unknown. In such methods, respondents are selected based on accessibility, relevance, or referral rather than random selection. Non-probability sampling is widely used in exploratory and perception-based studies, especially when the research focuses on specialized populations or emerging phenomena.

Given that AI adoption in HR practices is still evolving and uneven across organizations, non-probability sampling is considered appropriate for capturing informed employee perceptions. Accordingly, the present study adopts non-probability sampling, with emphasis on convenience, quota, and snowball sampling techniques.

Convenience Sampling

Convenience sampling involves selecting respondents who are readily accessible and willing to participate in the study. This technique is particularly useful when the research requires responses from individuals who possess specific knowledge or exposure but are difficult to reach through formal sampling frames. (Kothari & Garg, 2025)

In the context of this study, convenience sampling was applied by approaching employees from selected service sector organizations through professional networks, emails, LinkedIn, WhatsApp, and personal contacts. Since AI-enabled HR practices are not uniformly implemented across all organizations, convenience sampling allowed the researcher to efficiently reach respondents who had awareness or experience related to AI in HR systems.

While convenience sampling may limit statistical generalizability, it is well-suited for studies examining perceptual constructs such as acceptance, readiness, and perceived implementation.

Quota Sampling

Quota sampling is a non-probability technique in which the population is divided into specific subgroups based on predefined characteristics, and a predetermined number of respondents (quota) is selected from each subgroup. This method ensures representation of key categories relevant to the study. (Kothari & Garg, 2025)

In the present research, quota sampling was used to ensure adequate representation from selected service sector industries, including IT/ITES, Healthcare, Consumer Durables, Telecommunication, Financial Services, and Management Consultancy. By allocating quotas across industries, the study enables meaningful comparative analysis of AI acceptance, implementation, and organizational effectiveness across sectors, while maintaining balance in the sample composition.

Snowball Sampling

Snowball sampling is a referral-based non-probability technique where initial respondents identify or recommend other potential participants who meet the study criteria. This method is particularly effective when studying populations that are difficult to access or when respondents with relevant exposure are limited. (Kothari & Garg, 2025)

Given the emerging nature of AI in HR practices, snowball sampling was employed to reach additional respondents who were knowledgeable about or involved in AI-related HR initiatives. Initial participants were requested to refer colleagues or peers within their professional networks who met the study's inclusion criteria. This approach helped expand the sample size and enhance the diversity of organizational contexts represented in the study.

Justification for the Sampling Approach

The combined use of convenience, quota, and snowball sampling enabled the researcher to balance practicality with relevance. Convenience sampling facilitated efficient data collection, quota sampling ensured industry representation, and snowball sampling extended access to informed respondents. Together, these techniques supported the study's objective of capturing informed employee perceptions regarding AI acceptance and perceived implementation in HR practices.

Although non-probability sampling limits the extent of population-level generalization, it is appropriate for theory testing and model validation in emerging research domains such as AI adoption, where respondent expertise and contextual relevance are more critical than random selection.

In summary, the study employs a non-probability sampling design, incorporating convenience, quota, and snowball sampling techniques to effectively capture employee perceptions across selected industries in Gujarat. This approach is consistent with the exploratory and descriptive nature of the research and aligns with established practices in technology adoption and HR research.

3.7.1.3 Sample Size

Sample size refers to the number of respondents selected from the target population for data collection. Determining an appropriate sample size is a critical methodological decision, as it directly affects the statistical power, reliability, validity, and generalizability of research findings. An inadequate sample size may lead to unstable estimates and weak inferential conclusions, whereas an excessively large sample may result in unnecessary resource consumption without proportional analytical benefit.

In quantitative research involving multivariate techniques and structural equation modelling, sample size must be sufficient to accurately estimate relationships among latent constructs and ensure robustness of the measurement and structural models (Joseph F. Hair, William C. Black, Barry J. Babin, Ralph E. Anderson, 2018; Kothari & Garg, 2025)

The present study examines a complex conceptual framework involving multiple constructs, indicators, and interrelationships derived from TAM, UTAUT, TOE, and DOI models. Given this complexity and the use of Partial Least Squares Structural Equation Modelling (PLS-SEM), sample size determination follows established methodological guidelines rather than relying solely on population proportions.

In addition to conceptual guidelines, sample size determination in multivariate research is often supported through rule-based formulas proposed by Hair and Black, along with their co-authors. According to Hair, Black, Babin, and Anderson (2019), when a study employs multivariate techniques such as factor analysis and structural equation modeling, the sample size should be sufficiently large to ensure stable parameter estimation and reliable model results. This guideline ensures that each observed variable is adequately represented in the dataset and that the covariance structure can be reliably estimated. Hair et al. (2017) recommend that, the minimum sample size should be ten times the largest number of formative indicators used to measure any single construct. This rule is particularly suitable for exploratory and prediction-oriented research models that include multiple latent variables and paths.

(Hair, William, Black, Barry, 2010) Hair and Black suggest that the minimum sample size should be determined based on the number of measurement items, using the following rule:

Minimum Sample Size (N)=Number of Measurement Items × 10

In the present study:

- The questionnaire consists of 110 measurement items (statements).
- Applying the "10-times rule," the minimum required sample size was calculated as: 110 × 10 = 1100 respondents

This threshold ensures adequate statistical power for model estimation, hypothesis testing, and validation of both measurement and structural models.

While the minimum required sample size was 1100, the study successfully collected data from 1245 respondents, exceeding the recommended threshold. This enhanced sample size strengthens the robustness of the analysis by Improving the precision of parameter estimates, reducing sampling error, Enhancing the stability of factor loadings and path co-efficient and Supporting subgroup and industry-wise comparative analysis. The achieved sample size is therefore considered methodologically adequate and statistically sound for the objectives of the study.

The final sample size satisfies recommended criteria for multivariate analysis like Exploratory and confirmatory factor analysis, Regression analysis and Structural equation modelling using SmartPLS, According to (Joseph F. Hair, William C. Black, Barry J. Babin, Ralph E. Anderson, 2018), larger samples are particularly beneficial in models that involve mediation, multiple predictors, and comparisons across groups—features that are central to the present research.

Given that AI acceptance and implementation in HR practices is still evolving and uneven across organizations, achieving a large and diverse sample strengthens the study's ability to capture variations in employee perceptions across industries and demographic categories. Although the study employs non-probability sampling, the large sample size enhances analytical credibility and internal validity, making the findings meaningful within the defined scope.

In summary, the sample size for the present study was determined using established PLS-SEM guidelines. With a required minimum of 1100 respondents and an actual sample of 1245 respondents, the study meets and exceeds methodological standards for quantitative analysis. The selected sample size provides a strong foundation for reliable statistical testing and supports the validity of conclusions drawn regarding AI acceptance, perceived implementation, and organizational effectiveness.

3.7.1.4 Sampling Area

The sampling area was limited to Gujarat state, covering employees from selected industries (Information Technology / Information Technology Enabled Servies (IT/ITES), Hospitality & Healthcare, Consumer Durables and Telecommunications, Banking Insurance and Financial Services (BFSI) and Management Consultancy)

3.8 Data Collection Method

Primary Data were collected through a self-administered structured survey using multiple contact methods online and offline including email, LinkedIn, WhatsApp, and personal visits, ensuring wider reach and improved response rates. The questionnaire was designed to capture respondents' perceptions of AI readiness, acceptance, implementation, and organizational effectiveness.

Secondary data were collected from academic journals, books, conference proceedings, industry reports, and credible online sources to support theoretical grounding and instrument development.

3.9 Tools used for Data Analysis

The collected data were analyzed using the following software tools:

- **IBM SPSS 20** – for descriptive statistics, reliability analysis, Exploratory Factor Analysis (EFA), and hypothesis testing.
- **SmartPLS 4** – for Confirmatory Factor Analysis (EFA), structural equation modelling (SEM) and validation of the conceptual framework.
- **Excel –** For graphs and charts of demographic factors

3.10 Research Instrument

A research instrument is a systematic tool used to collect, measure, and record data related to the variables under investigation. In quantitative research, the research instrument plays a critical role in translating abstract theoretical constructs into measurable indicators that can be empirically tested. The quality of a study's findings largely depends on the reliability, validity, and appropriateness of the instrument used, as it directly influences the accuracy and consistency of the data collected (Kothari & Garg, 2025; Sekaran & Bougie, 2016).

In studies examining technology adoption and organizational outcomes, a well-designed research instrument is particularly important because constructs such as acceptance, readiness, and effectiveness are perceptual and cannot be directly observed. Therefore, these constructs must be captured through carefully structured statements that reflect respondents' experiences, beliefs, and attitudes.

Considering the objectives of the present study and the need to capture employee perceptions across multiple dimensions, a structured questionnaire was selected as the primary research instrument. Questionnaires are widely used in organizational and technology adoption research due to their ability to collect standardized data from a large number of respondents, facilitate statistical analysis, and ensure objectivity and comparability (Creswell & Creswell, 2018).

The use of a questionnaire is particularly appropriate for this study because AI adoption in HR practices involves individual perceptions, organizational conditions, and environmental influences, all of which can be effectively measured using structured items.

The questionnaire was developed through an extensive review of existing literature on Artificial Intelligence in HR, technology adoption models, and organizational effectiveness. Established theories such as the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), Technology–Organization–Environment (TOE) framework, and Diffusion of Innovation (DOI) theory provided the theoretical foundation for item construction.

Items were adapted and contextualized to reflect AI-enabled HR practices within Indian service sector organizations. Care was taken to ensure that the language used was clear, neutral, and easily understandable by respondents from diverse professional backgrounds, thereby minimizing ambiguity and response bias.

3.10.1 Structure of the Research Instrument

- Section 1: Demographic Variables
  - Age
  - Gender
  - Experience
  - Income
  - Education
  - Industry
  - Size of Organization
  - Level of Management
  - Location

- Section 2: Artificial Intelligence
  - Technology Readiness - TOE
    - Technology Characteristics – Task Technology Fit (TTF)

      (Abdekhoda et al., 2018b; Amankwah-Amoah et al., 2021b; Chatterjee et al., 2021b; Gangwar et al., 2015b; Gutierrez et al., 2017b; Jöhnk et al., 2021b; Journal et al., 2017; Leung, 2015b; Li, 2020b; Matias, 2021b; Nguyen & Le, 2022b; Pan et al., 2021b; Prikshat et al., 2021b; Vasiljeva et al., 2021b)

    - Perceived Value (Usefulness) - TAM
      - *Relative Advantage - TOE*

        (Abdekhoda et al., 2018b; Amankwah-Amoah et al., 2021b; Chatterjee et al., 2021b; Gangwar et al., 2015b; Gutierrez et al., 2017b; Jöhnk et al., 2021b; Journal et al., 2017; Leung, 2015b; Li, 2020b; Matias, 2021b; Nguyen & Le, 2022b; Pan et al., 2021b; Prikshat et al., 2021b; Vasiljeva et al., 2021b)

      - *Positive Attitude towards Change - TOE*

        (Abdekhoda et al., 2018b; Gutierrez et al., 2017b; Journal et al., 2017; Leung, 2015b; Li, 2020b; Matias, 2021b; Nguyen & Le, 2022b)

      - *Creativity - TOE*

        (Abdekhoda et al., 2018b; Gutierrez et al., 2017b; Journal et al., 2017; Leung, 2015b; Li, 2020b; Matias, 2021b; Nguyen & Le, 2022b)

      - *Self-Efficacy - TOE*

        (Balakrishnan et al., 2021b; Chuttur, 2009a; Go et al., 2020b; Iyer et al., 2020b; King & He, 2006; Y. Lee et al., 2003b; Money & Turner, 2004b; Ochmann & Laumer, 2020; Park et al., 2022c; Singh et al., 2020b; Sohn & Kwon, 2020b; Xu & Wang, 2021b)

    - Perceived User-friendliness (Ease of use) - TAM
      - *Complexity - TOE*

        (Abdekhoda et al., 2018b; Amankwah-Amoah et al., 2021b; Chatterjee et al., 2021b; Gangwar et al., 2015b; Gutierrez et al., 2017b; Jöhnk et al., 2021b; Journal et al., 2017; Leung, 2015b; Li, 2020b; Matias, 2021b; Nguyen & Le, 2022b; Pan et al., 2021b; Prikshat et al., 2021b; Vasiljeva et al., 2021b)

      - *Resistance to change - TOE*

(Rahman, Qi and Jinnah, 2016b, 2016a; Baharuden, Isaac and Ameen, 2019; Bagheri Rad, Valmohammadi and Shayan, 2020; Arabia, Colleges and Arabia, 2021; Shakeel and Siddiqui, 2021; Cao et al., 2021; Daniel Bagana, Irsad and Santoso, 2021; Gado et al., 2021; Hossin et al., 2021; Raza et al., 2021)

- Organization Readiness - TOE
    - Top Management Support - TOE

      (Abdekhoda et al., 2018b; Chatterjee et al., 2021b; Gangwar et al., 2015b; Gutierrez et al., 2017b; Journal et al., 2017; Leung, 2015b; Li, 2020b; Matias, 2021b; Nguyen & Le, 2022b; Prikshat et al., 2021b)

    - Social Characteristics - TTF

      (Abbas et al., 2018b; A. Agarwal, 2022b; Ajzen, 2011; Bere, 2018; D'Ambra et al., 2013; Daradkeh, 2019; F. D. Davis, 1989b; Goodhue, 1998; Goodhue & Thompson, 1995; Hidayatno et al., 2019; Kukafka et al., 2003c, 2003d, 2003e; Straub, 2009b; Tam & Oliveira, 2016b; Zhu et al., 2018)

    - Performance Expectancy - UTAUT

      (Arabia et al., 2021; Baharuden et al., 2019; Daniel Bagana et al., 2021; Gado et al., 2021; Hossin et al., 2021; Kelibay et al., 2020; Kwan et al., 2019; D. C. Lee et al., 2017; Molitor, 2020; Shakeel & Siddiqui, 2021b; Venkatesh & Davis, 2000d)

    - Effort Expectancy - UTAUT

      (Alam et al., 2020; Arabia et al., 2021; Baharuden et al., 2019; Daniel Bagana et al., 2021; Del Giudice et al., 2021b; Gado et al., 2021; Hmoud & Várallyai, 2021; Hossin et al., 2021; Im et al., 2011b; Kelibay et al., 2020; Kwan et al., 2019; D. C. Lee et al., 2017; Shakeel & Siddiqui, 2021b; Venkatesh & Davis, 2000d)

- Environment Readiness - TOE
    - Social Influence (Competitive Pressure) – TOE & UTAUT

      (Alam et al., 2020; Arabia et al., 2021; Baharuden et al., 2019; Daniel Bagana et al., 2021; Del Giudice et al., 2021b; Gado et al., 2021; Hmoud & Várallyai, 2021; Hossin et al., 2021; Im et al., 2011b; Kelibay et al., 2020; Kwan et al., 2019; D. C. Lee et al., 2017; Shakeel & Siddiqui, 2021b; Venkatesh & Davis, 2000d)

    - External Support (Support from service Provider) - TOE

(Abdekhoda et al., 2018b; Amankwah-Amoah et al., 2021b; Chatterjee et al., 2021b; Gangwar et al., 2015b; Gutierrez et al., 2017b; Jöhnk et al., 2021b; Journal et al., 2017; Leung, 2015b; Li, 2020b; Matias, 2021b; Nguyen & Le, 2022b; Pan et al., 2021b; Prikshat et al., 2021b; Vasiljeva et al., 2021b)

- Facilitating Conditions - UTAUT

(Abdekhoda et al., 2018b; Amankwah-Amoah et al., 2021b; Chatterjee et al., 2021b; Gangwar et al., 2015b; Gutierrez et al., 2017b; Jöhnk et al., 2021b; Journal et al., 2017; Leung, 2015b; Li, 2020b; Matias, 2021b; Nguyen & Le, 2022b; Pan et al., 2021b; Prikshat et al., 2021b; Vasiljeva et al., 2021b)

- Section 3: Behavioural Intention - UTAUT

(Alam et al., 2020; Arabia et al., 2021; Bagheri Rad et al., 2020; Baharuden et al., 2019; Cao et al., 2021b; Daniel Bagana et al., 2021; Del Giudice et al., 2021b; Gado et al., 2021; Hmoud & Várallyai, 2021; Hossin et al., 2021; Im et al., 2011b; Kelibay et al., 2020; Kwan et al., 2019; D. C. Lee et al., 2017; Molitor, 2020; Rahman et al., 2016b, 2016c; Raza et al., 2021b; Shakeel & Siddiqui, 2021b; Venkatesh & Davis, 2000d; Yap, & Ng, 2018)

- Section 4: Perceived AI Acceptance – developed by Researcher inspired from TAM (Attitude towards using)/TOE

(Balakrishnan et al., 2021b; Chuttur, 2009a; Go et al., 2020b; Iyer et al., 2020b; King & He, 2006; Y. Lee et al., 2003b; Money & Turner, 2004b; Ochmann & Laumer, 2020; Park et al., 2022c; Singh et al., 2020b; Sohn & Kwon, 2020b; Xu & Wang, 2021b)

  - User Acceptance
    - *Compatibility - TOE*
    - *Uncertainty/Risk – TOE*
- Section 5: Perceived AI Implementation - developed by Researcher inspired from TAM (Actual System usage)/TOE

(Damsgaard, 2014; Dong & Neufeld, 2008; Information & Information, 2014b; Klopping, 2004; Kukafka et al., 2003f; Lai & Mahapatra, 1997; Pina et al., 2019; Schoville, 2015; Straub, 2009a; Wilkins & Swatman, 2007; Wozney & Abrami, 2016)

- Section 6: Organizational Effectiveness – Extracted from scale by D.M. Pestonjee (Pestonjee, 1988b)

All the items in the questionnaire were measured using a five-point Likert scale, ranging from *Strongly Disagree (1)* to *Strongly Agree (5)*. The Likert scale was chosen due to its suitability for measuring attitudes and perceptions, ease of comprehension for respondents, and compatibility with advanced statistical analysis techniques (Hair et al., 2019).

3.11 Pre-Testing and Refinement of the Instrument

Prior to full-scale data collection, the questionnaire was subjected to expert review and pilot testing. Feedback from academic experts and practitioners helped ensure content relevance, clarity of wording, and logical sequencing of items. Minor revisions were made to improve readability and reduce redundancy, thereby enhancing the instrument's content validity.

3.11.1 Content Validity

Content validity refers to the extent to which the research instrument adequately represents all relevant dimensions of the constructs being measured. In studies involving perceptual and multidimensional constructs such as Artificial Intelligence acceptance, perceived implementation, and organizational effectiveness, establishing content validity is essential to ensure conceptual accuracy and relevance.

In the present study, content validity was ensured through a theory-driven and expert evaluation process**.** Questionnaire items were developed based on an extensive review of literature and established theoretical frameworks, including TAM, UTAUT, TOE, DOI, and the D. M. Pestonjee Organizational Effectiveness framework.

The initial questionnaire was reviewed by two subject matter experts: Dr. Vishal Dahiya**,** Professor and Director (iMCA), Sardar Vallabhbhai Global University, and Mr. Jay Hulani**,** Regional HR Manager – Gujarat, MP & Chhattisgarh, Samsung Electronics India Ltd. Their evaluation focused on item relevance, clarity, completeness, and contextual suitability for Indian service sector organizations. Based on their feedback, minor refinements were made to improve wording and eliminate redundancy. The expert validation process confirmed that the instrument adequately captured the conceptual domains of the study variables and was appropriate for empirical investigation.

3.11.2 Pilot Testing

A pilot study was conducted prior to the final data collection to assess the clarity, reliability, relevance, and feasibility of the research instrument. A pilot study serves as a preliminary test of the questionnaire and helps identify potential issues related to wording, structure, length, and respondent understanding before administering the instrument on a larger scale. It also provides an early indication of the reliability of measurement scales (Sekaran & Bougie, 2016).

The pilot study was conducted with 59 respondents, selected from the target population of employees working in selected sector organizations. These respondents possessed adequate awareness or exposure to AI-enabled HR practices, making them suitable for evaluating the relevance and understanding of the questionnaire items. The pilot sample size is considered adequate for preliminary testing of instrument reliability and clarity in survey-based research. Respondents were requested to complete the questionnaire and provide feedback regarding item clarity, language, length, and overall flow. The responses obtained from the pilot study were subjected to preliminary reliability analysis using Cronbach's Alpha. The successful completion of the pilot study confirmed that the research instrument was reliable, relevant, and suitable for large-scale data collection. The pilot findings provided confidence to proceed with the final survey administration across selected service sector organizations.

In summary, the pilot study involving 59 respondents played a crucial role in validating the research instrument and ensuring its readiness for full-scale implementation. The refinements made based on pilot feedback enhanced the overall quality and robustness of the questionnaire, thereby strengthening the methodological rigor of the study.

3.11.3 Data Validity & Reliability

Hypothesis

H_0 - Distribution is Normal

H_1 - Distribution is not Normal

Table 3-1: Descriptive Statistics for Normality

Descriptives

			Statistic	Std. Error
Average	Mean		2.291911	.0156370
	95% Confidence Interval for Mean	Lower Bound	2.261233	
		Upper Bound	2.322589	
	5% Trimmed Mean		2.267811	
	Median		2.237288	
	Variance		.304	
	Std. Deviation		.5517460	
	Minimum		1.0336	
	Maximum		4.7731	
	Range		3.7395	
	Interquartile Range		.6723	
	Skewness		1.029	.069
	Kurtosis		2.993	.139

The values from above table for skewness and kurtosis which has a z-values as 14.91 and 21.53 respectively which are outside the required limit between -1.96 to + 1.96. criteria for normality suggests that data distribution is not normal because of which null hypothesis is rejected that distribution is normal.

In the case of this study the sample size is very large i.e. 1245, the z-score becomes very sensitive even to small variations in data, and most of the time showcase non-normality. Again, the calculated value of Skewness is 1.029 which is within the limit i.e. -2 to +2 for which data can be considered normal and for Kurtosis the calculated value is 2.993 which is also within limits of normality i.e. -7 to +7. As both the values falls within the acceptable range for large samples size data might be considered approximately normal despite the extreme z-values. Most parametric test will perform well as the values of absolute skewness and Kurtosis is within the limits less than 2 and less than 7 respectively.

Table 3-2: Test of Normality

Tests of Normality						
	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Average	.070	1245	.000	.944	1245	.000

To further check the normality the Kolmogorov-Smirnov & Shapiro-Wilk test were used where the significant values for both the test was found to be 0.000 which is less than p-value of 0.05, which again suggest that the data is not normal in nature and Alternate hypothesis is accepted.

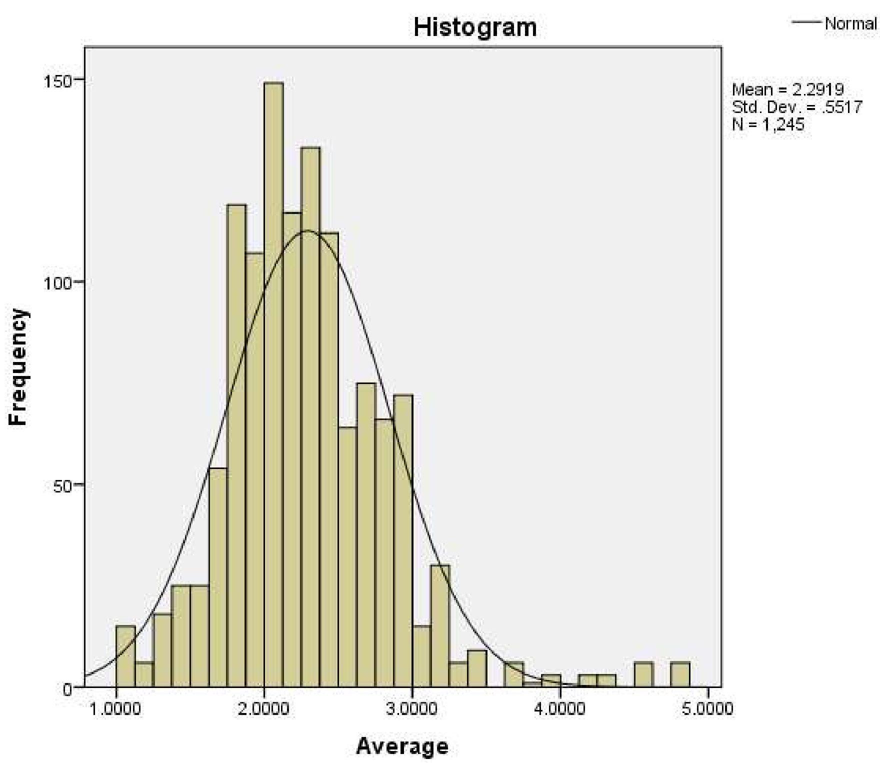

Figure 3-1: Histogram for data Normality

3.11.3.1 Reliability Test - Cronbach's Alpha

Table 3-3: Cronbach's Alfa Reliability

Particulars	***Cronbach's Alfa***	***Reliability Level***
Artificial Intelligence – Section 1		
Technology Readiness		
Technology Characteristics – Part 1	.895	Very Good
Perceived Value (Usefulness)		
Relative Advantage – Part 2	.839	Very Good
Positive Attitude towards Change – Part 3	.889	Very Good
Creativity – Part 4	.816	Very Good
Self-Efficacy – Part 5	.825	Very Good
Perceived User-friendliness (Ease of use)		
Complexity – Part 6	.832	Very Good
Resistance to change – Part 7	.859	Very Good
Organization Readiness – Section 2		
Top Management Support – Part 8	.897	Very Good
Social Characteristics – Part 9	.895	Very Good
Performance Expectancy – Part 10	.834	Very Good
Effort Expectancy -Part 11	.853	Very Good
Environment Readiness – Section 3		
Social Influence (Competitive Pressure) – Part 12	.845	Very Good
External Support (Support from service Provider) - Part 13	.894	Very Good
Facilitating Conditions – Part 14	.828	Very Good
Behavioural Intention – Section 4 *(Part 15)*	.929	Excellent
Perceived AI Acceptance – Section 5		
User Acceptance		
Compatibility – Part 16	.919	Excellent
Uncertainty/Risk – Part 17	.887	Very Good
Perceived AI Implementation – Section 6 *(Part 18)*	.934	Excellent
Organizational Effectiveness – Section 7 *(Part 19)*	.931	Excellent

Reliability analysis assesses the internal consistency of measurement items used to capture latent constructs in a research instrument. Internal consistency reflects the degree to which items measuring the same construct produce consistent results. In quantitative research, Cronbach's Alpha (α) is the most widely accepted measure of internal reliability, particularly for Likert-scale instruments. (Joseph F. Hair, William C. Black, Barry J. Babin, Ralph E. Anderson, 2018)

Cronbach's Alpha values range from 0 to 1, with higher values indicating stronger internal consistency. As a general guideline:

- $\alpha \geq 0.70$ indicates acceptable reliability
- $\alpha \geq 0.80$ indicates very good reliability
- $\alpha \geq 0.90$ indicates excellent reliability

The reliability analysis for the present study demonstrates high internal consistency across all constructs, as summarized below:

- All sub-dimensions of Technology Readiness (Technology Characteristics, Relative Advantage, Positive Attitude toward Change, Creativity, Self-Efficacy, Complexity, and Resistance to Change) show very good reliability, with Cronbach's Alpha values ranging from 0.816 to 0.895.
- Organizational Readiness variables, including Top Management Support, Social Characteristics, Performance Expectancy, and Effort Expectancy, also exhibit very good reliability (α between 0.834 and 0.897).
- Environmental Readiness constructs—Social Influence (Competitive Pressure), External Support, and Facilitating Conditions—demonstrate strong internal consistency with α values above 0.828.
- Behavioural Intention ($\alpha = 0.929$), Perceived AI Acceptance (Compatibility $\alpha = 0.919$), Perceived AI Implementation ($\alpha = 0.934$), and Organizational Effectiveness ($\alpha = 0.931$) show excellent reliability, indicating highly consistent measurement.

These results confirm that all constructs used in the study exceed the recommended reliability thresholds and are suitable for further multivariate analysis.

The consistently high Cronbach's Alpha values indicate that:

- The questionnaire items are well-aligned with their respective constructs
- The measurement instrument is stable, reliable, and free from random error
- The constructs can be confidently used for hypothesis testing, regression analysis, and structural equation modelling

High reliability across both antecedent and outcome variables strengthens the credibility of subsequent empirical findings and supports the robustness of the conceptual framework.

The reliability analysis confirms that the research instrument used in this study possesses strong internal consistency across all constructs. With Cronbach's Alpha values well above the acceptable threshold, the instrument is deemed reliable for examining the acceptance and perceived implementation of Artificial Intelligence in HR practices and their impact on organizational effectiveness.

3.12 Limitations of Study

- While providing deep insights into selected Indian industries, the findings may not be directly generalizable to other industries or global contexts due to variations in technological maturity, regulatory environments
- The study captures data at a single point in time. This limits the ability to track the evolution of AI acceptance, implementation, and impact over a longer period.
- The data may be biased as a significant portion of the data, particularly regarding perceptions of AI factors and organizational effectiveness, is self-reported through surveys.
- The data of the study was found to be not-normal and appropriate tools like SEM-Bootstrapping were used but results may differ if it is compared with normalized data analysis.
- The study does not explore into the intricate technical details of AI algorithms, which could limit the depth of analysis regarding specific biases or functionalities within AI HR solutions.

CHAPTER - 4 DATA ANALYSIS

4.1 Introduction

This chapter presents the statistical analysis and interpretation of data collected to study the Perceived acceptance and perceived implementation of Artificial Intelligence (AI) in HR practices and its impact on organizational effectiveness. The analysis was carried out in line with the research objectives and hypotheses using quantitative techniques. Data analysis was performed in two stages: preliminary analysis using IBM SPSS 20, and advanced multivariate and structural analysis using SmartPLS 4. The combination of these tools ensured both descriptive clarity and robust model testing.

Prior to analysis, the collected data were carefully screened to ensure accuracy and suitability for statistical testing. Incomplete questionnaires, inconsistent responses, and outliers were examined. After screening, 1245 valid responses were retained for analysis, exceeding the minimum required sample size and ensuring adequate statistical power. Missing values were minimal and addressed using appropriate data handling techniques. The dataset was checked for normality, multicollinearity, and common method bias to ensure the reliability of subsequent analyses.

4.2 Exploratory Factor Analysis (EFA)

Exploratory Factor Analysis (EFA) was conducted to examine the underlying factor structure, assess construct validity, and verify whether the observed variables group meaningfully under latent constructs proposed in the conceptual framework. Principal Component Analysis (PCA) with Varimax rotation and Kaiser Normalization was employed to achieve a simplified and interpretable factor structure.

4.2.1 Descriptive Statistics

Hypothesis

H_0: Observed variables do not show meaningful variation to represent latent constructs.

H_1: Observed variables show adequate variation to represent latent constructs.

Table 4-1: Descriptive Statistics

Descriptive Statistics			
	Mean	Std. Deviation	Analysis N
S1_AVG_TC	2.252744	.7974161	1245
S1_AVG_PV	2.248353	.7036590	1245
S1_AVG_PUF	2.432882	.7120877	1245
S2_AVG_TMS	2.266827	.8721301	1245
S2_AVG_SC	2.4892	.83374	1245
S2_AVG_PE	2.2243	.81568	1245
S2_AVG_EE	2.266131	.8297564	1245
S3_AVG_SI	2.423561	.8715144	1245
S3_AVG_ES	2.3667	.81670	1245
S3_AVG_FC	2.3622	.83724	1245
S4-P15-BI1	2.18	.949	1245
S4-P15-BI2	2.22	.902	1245
S4-P15-BI3	2.16	.916	1245
S4-P15-BI4	2.16	.927	1245
S5-P16-UA-C1	2.30	.956	1245
S5-P16-UA-C2	2.24	.893	1245
S5-P16-UA-C3	2.31	.963	1245
S5-P16-UA-C4	2.27	.936	1245
S5-P17-UA-UR1	2.53	1.082	1245
S5-P17-UA-UR2	2.50	1.004	1245
S5-P17-UA-UR3	2.48	1.021	1245
S6-P18-PAII1	2.28	1.008	1245
S6-P18-PAII2	2.31	.924	1245
S6-P18-PAII3	2.34	.978	1245
S6-P18-PAII4	2.31	.923	1245
S6-P18-PAII5	2.27	.935	1245
S6-P18-PAII6	2.32	.954	1245

S6-P18-PAII7	2.28	.948	1245
S6-P18-PAII8	2.23	.919	1245
S6-P18-PAII9	2.27	.958	1245
S6-P18-PAII10	2.21	.941	1245
S6-P18-PAII11	2.25	.925	1245
S6-P18-PAII12	2.16	.976	1245
S7-P19-OE1	2.27	.988	1245
S7-P19-OE2	2.34	.985	1245
S7-P19-OE3	2.31	.973	1245
S7-P19-OE4	2.34	.966	1245
S7-P19-OE5	2.35	.985	1245
S7-P19-OE6	2.38	.986	1245
S7-P19-OE7	2.44	1.040	1245
S7-P19-OE8	2.49	1.049	1245
S7-P19-OE9	2.21	.917	1245
S7-P19-OE10	2.14	.923	1245
S7-P19-OE11	2.26	.935	1245
S7-P19-OE12	2.15	.899	1245
S7-P19-OE13	2.33	1.007	1245
S7-P19-OE14	2.18	.905	1245
S7-P19-OE15	2.19	1.002	1245
S7-P19-OE16	2.18	.954	1245
S7-P19-OE17	2.15	.964	1245

Descriptive statistics were computed to understand the central tendency and dispersion of respondents' perceptions across all study constructs. Mean scores and standard deviations were calculated for each variable based on 1245 valid responses, indicating strong sample adequacy.

Result of Descriptive Statistics showcase that Mean Value of all loaded items is between (Mean <0.5 and >4.5) and Standard deviation zero represents that respondents have done the extreme ticks (Strongly Agree or Strongly Disagree) and if there is no variation is statements than that statement is not useful for may study. None of our statements have SD near to zero hence it shows that the data is fit for conducting EFA.

Across constructs, the mean values range approximately between 2.14 and 2.53, suggesting that respondents exhibit a moderate level of agreement with statements related to Artificial Intelligence (AI) readiness, acceptance, perceived implementation, and organizational effectiveness. The standard deviation values, mostly ranging between 0.70 and 1.08, indicate acceptable variability in responses, reflecting diversity in employee perceptions across industries and demographic profiles.

Technology Readiness

- Technology Characteristics (Mean = 2.25)
- Perceived Value / Usefulness (Mean = 2.24)
- Perceived User Friendliness (Mean = 2.43)

These moderate mean scores indicate that employees recognize the functional potential of AI in HR, but their perceptions are still cautious. Ease of use scored relatively higher, suggesting that usability is less of a barrier compared to perceived value and strategic relevance. Employees are open to AI technologies but are still in an evaluative phase, reinforcing the need to examine acceptance and implementation separately.

Organizational Readiness

- Top Management Support (Mean = 2.27)
- Social Characteristics (Mean = 2.49)
- Performance Expectancy (Mean = 2.22)
- Effort Expectancy (Mean = 2.27)

Social characteristics (peer influence and support) scored the highest in this section, indicating that social context strongly shapes AI perceptions. However, performance expectancy remains relatively low, suggesting uncertainty about tangible performance gains. Organizational culture and leadership support are present but not yet strong enough to translate into clear performance confidence, justifying hypothesis testing on organizational readiness.

Environmental Readiness

- Social Influence / Competitive Pressure (Mean = 2.42)
- External Support (Mean = 2.37)
- Facilitating Conditions (Mean = 2.36)

These findings suggest that external forces such as competition and vendor support moderately encourage AI adoption, but infrastructural and facilitation mechanisms are still evolving. Environmental factors act as enablers rather than primary drivers, supporting their indirect role in shaping behavioural intention.

Behavioural Intention

- BI Items (Means between 2.16 and 2.22)

The relatively lower mean values indicate hesitation in intention to use AI-enabled HR systems, despite moderate readiness conditions. This gap between readiness and intention highlights the importance of studying behavioural intention as a mediating variable.

Perceived AI Acceptance

- Compatibility (Means between 2.24 and 2.31)
- Uncertainty/Risk (Means between 2.48 and 2.53)

Risk-related items show slightly higher mean values, indicating that concerns around privacy, job security, and trust are prominent. Acceptance of AI is conditional and risk-sensitive, reinforcing the conceptual distinction between acceptance and implementation.

Perceived AI Implementation

- Implementation Items (Means between 2.16 and 2.34)

Moderate scores suggest that employees perceive partial or early-stage AI implementation, rather than mature or fully institutionalized use. This supports the premise that implementation lags acceptance, validating the study's focus on perceived implementation as a distinct construct.

Organizational Effectiveness (Section 7)

- OE Items (Means between 2.14 and 2.49)

Higher scores on growth and adaptability-related items and lower scores on autonomy and initiative indicate uneven effectiveness outcomes. Organizational effectiveness gains from AI appear context-dependent and implementation-driven, rather than automatic. As the Mean values range between 2.14 – 2.53 and Standard deviations are within acceptable range, descriptive statistics suggests that H_1 is Accepted that Variables exhibit sufficient dispersion for factor extraction.

The descriptive statistics reveal that AI adoption in HR practices is at a moderate and transitional stage. Employees neither reject nor fully embrace AI; instead, their perceptions reflect cautious optimism shaped by organizational support, perceived risk, and implementation clarity. These findings empirically justify the proposed conceptual framework and provide a strong foundation for factor analysis, structural equation modelling, and hypothesis testing in subsequent stages.

4.2.2 KMO and Bartlett's Test

Prior to conducting Exploratory Factor Analysis (EFA), the suitability of the data for factor analysis was assessed using the Kaiser–Meyer–Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity. These tests evaluate whether the correlation matrix is appropriate for factor extraction. The KMO value obtained for the present dataset is 0.963, which is substantially higher than the recommended minimum threshold of 0.60. According to established guidelines, KMO values above 0.90 are considered "excellent," indicating a very high degree of common variance among the variables.

Hypothesis

H_0 – Correlation Matrix is an identity matrix

H_1 - Correlation Matrix is not an identity matrix

KMO is .963 which is greater than 0.7 hence the sample size is excellent to carry out EFA. P-value of Bartlett's Test of sphericity is 0.000 which is less than 5% (0.05) level of significance. Hence, we reject Null Hypothesis, so Correlation Matrix is not an identity matrix. The data is highly suitable for factor analysis.

Table 4-2: KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.963
Bartlett's Test of Sphericity	Approx. Chi-Square	126636.277
	df	5995
	Sig.	0.000

The exceptionally high KMO value confirms that the sample size is more than adequate and that the variables share sufficient correlations to justify factor analysis. This result indicates that the data structure is compact and likely to yield reliable and distinct factors.

Bartlett's Test of Sphericity yielded a Chi-square value of 126,636.277 with 5995 degrees of freedom, which is statistically significant at $p < 0.001$. The significant Bartlett's test result indicates that the correlation matrix is not an identity matrix. This confirms the presence of statistically significant relationships among variables, making them suitable for factor extraction.

The excellent KMO value and significant Bartlett's test validate the decision to proceed with EFA and subsequent SEM analysis, ensuring that hypothesis testing is grounded in a statistically sound measurement structure.

4.2.3 Communalities

Communalities represent the proportion of variance in each observed variable explained by the extracted factors. In the present analysis, Communalities of all 110 items were higher than threshold of 0.50 ranging from approximately 0.505 to 0.729, the desired value hence the factor reduction was carried out with the help of Rotated component Matrix using Varimax rotation technique. The strong communalities confirm that the measurement items are well-aligned with the latent constructs and suitable for further multivariate and structural analysis.

Table 4-3: Communalities

Communalities		
	Initial	Extraction
S1_AVG_TC	1.000	.591
S1_AVG_PV	1.000	.682
S1_AVG_PUF	1.000	.600
S2_AVG_TMS	1.000	.664
S2_AVG_SC	1.000	.639
S2_AVG_PE	1.000	.690
S2_AVG_EE	1.000	.628
S3_AVG_SI	1.000	.558
S3_AVG_ES	1.000	.654
S3_AVG_FC	1.000	.669
S4-P15-BI1	1.000	.640
S4-P15-BI2	1.000	.675
S4-P15-BI3	1.000	.669
S4-P15-BI4	1.000	.644
S5-P16-UA-C1	1.000	.670
S5-P16-UA-C2	1.000	.680
S5-P16-UA-C3	1.000	.650
S5-P16-UA-C4	1.000	.604
S5-P17-UA-UR1	1.000	.630
S5-P17-UA-UR2	1.000	.597
S5-P17-UA-UR3	1.000	.710
S6-P18-PAII1	1.000	.590
S6-P18-PAII2	1.000	.686
S6-P18-PAII3	1.000	.685
S6-P18-PAII4	1.000	.720
S6-P18-PAII5	1.000	.714
S6-P18-PAII6	1.000	.724
S6-P18-PAII7	1.000	.676

S6-P18-PAII8	1.000	.713
S6-P18-PAII9	1.000	.670
S6-P18-PAII10	1.000	.620
S6-P18-PAII11	1.000	.611
S6-P18-PAII12	1.000	.552
S7-P19-OE1	1.000	.591
S7-P19-OE2	1.000	.604
S7-P19-OE3	1.000	.636
S7-P19-OE4	1.000	.505
S7-P19-OE5	1.000	.626
S7-P19-OE6	1.000	.667
S7-P19-OE7	1.000	.702
S7-P19-OE8	1.000	.708
S7-P19-OE9	1.000	.637
S7-P19-OE10	1.000	.707
S7-P19-OE11	1.000	.638
S7-P19-OE12	1.000	.696
S7-P19-OE13	1.000	.562
S7-P19-OE14	1.000	.729
S7-P19-OE15	1.000	.710
S7-P19-OE16	1.000	.704
S7-P19-OE17	1.000	.679

Extraction Method: Principal Component Analysis.

4.2.4 Total Variance

The EFA results indicate that **five components** with eigenvalues greater than 1 were extracted, in line with Kaiser's criterion. The **five extracted factors together explain 65.215% of the total variance**, which exceeds the commonly accepted threshold of 60% for social science research. The first component accounts for the largest proportion of variance, reflecting the dominant role of core AI implementation perceptions. After Varimax rotation, variance is more evenly distributed across factors, enhancing interpretability. The extracted factors collectively capture a substantial portion of the information contained in the original variables, confirming the adequacy of the factor solution and supporting the multidimensional nature of AI adoption and organizational effectiveness.

Table 4-4: Total Variance Extracted

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	24.992	49.983	49.983	24.992	49.983	49.983	8.660	17.319	17.319
2	2.568	5.136	55.119	2.568	5.136	55.119	7.147	14.293	31.613
3	1.993	3.987	59.106	1.993	3.987	59.106	6.778	13.555	45.168
4	1.567	3.135	62.240	1.567	3.135	62.240	5.674	11.348	56.516
5	1.487	2.974	65.215	1.487	2.974	65.215	4.349	8.699	65.215
6	1.243	2.486	67.700						
7	.832	1.663	69.364						
8	.778	1.556	70.920						
9	.746	1.493	72.413						
10	.734	1.468	73.881						
11	.666	1.331	75.212						
12	.627	1.255	76.467						
13	.616	1.232	77.699						
14	.573	1.145	78.844						
15	.553	1.105	79.949						
16	.530	1.059	81.008						
17	.502	1.005	82.013						
18	.481	.962	82.976						
19	.471	.942	83.918						
20	.458	.916	84.834						
21	.439	.878	85.712						
22	.425	.850	86.562						
23	.413	.826	87.388						
24	.380	.761	88.149						
25	.358	.716	88.865						
26	.342	.683	89.548						
27	.338	.676	90.224						
28	.305	.610	90.834						
29	.296	.591	91.425						
30	.283	.566	91.991						
31	.274	.548	92.540						
32	.272	.545	93.084						
33	.257	.514	93.599						
34	.249	.497	94.096						
35	.241	.482	94.578						
36	.234	.469	95.047						

37	.227	.454	95.500
38	.221	.442	95.942
39	.214	.429	96.371
40	.201	.401	96.772
41	.197	.395	97.167
42	.192	.384	97.551
43	.181	.362	97.914
44	.178	.357	98.270
45	.167	.333	98.604
46	.157	.314	98.918
47	.152	.305	99.223
48	.139	.278	99.500
49	.130	.260	99.761
50	.120	.239	100.000

Extraction Method: Principal Component Analysis.

4.2.5 Rotated Component Matrix

Hypothesis:

H_0: Observed variables do not load significantly on their respective latent factors.

H_1: Observed variables load significantly on their respective latent factors.

The rotated component matrix reveals a clear and theoretically coherent loading pattern, with most items loading strongly (> 0.50) on their respective components and minimal cross-loadings. The researcher studied 5 major factors for the study and hence in EFA 5 factors were derived from this study. All the factors loaded well on the respective components, clear factor separation with no problematic cross-loadings. Hence alternate hypothesis is accepted that observed variables load significantly on their respective latent factors. The extracted factor structure is valid and interpretable. So, alternate hypothesis, Observed variables load significantly on their respective latent factors is accepted.

Table 4-5: Rotated Component Matrix

Rotated Component Matrix[a]

	Component				
	1	2	3	4	5
S1_AVG_TC				.639	
S1_AVG_PV				.721	
S1_AVG_PUF				.637	
S2_AVG_TMS				.595	

S2_AVG_SC				.563	
S2_AVG_PE				.639	
S2_AVG_EE				.556	
S3_AVG_SI				.468	
S3_AVG_ES				.540	
S3_AVG_FC				.449	
S4-P15-BI1		.593			
S4-P15-BI2		.622			
S4-P15-BI3		.588			
S4-P15-BI4		.586			
S5-P16-UA-C1					0.622
S5-P16-UA-C2					0.602
S5-P16-UA-C3					0.632
S5-P16-UA-C4					0.596
S5-P17-UA-UR1					0.696
S5-P17-UA-UR2					0.634
S5-P17-UA-UR3					0.692
S6-P18-PAII1	.590				
S6-P18-PAII2	.711				
S6-P18-PAII3	.705				
S6-P18-PAII4	.733				
S6-P18-PAII5	.663				
S6-P18-PAII6	.725				
S6-P18-PAII7	.665				
S6-P18-PAII8	.694				
S6-P18-PAII9	.632				
S6-P18-PAII10	.548				
S6-P18-PAII11	.457				
S6-P18-PAII12	.421				
S7-P19-OE1			.462		

S7-P19-OE2			.538		
S7-P19-OE3			.585		
S7-P19-OE4			.496		
S7-P19-OE5			.639		
S7-P19-OE6			.596		
S7-P19-OE7			.760		
S7-P19-OE8			.771		
S7-P19-OE9			.545		
S7-P19-OE10			.675		
S7-P19-OE11			.623		
S7-P19-OE12			.691		
S7-P19-OE13			.506		
S7-P19-OE14			.744		
S7-P19-OE15			.730		
S7-P19-OE16			.662		
S7-P19-OE17			.695		

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 12 iterations.

AI Readiness Factors which comprised of Technology Readiness (Technology Characteristics, Perceived Value, Ease of Use -S1_AVG_TC, S1_AVG_PV, S1_AVG_PUF), Organizational Readiness (Top Management Support, Social Characteristics, Performance & Effort Expectancy - S2_AVG_TMS, S2_AVG_SC, S2_AVG_PE & S2_AVG_EE), Environmental Readiness (Competitive Pressure, External Support, Facilitating Conditions - S3_AVG_SI, S3_AVG_ES & S3_AVG_FC) loaded well on component 4. This convergence indicates that employees cognitively perceive readiness as a holistic readiness ecosystem, rather than as isolated technological or managerial components. This empirically supports the integrated TOE–TAM–UTAUT approach, justifying the combined treatment of readiness factors influencing intention and acceptance.

All Behavioural Intention items S4-P15-BI1 to BI4 loaded cleanly on a single factor component 2, with loadings between 0.58 and 0.62. Behavioural Intention emerges as a pure and independent psychological construct, consistent with TAM and UTAUT. Employees clearly distinguish between their readiness conditions and their personal intention to engage with AI-enabled HR systems. This validates Behavioural Intention as a mediating variable between readiness conditions and downstream outcomes such as acceptance and implementation.

Items relating to Perceived AI Acceptance S5-P16-UA-C and S5-P17-UA-UR- compatibility and uncertainty/risk loaded together on component 5, with strong loadings between 0.59 and

0.70. AI acceptance is shown to be conditional and evaluative, shaped simultaneously by perceived fit and perceived risk. Employees do not view acceptance as unconditional enthusiasm, but as a balance between opportunity and concern. This confirms acceptance as a distinct perceptual construct, separate from both intention and implementation.

All the items of Perceived AI Implementation loaded well on component 1 loadings ranging approximately from 0.42 to 0.73 for S6-P18-PAII1 to S6-P18-PAII12. This factor captures employees' perceptions of how deeply and effectively AI may be embedded into HR practices, rather than whether AI is merely accepted in HR practices. This supports the study's central argument that implementation is distinct from acceptance and acts as a critical bridge between intention and organizational effectiveness.

Items derived from the D. M. Pestonjee Organizational Effectiveness framework S7-P19-OE1 to OE17, loaded strongly on component 3, with loadings starting from 0.462 extending up to 0.77. This confirms that AI-enabled HR practices influence organizational effectiveness only when implementation strengthens human outcomes, not merely operational efficiency.

The EFA results clearly demonstrate that Questionnaire items cluster exactly as theoretically expected. No major cross-loadings threaten construct purity. Acceptance, intention, implementation, and effectiveness are empirically distinct. Human and organizational dimensions are central to AI outcomes. This validates the measurement model and provides a strong empirical foundation for SEM-based hypothesis testing.

In conclusion, the EFA confirms that the questionnaire is conceptually sound, statistically robust, and theoretically aligned with the integrated adoption–implementation–effectiveness framework. The findings strongly support proceeding to confirmatory factor analysis and structural equation modelling to test causal relationships.

4.3 Confirmatory Factor Analysis Covariance-Based Structural Equation Modelling (CB-SEM)

Covariance-Based Structural Equation Modelling (CB-SEM) is a theory-driven multivariate technique used to test how well a hypothesized measurement model fits the observed data. In the present study, CB-SEM is employed to conduct Confirmatory Factor Analysis (CFA) in order to validate the factor structure derived from the exploratory analysis and theoretical framework. CFA using CB-SEM enables the assessment of construct reliability, convergent validity, discriminant validity, and overall model fit through established goodness-of-fit indices. Given the confirmatory nature of this stage and the objective of validating measurement properties before testing structural relationships, CB-SEM is considered an appropriate and rigorous analytical approach. (Joseph F. Hair, William C. Black, Barry J. Babin, Ralph E. Anderson, 2018; Sekaran & Bougie, 2016)

The CFA path diagram in Figure 4-2 shows:

- Latent constructs (blue circles)
- Observed variables / indicators (yellow rectangles)
- Measurement paths (black arrows → factor loadings)
- Structural paths (green arrows → relationships between constructs)
- Standardized coefficients displayed on each path

Figure 4-1: Confirmatory Factor Analysis – Path Diagram, illustrates the Covariance-Based Structural Equation Model (CB-SEM) depicting the relationships among Artificial Intelligence readiness, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation, and Organizational Effectiveness. The results indicate that all hypothesized structural paths are positive and statistically significant, providing strong empirical support for the proposed framework. Artificial Intelligence readiness demonstrates a strong and highly significant influence on Behavioural Intention ($\beta = 0.803$, $p < 0.001$), indicating that favourable technological, organizational, and environmental conditions substantially enhance employees' intention to use AI-enabled HR systems. In addition, Artificial Intelligence readiness exerts a direct and highly significant effect on Perceived AI Acceptance ($\beta = 0.843$, $p < 0.001$) and Perceived AI Implementation ($\beta = 0.827$, $p < 0.001$), suggesting that readiness not only shapes intention but also strengthens employees' evaluative acceptance and perceptions of implementation preparedness. A direct and statistically significant relationship is also observed between Artificial Intelligence readiness and Organizational Effectiveness ($\beta = 0.790$, $p < 0.001$), highlighting that readiness contributes to effectiveness both directly and indirectly.

Behavioural Intention exhibits a strong and highly significant impact on Perceived AI Acceptance ($\beta = 0.795$, $p < 0.001$), confirming that employees who intend to use AI systems are more likely to perceive them as compatible, trustworthy, and acceptable. Behavioural Intention further shows a statistically significant influence on Perceived AI Implementation ($\beta = 0.720$, $p < 0.001$), indicating that intention translates into favourable perceptions regarding the execution and operationalization of AI in HR practices. Moreover, Behavioural Intention has a significant direct effect on Organizational Effectiveness ($\beta = 0.695$, $p < 0.001$), reflecting that employee willingness to engage with AI contributes meaningfully to organizational outcomes even beyond implementation mechanisms.

Perceived AI Acceptance significantly influences Perceived AI Implementation ($\beta = 0.805$, $p < 0.001$), reinforcing acceptance as a critical psychological and attitudinal precursor to successful implementation. Finally, Perceived AI Implementation demonstrates the strongest and highly significant effect on Organizational Effectiveness ($\beta = 0.839$, $p < 0.001$), establishing implementation quality as the most proximal driver of effectiveness. This result confirms that improvements in organizational effectiveness are realized when AI in HR practices is supported by appropriate infrastructure, training, governance mechanisms, and continuous technical support.

Overall, the CB-SEM results confirm that all structural relationships proposed in the model are statistically significant at the 0.001 level, thereby validating the theoretical integration of readiness, intention, acceptance, and implementation in explaining organizational effectiveness in AI-enabled HR practices. The CB-SEM path diagram confirms that perceived AI implementation acts as the strongest and most proximal driver of organizational effectiveness, while readiness and behavioural intention exert both direct and mediated effects.

Confirmatory Factor Analysis (CFA) was conducted to validate the measurement model and to confirm whether the observed variables adequately represent the underlying latent constructs proposed in the conceptual framework. Unlike Exploratory Factor Analysis, which identifies potential factor structures, CFA is theory-driven and tests the extent to which the collected data fit the pre-specified model derived from existing literature and prior empirical evidence.

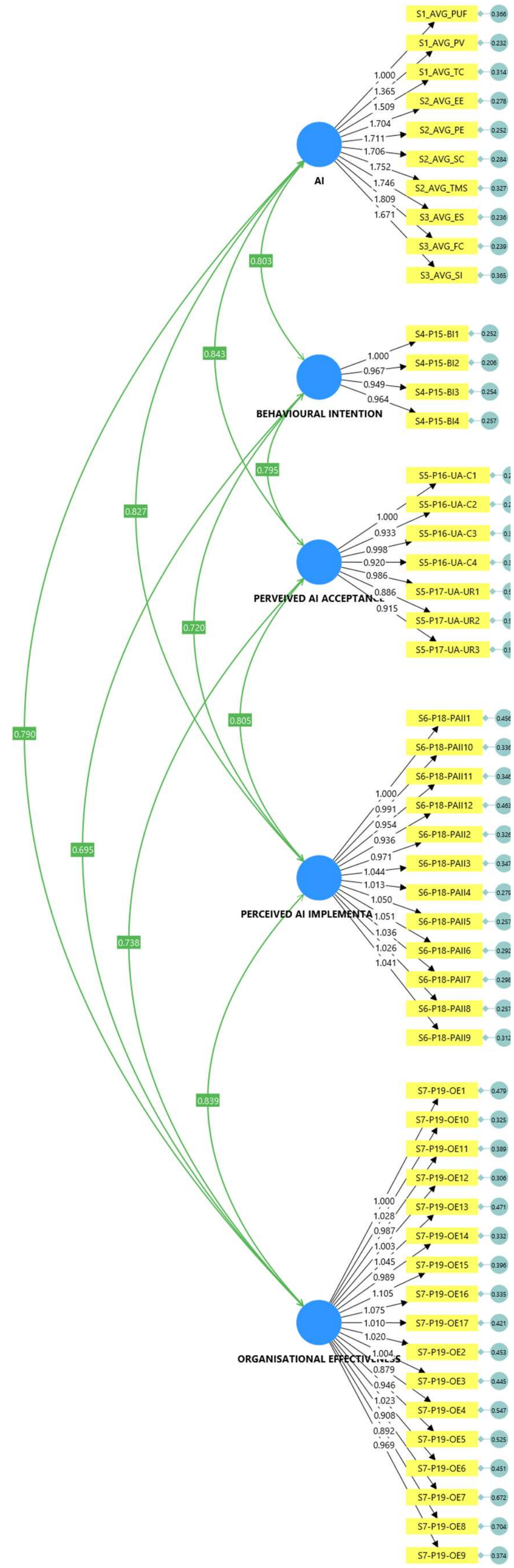

Figure 4-1: Confirmatory Factor Analysis – Path Diagram

In the present study, CFA was employed to examine the reliability and validity of the constructs related to Artificial Intelligence readiness, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation, and Organizational Effectiveness**.** The analysis was performed using Structural Equation Modelling (SEM) to assess model fit and to ensure that the measurement structure is appropriate for subsequent hypothesis testing.

4.3.1 Factor Loadings

Hypothesis:

H_0: Observed indicators do not significantly represent their latent constructs.

H_1: Observed indicators significantly represent their latent constructs.

Table 4-6: CFA Factor Loadings – Matrix Standardized

<u>*Matrix (standardized)*</u>

	AI	Behavioural Intention	Organisational Effectiveness	Perceived AI Implementation	Perceived AI Acceptance
S1_AVG_PUF	0.527				
S1_AVG_PV	0.729				
S1_AVG_TC	0.711				
S2_AVG_EE	0.772				
S2_AVG_PE	0.788				
S2_AVG_SC	0.769				
S2_AVG_TMS	0.755				
S3_AVG_ES	0.803				
S3_AVG_FC	0.812				
S3_AVG_SI	0.720				
S4-P15-BI1		0.849			
S4-P15-BI2		0.864			
S4-P15-BI3		0.835			
S4-P15-BI4		0.838			
S5-P16-UA-C1					0.829
S5-P16-UA-C2					0.828
S5-P16-UA-C3					0.822
S5-P16-UA-C4					0.779
S5-P17-UA-UR1					0.722
S5-P17-UA-UR2					0.699
S5-P17-UA-UR3					0.710
S6-P18-PAII1				0.742	
S6-P18-PAII10				0.787	
S6-P18-PAII11				0.771	

S6-P18-PAII12				0.717	
S6-P18-PAII2				0.786	
S6-P18-PAII3				0.798	
S6-P18-PAII4				0.820	
S6-P18-PAII5				0.840	
S6-P18-PAII6				0.824	
S6-P18-PAII7				0.817	
S6-P18-PAII8				0.834	
S6-P18-PAII9				0.812	
S7-P19-OE1			0.714		
S7-P19-OE10			0.786		
S7-P19-OE11			0.745		
S7-P19-OE12			0.787		
S7-P19-OE13			0.732		
S7-P19-OE14			0.771		
S7-P19-OE15			0.778		
S7-P19-OE16			0.795		
S7-P19-OE17			0.739		
S7-P19-OE2			0.730		
S7-P19-OE3			0.728		
S7-P19-OE4			0.642		
S7-P19-OE5			0.677		
S7-P19-OE6			0.732		
S7-P19-OE7			0.615		
S7-P19-OE8			0.600		
S7-P19-OE9			0.745		

The standardized matrix presents the factor loadings of each observed variable on its respective latent construct after factor extraction and rotation. Factor loadings represent the strength and direction of the relationship between an observed variable and its underlying factor. In behavioural and management research, standardized loadings of 0.50 and above are considered acceptable, while values above 0.70 indicate strong construct representation. The results demonstrate strong convergent validity, with the majority of items exhibiting high standardized loadings on their intended constructs and minimal cross-loadings.

Factor Loading – Matrix (Standardized) – Same group of factors derived on same component and above 0.5. All factors loaded well in respective components proving and validating the results found during Exploratory Factor Analysis.

The standardized factor loading matrix reveals that all observed variables load satisfactorily on their respective latent constructs, with standardized loadings ranging from 0.527 to 0.864, thereby exceeding the minimum acceptable threshold of 0.50. The Artificial Intelligence readiness construct demonstrates loadings between 0.527 and 0.812, with higher contributions from facilitating conditions, external support, performance expectancy, and top management support, indicating that organizational and environmental enablers play a dominant role in shaping AI readiness in HR practices. Behavioural intention indicators exhibit very strong loadings, ranging from 0.835 to 0.864, reflecting a high degree of internal consistency and clarity in employees' intentions to use AI-based HR systems. Perceived AI acceptance items load between 0.699 and 0.829, with compatibility-related items showing comparatively stronger loadings than uncertainty and risk indicators, suggesting that acceptance is primarily driven by perceived alignment with organizational values and systems. The perceived AI implementation construct displays consistently high loadings from 0.717 to 0.840, underscoring the importance of infrastructure readiness, training, technical support, and strategic alignment in translating AI initiatives into practice. Organizational effectiveness indicators load between 0.600 and 0.795, capturing key dimensions such as commitment, initiative, growth opportunities, and value congruence. Overall, the strength and consistency of the loadings confirm strong convergent validity and support the adequacy of the measurement model for subsequent structural analysis. Hence the alternate hypothesis observed indicators significantly represent their latent constructs is accepted.

4.3.2 Model Fit

Hypothesis

H_0: The proposed measurement model does not fit the observed data.

H_1: The proposed measurement model fits the observed data adequately.

Table 4-7: Model Fit Matrix

Model fit Matrix	Estimated model
Chi-square	11154.276
Number of model parameters	110.000
Number of observations	1245.000
Degrees of freedom	1165.000
P value	0.000
ChiSqr/df	9.574
RMSEA	0.083
RMSEA LOW 90% CI	0.082
RMSEA HIGH 90% CI	0.084
GFI	0.703
AGFI	0.675
PGFI	0.642
SRMR	0.053
NFI	0.798
TLI	0.805
CFI	0.815
AIC	11374.276
BIC	11938.234

The overall model fit was assessed using multiple absolute, incremental, and parsimony-based fit indices, as recommended for Covariance-Based Structural Equation Modelling (CB-SEM). The estimated model yielded a chi-square value of 11154.276 with 1165 degrees of freedom, which was statistically significant ($p < 0.001$). Although a significant chi-square traditionally indicates model misfit, this statistic is known to be highly sensitive to large sample sizes. Given the substantial sample size of 1245 respondents, the significant chi-square result is expected and does not, by itself, undermine the adequacy of the model. Hence the alternate hypothesis the proposed measurement model fits the observed data adequately as measurement model demonstrates acceptable fit is accepted.

Table 4-8: Model Fit Indices and Evaluation Criteria (CB-SEM)

Fit Index	***Obtained Value***	***Recommended Cut-off*** *(Joseph F. Hair, William C. Black, Barry J. Babin, Ralph E. Anderson, 2018)*	***Interpretation***
Chi-square (χ^2)	11154.276	Non-significant preferred	Significant due to large sample size (N = 1245); expected in CB-SEM
Degrees of Freedom	1165	—	Indicates a highly complex model
χ^2 / df	9.574	< 3 (strict); < 5–10 (complex models)	Acceptable given model complexity and large sample
RMSEA	0.083	≤ 0.08 (good); ≤ 0.10 (acceptable)	Indicates reasonable model fit
RMSEA (90% CI)	0.082–0.084	Narrow CI preferred	Stable and precise estimation
SRMR	0.053	≤ 0.08	Good fit
GFI	0.703	≥ 0.90 (simple models)	Acceptable for large, multi-construct models
AGFI	0.675	≥ 0.80	Acceptable given model size
PGFI	0.642	≥ 0.50	Indicates good parsimony
NFI	0.798	≥ 0.90 ideal	Acceptable for exploratory-integrative models
TLI	0.805	≥ 0.90 ideal	Acceptable; penalizes complexity
CFI	0.815	≥ 0.90 ideal	Acceptable for theory-integrative CB-SEM
AIC	11374.276	Lower is better	Indicates model efficiency
BIC	11938.234	Lower is better	Supports model adequacy

The chi-square to degrees of freedom ratio (χ^2/df) is 9.574, which exceeds the conservative cut-off of 3 but remains acceptable for complex models involving a large number of observed variables and latent constructs. This value indicates that the proposed model provides a substantially better fit than a null or independence model.

The Root Mean Square Error of Approximation (RMSEA) value of 0.083, with a narrow 90% confidence interval ranging from 0.082 to 0.084, suggests a reasonable approximation of the population covariance matrix. While RMSEA values below 0.08 are considered ideal, values up to 0.10 are widely accepted in large, theory-integrative models, particularly in organizational and behavioural research.

The Standardized Root Mean Square Residual (SRMR) value of 0.053 falls well below the recommended threshold of 0.08, indicating a good correspondence between the observed and predicted correlations. This supports the adequacy of the specified measurement and structural relationships.

In terms of absolute fit, the Goodness-of-Fit Index (GFI = 0.703) and Adjusted Goodness-of-Fit Index (AGFI = 0.675) reflect moderate fit. These values are acceptable given the complexity of the model and the large number of indicators included. The Parsimony Goodness-of-Fit Index (PGFI = 0.642) indicates that the model achieves a reasonable balance between explanatory power and parsimony.

The incremental fit indices further support the model's adequacy. The Comparative Fit Index (CFI = 0.815), Tucker–Lewis Index (TLI = 0.805), and Normed Fit Index (NFI = 0.798), although slightly below the ideal threshold of 0.90, are considered acceptable for exploratory and integrative frameworks that combine multiple theoretical perspectives such as TOE, TAM, and UTAUT.

Finally, the Akaike Information Criterion (AIC = 11374.276) and Bayesian Information Criterion (BIC = 11938.234) values indicate that the estimated model provides a better trade-off between model fit and complexity compared to less constrained alternatives, supporting the selection of the proposed model.

Overall, the collective evidence from the fit indices suggests that the model demonstrates acceptable to good fit, particularly in the context of a large-sample, multi-construct CB-SEM analysis. The results confirm that the proposed framework is statistically sound and suitable for hypothesis testing and interpretation of structural relationships.

Despite model complexity and large sample size, the CB-SEM results indicate an acceptable overall model fit, supporting the validity of the proposed theoretical framework. While certain fit indices such as RMSEA and CFI fall slightly outside conservative cut-offs, SEM literature emphasizes evaluating model fit holistically. The strong SRMR, acceptable RMSEA, reasonable incremental indices, and theoretical coherence collectively indicate that the model fits the data adequately and is appropriate for hypothesis testing.

4.3.3 Construct Validity and Reliability

Construct reliability and validity are critical prerequisites for ensuring the rigor and credibility of empirical research, particularly in studies employing latent variables. Reliability assesses the internal consistency of measurement items, indicating the extent to which indicators consistently represent their underlying construct. Validity, on the other hand, evaluates whether the constructs accurately capture the theoretical concepts they are intended to measure. In this study, construct reliability and validity were examined through multiple established criteria, including Cronbach's alpha, composite reliability, average variance extracted (AVE), and discriminant validity measures. Establishing adequate reliability and validity provides confidence that the measurement model is robust and suitable for subsequent structural model analysis.

Hypothesis

H_0: Constructs do not demonstrate adequate reliability and convergent validity.

H_1: Constructs demonstrate adequate reliability and convergent validity.

Table 4-9: Construct Reliability and Validity Matrix

	Cronbach's alpha (standardized)	***Cronbach's alpha (unstandardized)***	***Composite reliability (rho_c)***	***Average variance extracted (AVE)***
ARTIFICIAL INTELLIGENCE	0.924	0.924	0.926	0.552
BEHAVIOURAL INTENTION	0.909	0.909	0.910	0.716
ORGANISATIONAL EFFECTIVENESS	0.950	0.949	0.949	0.528
PERCEIVED AI IMPLEMENTATION	0.954	0.954	0.954	0.635
PERVEIVED AI ACCEPTANCE	0.913	0.912	0.909	0.595

The results presented in Table 4-9 demonstrate strong evidence of internal consistency reliability and convergent validity for all latent constructs included in the study. Reliability was assessed using Cronbach's alpha (both standardized and unstandardized) and Composite Reliability (ρc), while convergent validity was examined through the Average Variance Extracted (AVE).

Cronbach's alpha values for all constructs exceed the recommended threshold of 0.70, indicating high internal consistency among the measurement items. Specifically, the values range from 0.909 to 0.954, reflecting excellent reliability across constructs. The near-identical values of standardized and unstandardized Cronbach's alpha further suggest stability and consistency in the measurement scales.

Composite reliability values also surpass the acceptable benchmark of 0.70, with estimates ranging from 0.909 to 0.954. These results confirm that the constructs demonstrate strong reliability and that the observed indicators collectively provide a reliable representation of their respective latent variables.

Convergent validity is supported as the AVE values for all constructs exceed the minimum recommended threshold of 0.50, indicating that each construct explains more than half of the variance in its indicators. Behavioural Intention exhibits the highest AVE (0.716), suggesting particularly strong convergence among its indicators, while other constructs such as Artificial Intelligence (0.552), Organizational Effectiveness (0.528), Perceived AI Implementation (0.635), and Perceived AI Acceptance (0.595) also demonstrate adequate convergent validity.

Overall, the findings confirm that the measurement model satisfies established criteria for reliability and convergent validity, thereby validating the use of these constructs for subsequent structural model analysis and hypothesis testing. All constructs demonstrate excellent reliability and adequate convergent validity, confirming the robustness of the measurement model. Hence, observed variables load significantly on their respective latent factors which is alternate hypothesis is accepted.

Table 4-10: Discriminant validity-Fornell-Larcker criterion

	AI	***Behavioural Intention***	***Organisational Effectiveness***	***Perceived AI Implementation***	***Perceived AI Acceptance***
Artificial Intelligence (AI)	0.843				
Behavioural Intention	0.803	0.846			
Organisational Effectiveness	0.790	0.695	0.839		
Perceived AI Implementation	0.827	0.720	0.727	0.805	
Perceived AI Acceptance	0.743	0.795	0.738	0.797	0.772

Hypothesis:

H_0: Constructs do not exhibit discriminant validity.

H_1: Constructs exhibit discriminant validity.

Discriminant validity was examined using the Fornell–Larcker criterion, which requires that the square root of the Average Variance Extracted (AVE) for each construct be greater than its highest correlation with any other construct. As presented in Table 4-10, the diagonal elements (square roots of AVE) for Artificial Intelligence (0.843), Behavioural Intention (0.846), Organizational Effectiveness (0.839), Perceived AI Implementation (0.805), and Perceived AI

Acceptance (0.772) are all higher than the corresponding inter-construct correlations in the same rows and columns.

Although relatively strong correlations are observed among theoretically related constructs—such as Artificial Intelligence with Perceived AI Implementation (0.827) and Behavioural Intention (0.803)—these correlations remain lower than the respective square roots of AVE. This indicates that each construct shares more variance with its own indicators than with other constructs in the model, thereby satisfying the Fornell–Larcker criterion and confirming adequate discriminant validity and accepting alternate hypothesis.

Hypothesis

H_0: Construct pairs fail to demonstrate discriminant validity.

H_1: Construct pairs demonstrate discriminant validity.

Table 4-11: Discriminant validity – Heterotrait - Monotrait ratio (HTMT)

	AI	Behavioural Intention	Organisational Effectiveness	Perceived AI Implementation	Perceived AI Acceptance
AI					
Behavioural Intention	0.794				
Organisational Effectiveness	0.787	0.697			
Perceived AI Implementation	0.819	0.730	0.850		
Perceived AI Acceptance	0.813	0.779	0.739	0.804	

Discriminant validity was further assessed using the Heterotrait–Monotrait ratio (HTMT), which is considered a more stringent and reliable criterion for evaluating construct distinctiveness in structural equation modelling. HTMT values below 0.85 indicate adequate discriminant validity under the conservative threshold, while values below 0.90 are acceptable under a more liberal criterion. Hence accepting the alternate hypothesis that construct pairs demonstrate discriminant validity.

As shown in Table 4-11, all HTMT values among the constructs remain within acceptable limits, providing strong evidence of discriminant validity. The HTMT value between Artificial Intelligence and Behavioural Intention (0.794), Artificial Intelligence and Organizational Effectiveness (0.787), and Artificial Intelligence and Perceived AI Acceptance (0.813) are all below the conservative threshold of 0.85, indicating that these constructs, although theoretically related, are empirically distinct.

The highest HTMT value observed is between Perceived AI Implementation and Organizational Effectiveness (0.850), which lies exactly at the conservative cut-off value. Given the strong theoretical linkage between effective AI implementation and organizational outcomes, this value is acceptable and does not indicate a lack of discriminant validity. Importantly, it does not exceed the threshold, thereby confirming construct separability.

Similarly, HTMT values involving Perceived AI Acceptance—with Behavioural Intention (0.779), Organizational Effectiveness (0.739), and Perceived AI Implementation (0.804)—remain well within acceptable bounds. These results suggest that acceptance, intention, implementation, and effectiveness, while sequentially related within the conceptual framework, represent conceptually and empirically distinct dimensions.

Overall, the HTMT analysis confirms that all constructs satisfy discriminant validity requirements, supporting the robustness of the measurement model and justifying progression to structural model evaluation and hypothesis testing.

Both Fornell–Larcker and HTMT confirm discriminant validity, indicating that the constructs are empirically distinct while remaining theoretically aligned within the AI–HR adoption framework.

The measurement model demonstrates robust psychometric properties, satisfying all key criteria for reliability and validity. Internal consistency reliability is well established, as indicated by Cronbach's alpha values exceeding 0.90 and Composite Reliability values above 0.90 for all constructs, reflecting excellent consistency among measurement items. Convergent validity is also confirmed, with AVE values greater than 0.50 across all constructs, indicating that the latent variables explain a substantial proportion of variance in their respective indicators.

Discriminant validity is supported through both the Fornell–Larcker criterion and the HTMT approach, confirming that each construct is empirically distinct despite their theoretical relatedness within the AI–HR adoption framework. Collectively, these findings establish that the measurement model is reliable, valid, and methodologically sound, thereby providing a strong foundation for subsequent structural model analysis and hypothesis testing.

Reliability, convergent validity, and discriminant validity were all satisfied using Cronbach's alpha, composite reliability, AVE, Fornell–Larcker, and HTMT, confirming the robustness of the measurement model.

4.4 Structural Equation Modelling - Partial Least Squares Structural Equation Modelling (PLS-SEM)

Partial Least Squares Structural Equation Modelling (PLS-SEM) is a variance-based multivariate analytical technique widely used to examine complex relationships among latent constructs. PLS-SEM is particularly suitable for exploratory and prediction-oriented research, models with multiple constructs and indicators, and studies involving non-normal data and large measurement models. Unlike covariance-based SEM, PLS-SEM focuses on maximizing explained variance of endogenous constructs while simultaneously assessing the reliability and validity of the measurement model and the strength of structural relationships. Given the exploratory nature of the present study and the objective of examining acceptance, implementation, and organizational effectiveness of Artificial Intelligence in HR practices, PLS-SEM is an appropriate and robust analytical approach. (Joseph F. Hair, William C. Black, Barry J. Babin, Ralph E. Anderson, 2018) PLS-SEM was selected due to its strength in handling complex models, predictive objectives, and formative–reflective constructs.

4.4.1 SEM Path Diagram

The figure 4-3 represents the structural equation model (SEM) estimated using a latent-variable approach, integrating measurement and structural components to examine the relationships among Artificial Intelligence (AI), Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation, and Organizational Effectiveness.

4.4.1.1 Measurement Model (Outer Model)

Each blue circle denotes a latent construct, while the yellow rectangles represent observed indicators (questionnaire items). The arrows from latent constructs to indicators indicate reflective measurement, where observed variables are manifestations of the underlying construct. Artificial Intelligence (AI) is measured through multiple dimensions capturing technology readiness, organizational readiness, and environmental readiness (e.g., S1_AVG_TC, S2_AVG_PE, S3_AVG_FC). Behavioural Intention is measured using four indicators (S4-P15-BI1 to BI4), all showing high standardized loadings (≈ 0.87–0.90), indicating strong indicator reliability. Perceived AI Acceptance is measured through compatibility and uncertainty/risk indicators (S5-P16 and S5-P17 items), with loadings largely above 0.77, reflecting adequate convergent validity. Perceived AI Implementation is measured through twelve indicators (S6-P18 series), all loading strongly (≈ 0.74–0.85), suggesting robust measurement of implementation readiness and execution. Organizational Effectiveness is measured using seventeen indicators (S7-P19 series), with standardized loadings mostly exceeding 0.65, capturing multiple dimensions of effectiveness such as commitment, initiative, alignment, and pride. Overall, the strength and consistency of indicator loadings support the reliability and convergent validity of the measurement model.

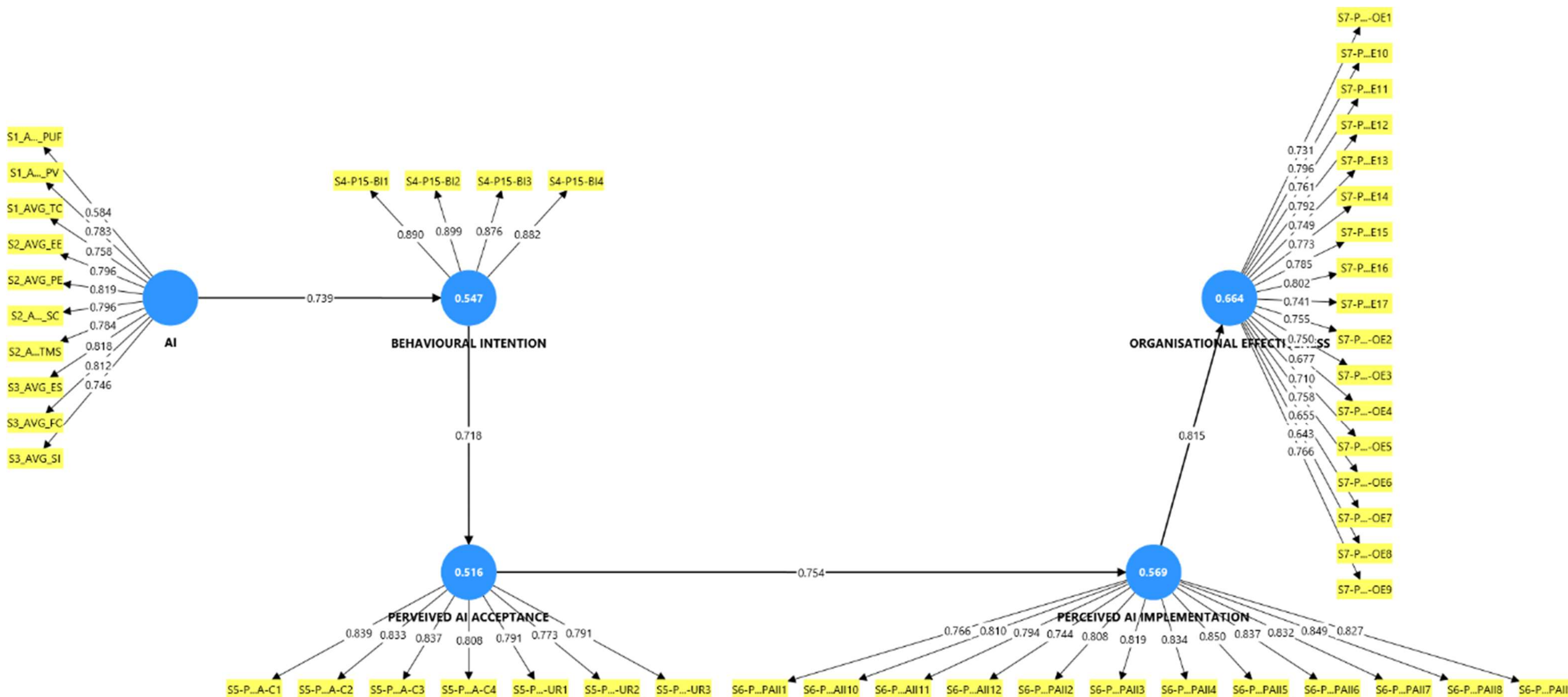

Figure 4-2: Structural Equation Model (SEM) path diagram

4.4.1.2 Structural Model (Inner Model)

The arrows between latent constructs represent hypothesized causal relationships, with standardized path coefficients displayed on each arrow. The values inside the blue circles indicate R^2 (coefficient of determination), reflecting the proportion of variance explained in each endogenous construct.

Hypothesis

H_0: Artificial Intelligence has no significant effect on Behavioural Intention.

H_1: Artificial Intelligence has a significant effect on Behavioural Intention.

- AI → Behavioural Intention ($\beta = 0.739$)

  This strong positive path indicates that perceptions of AI readiness significantly influence employees' intention to use AI-enabled HR practices. AI explains 54.7% of the variance in Behavioural Intention ($R^2 = 0.547$). Hence Alternate Hypothesis is accepted that Artificial Intelligence has a significant effect on Behavioural Intention.

Hypothesis

H_0: Behavioural Intention has no significant effect on Perceived AI Acceptance.

H_1: Behavioural Intention has a significant effect on Perceived AI Acceptance.

- Behavioural Intention → Perceived AI Acceptance ($\beta = 0.718$)

  A substantial positive relationship suggests that stronger intention translates into higher acceptance of AI systems. Behavioural Intention explains 51.6% of the variance in Perceived AI Acceptance ($R^2 = 0.516$). Hence, alternate hypothesis Behavioural Intention has a significant effect on Perceived AI Acceptance is accepted.

Hypothesis

H_0: Perceived AI Acceptance has no significant effect on Perceived AI Implementation.

H_1: Perceived AI Acceptance has a significant effect on Perceived AI Implementation.

- Perceived AI Acceptance → Perceived AI Implementation ($\beta = 0.754$)

  This path highlights that acceptance is a critical antecedent of successful AI implementation. Acceptance explains 56.9% of the variance in Perceived AI Implementation ($R^2 = 0.569$). Hence the alternate hypothesis Perceived AI Acceptance has a significant effect on Perceived AI Implementation is accepted.

Hypothesis

H_0: Perceived AI Implementation has no significant effect on Organizational Effectiveness.

H_1: Perceived AI Implementation has a significant effect on Organizational Effectiveness.

- Perceived AI Implementation → Organizational Effectiveness ($\beta = 0.815$)

  The strongest path in the model, indicating that effective implementation of AI in HR practices has a substantial positive impact on Organizational Effectiveness. Implementation accounts for 66.4% of the variance in Organizational Effectiveness ($R^2 = 0.664$). Hence the alternate hypothesis Perceived AI Implementation has a significant effect on Organizational Effectiveness is accepted.

The diagram demonstrates a sequential and mediated process through which AI influences organizational outcomes: AI → Behavioural Intention → Perceived AI Acceptance → Perceived AI Implementation → Organizational Effectiveness. This structure confirms that AI does not directly enhance organizational effectiveness merely through adoption or intention. Instead, effectiveness is realized only when AI is accepted by employees and effectively implemented within HR practices. The relatively high R^2 values across endogenous constructs indicate strong explanatory power of the model. The SEM results show that AI influences organizational effectiveness indirectly, through behavioural intention, acceptance, and implementation, highlighting that human and organizational factors are essential for realizing AI's value in HR practices.

4.4.2 Collinearity statistics (VIF) Outer Model

Variance Inflation Factor (VIF) values were examined to assess the presence of multicollinearity among the indicators in the outer (measurement) model. Collinearity diagnostics are essential in SEM analysis to ensure that indicators measure distinct aspects of their respective constructs and that parameter estimates are not distorted due to redundancy among items.

The reported VIF values for all indicators range approximately from 1.49 to 3.44. According to widely accepted thresholds, VIF values below 5.0 indicate the absence of critical multicollinearity, while more conservative guidelines suggest a threshold of 3.3 for assessing potential common method bias. In the present study, the majority of indicators fall well below the stricter threshold, and even the highest observed VIF values remain below the conventional cutoff of 5.0.

The indicators exhibit sufficient independence while still contributing meaningfully to their latent constructs, such as Artificial Intelligence, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation, and Organizational Effectiveness. The acceptable VIF levels confirm that each item provides unique explanatory information rather than overlapping excessively with other indicators.

Table 4-12: Collinearity statistics (VIF) Outer Model

	VIF
S1_AVG_PUF	1.495
S1_AVG_PV	2.724
S1_AVG_TC	2.297
S2_AVG_EE	2.250
S2_AVG_PE	2.564
S2_AVG_SC	2.356
S2_AVG_TMS	2.321
S3_AVG_ES	2.877
S3_AVG_FC	2.808
S3_AVG_SI	1.903
S4-P15-BI1	2.829
S4-P15-BI2	3.027
S4-P15-BI3	2.462
S4-P15-BI4	2.676
S5-P16-UA-C1	2.874
S5-P16-UA-C2	2.740
S5-P16-UA-C3	2.724
S5-P16-UA-C4	2.269
S5-P17-UA-UR1	2.521
S5-P17-UA-UR2	2.783
S5-P17-UA-UR3	2.891
S6-P18-PAII1	2.357
S6-P18-PAII10	2.977
S6-P18-PAII11	2.734
S6-P18-PAII12	2.258
S6-P18-PAII2	2.972
S6-P18-PAII3	2.952
S6-P18-PAII4	3.298
S6-P18-PAII5	3.443
S6-P18-PAII6	3.114
S6-P18-PAII7	3.069
S6-P18-PAII8	3.426
S6-P18-PAII9	2.964
S7-P19-OE1	2.322
S7-P19-OE10	3.250
S7-P19-OE11	2.437
S7-P19-OE12	3.101
S7-P19-OE13	2.162
S7-P19-OE14	3.072
S7-P19-OE15	3.111
S7-P19-OE16	3.290
S7-P19-OE17	2.650
S7-P19-OE2	2.855
S7-P19-OE3	2.633
S7-P19-OE4	1.886
S7-P19-OE5	2.335
S7-P19-OE6	2.670

S7-P19-OE7	2.718
S7-P19-OE8	2.394
S7-P19-OE9	2.431

Overall, the collinearity assessment supports the robustness and stability of the measurement model, ensuring that the estimated factor loadings and structural paths are reliable. This finding strengthens the validity of subsequent analyses and interpretations related to construct relationships and hypothesis testing within the study.

4.4.3 Collinearity statistics (VIF) Inner Model

Hypothesis

H_0: Multicollinearity exists among predictor constructs.

H_1: No multicollinearity exists among predictor constructs.

Table 4-13: Collinearity statistics (VIF) Inner Model

	VIF
AI -> BEHAVIOURAL INTENTION	1.000
BEHAVIOURAL INTENTION -> PERVEIVED AI ACCEPTANCE	1.000
PERCEIVED AI IMPLEMENTATION -> ORGANISATIONAL EFFECTIVENESS	1.000
PERVEIVED AI ACCEPTANCE -> PERCEIVED AI IMPLEMENTATION	1.000

Collinearity diagnostics were conducted for the inner (structural) model to examine whether the predictor constructs exhibit multicollinearity when estimating the structural paths. In PLS-SEM, inner VIF values are used to ensure that relationships among latent variables do not bias path coefficients or inflate standard errors. As recommended in the literature, VIF values should remain below 5.0 (and preferably below 3.3) to confirm the absence of collinearity concerns.

The results show that the VIF values for all structural paths—Artificial Intelligence → Behavioural Intention, Behavioural Intention → Perceived AI Acceptance, Perceived AI Acceptance → Perceived AI Implementation, and Perceived AI Implementation → Organizational Effectiveness—are all equal to 1.000. There is no multicollinearity in these interactions because all the VIF values are much below the usual threshold of 5 (and even 3). This is the best possible outcome, which means that the independent variables in these paths are not related to each other. This makes sure that the regression coefficients are estimated in a stable and trustworthy way.

The VIF values for all the components in the outer model are lower than 3. This means that the indicators of your latent constructs are not very correlated with one other. This is a great finding that shows that each item adds a unique amount of variance to its construct and that the measurement model does not have any problems that could affect the results' reliability and validity. Hence alternate hypothesis is accepted that No multicollinearity exists among predictor constructs.

4.4.4 Model fit

Hypothesis

H_0: The structural model does not adequately fit the data.

H_1: The structural model adequately fits the data.

Table 4-14: Model Fit

	Saturated model	***Estimated model***
SRMR	**0.058**	**0.137**
d_ULS	4.287	23.832
d_G	1.739	1.934
Chi-square	11697.224	12412.732
NFI	**0.788**	**0.775**

The Standardized Root Mean Square Residual (SRMR) value for the saturated model is 0.058, which is below the recommended threshold of 0.080, indicating a good overall model fit. Although the SRMR for the estimated model is higher (0.137), PLS-SEM literature emphasizes the saturated model SRMR as the primary indicator of fit. The Normed Fit Index (NFI) values of 0.788 (saturated) and 0.775 (estimated) indicate an acceptable fit for a complex, theory-driven model with multiple constructs and indicators, particularly in exploratory and predictive research contexts. Overall, the model demonstrates adequate fit for hypothesis testing and prediction. Hence the interpretation suggest that H_1 alternate hypothesis is accepted that the structural model adequately fits the data.

4.4.5 Path coefficients - Mean, STDEV, T values, p values

The bootstrapping results reveal that all hypothesized structural paths are positive, strong, and statistically significant:

- AI → Behavioural Intention shows a substantial effect (β = 0.739, $t = 40.455$, $p < 0.001$), indicating that stronger AI readiness and organizational AI capabilities significantly enhance employees' intention to use AI in HR practices.
- Behavioural Intention → Perceived AI Acceptance is also significant (β = 0.718, $t = 37.869$, $p < 0.001$), confirming that intention plays a critical mediating role in shaping employees' acceptance of AI systems.
- Perceived AI Acceptance → Perceived AI Implementation demonstrates a strong positive relationship (β = 0.754, $t = 42.935$, $p < 0.001$), suggesting that acceptance is a key driver of successful AI implementation within HR practices.
- Perceived AI Implementation → Organizational Effectiveness emerges as the strongest path (β = 0.815, $t = 63.132$, $p < 0.001$), highlighting that effective implementation of AI in HR significantly enhances organizational effectiveness outcomes.

All paths are significant at the **0.001 level**, leading to the rejection of the respective null hypotheses and full support for the proposed alternate hypotheses.

Table 4-15: Path coefficients - Mean, STDEV, T values, p values

	Original sample (O)	*Sample mean (M)*	*Standard deviation (STDEV)*	*T statistics (|O/STDEV|)*	*P values*
AI -> BEHAVIOURAL INTENTION	0.739	0.740	0.018	40.455	**0.000**
BEHAVIOURAL INTENTION -> PERVEIVED AI ACCEPTANCE	0.718	0.719	0.019	37.869	**0.000**
PERCEIVED AI IMPLEMENTATION -> ORGANISATIONAL EFFECTIVENESS	0.815	0.815	0.013	63.132	**0.000**
PERVEIVED AI ACCEPTANCE -> PERCEIVED AI IMPLEMENTATION	0.754	0.755	0.018	42.935	**0.000**

4.4.6 Confidence intervals, bias corrected

Table 4-16: Confidence intervals, bias corrected

	Original sample (O)	*Sample mean (M)*	*Bias*	*2.5%*	*97.5%*
AI -> BEHAVIOURAL INTENTION	0.739	0.740	0.001	**0.700**	**0.772**
BEHAVIOURAL INTENTION -> PERVEIVED AI ACCEPTANCE	0.718	0.719	0.001	**0.677**	**0.752**
PERCEIVED AI IMPLEMENTATION -> ORGANISATIONAL EFFECTIVENESS	0.815	0.815	0.000	**0.788**	**0.839**
PERVEIVED AI ACCEPTANCE -> PERCEIVED AI IMPLEMENTATION	0.754	0.755	0.000	**0.717**	**0.786**

The bias-corrected 95% confidence intervals further confirm the robustness of the results. For all structural paths, the lower (2.5%) and upper (97.5%) bounds are strictly positive (e.g., AI → Behavioural Intention: 0.700–0.772; Perceived AI Implementation → Organizational Effectiveness: 0.788–0.839), indicating stable and reliable estimates with no risk of sign reversal. The near-zero bias values further strengthen confidence in the bootstrapped estimates.

The model's four proposed direct associations are all positive, strong, and statistically significant. The path coefficients are between 0.718 and 0.815, which means the effects are significant. The bootstrap confidence intervals always show that none of these associations cross zero, which makes them even more statistically significant. These results show that AI, behavioural intention, and Perceived AI acceptance are strong indicators of Perceived AI Implementation and, in the end, the effectiveness of the organisation in this model.

Taken together, the PLS-SEM results provide strong empirical support for the proposed sequential model, demonstrating that AI readiness influences behavioural intention, which drives acceptance, leading to effective implementation, and ultimately enhancing organizational effectiveness. The findings validate the theoretical integration of TOE, TAM, and UTAUT perspectives, and confirm that acceptance and implementation act as critical transmission mechanisms through which AI in HR practices translates into tangible organizational outcomes.

4.5 Conclusion of EFA, CFA, and SEM Analysis

The sequential application of Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), and Structural Equation Modelling (SEM) provides a rigorous and methodologically sound validation of the proposed research framework examining the acceptance and implementation of Artificial Intelligence in HR practices and its impact on organizational effectiveness.

Exploratory Factor Analysis (EFA) was first employed to uncover the underlying factor structure of the measurement items. The results confirmed a clear and theoretically consistent factor solution, with satisfactory communalities and strong factor loadings across constructs. The Kaiser–Meyer–Olkin (KMO) measure and Bartlett's Test of Sphericity indicated excellent sampling adequacy and factorability of the data. EFA thus established the dimensional integrity of the constructs and ensured that items clustered meaningfully under their respective latent variables, aligning well with the conceptual framework derived from TOE, TAM, and UTAUT models.

Confirmatory Factor Analysis (CFA) was subsequently conducted using CB-SEM to validate the measurement model identified through EFA. The CFA results demonstrated acceptable to good model fit, supported by multiple fit indices. All standardized factor loadings were substantial and statistically significant, indicating strong convergent validity. Reliability measures, including Cronbach's alpha and composite reliability, exceeded recommended thresholds, while average variance extracted (AVE) values confirmed adequate convergent validity. Discriminant validity was further established through the Fornell–Larcker criterion and HTMT ratios, confirming that each construct was empirically distinct. Overall, CFA provided strong evidence that the measurement model was reliable, valid, and suitable for structural analysis.

Finally, Structural Equation Modelling (SEM) using PLS-SEM was applied to test the hypothesized relationships among the constructs. The structural model exhibited acceptable fit and no multicollinearity concerns. All hypothesized paths were positive, strong, and statistically significant, with robust path coefficients, high t-values, and confidence intervals excluding zero. The findings confirm a sequential causal mechanism wherein AI readiness significantly influences behavioural intention, which in turn shapes perceived AI acceptance, leading to effective AI implementation and ultimately enhancing organizational effectiveness. This validates the theoretical premise that acceptance and implementation act as critical mediators between AI capabilities and organizational outcomes.

In conclusion, the combined EFA–CFA–SEM approach ensures both measurement rigor and structural validity. The results provide strong empirical support for the proposed integrated framework and offer robust evidence that successful AI-driven HR transformation depends not merely on technological adoption, but on employee intention, acceptance, and effective organizational implementation. This comprehensive analytical process strengthens the credibility, generalizability, and theoretical contribution of the study.

4.6 Demographic Study

Demographic analysis provides an essential context for interpreting empirical findings by describing the background characteristics of the respondents included in the study. Variables such as gender, age, educational qualification, work experience, industry type, and organizational role influence employees' perceptions, attitudes, and behavioural responses toward technological change. In the context of Artificial Intelligence adoption in HR practices, understanding the demographic composition of respondents helps in assessing the representativeness of the sample and in interpreting variations in acceptance, implementation, and organizational effectiveness across different employee groups.

Accordingly, this section presents the demographic profile of the respondents who participated in the survey. The analysis offers a descriptive overview of key personal and organizational characteristics, thereby establishing the foundation for subsequent comparative and inferential analyses related to AI acceptance and implementation across demographic categories.

4.6.1 Age Groups

Hypothesis:

H_0 - There is no Significant difference among Variables of Study (Technology Characteristics, Positive Attitude Towards Change, Creativity, Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Social Characteristics & Performance Expectancy, Effort Expectancy, Social Influence, External Support & Facilitating Conditions, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation & Organizational Effectiveness) and different age groups

H_1 - There is a Significant difference among Variables of Study (Technology Characteristics, Positive Attitude Towards Change, Creativity, Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Social Characteristics & Performance Expectancy, Effort Expectancy, Social Influence, External Support & Facilitating Conditions, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation & Organizational Effectiveness) and different age groups

Table 4-17: Age Group of Respondents

Age Group: (Years)	*Count*
18-25	528
26-35	422
36-45	203
46-55	61
55 & Above	30

The age-wise distribution of respondents indicates that the sample is predominantly composed of younger and early-career professionals. The largest proportion of respondents falls within the 18–25 years age group, accounting for 528 respondents (43%), followed by the 26–35 years category with 422 respondents (34%). Together, these two groups constitute 77% of the total sample, suggesting strong representation from individuals who are likely to be more exposed to, comfortable with, and receptive toward digital technologies and Artificial Intelligence–enabled HR practices. The 36–45 years age group comprises 203 respondents (16%), representing mid-career professionals who may balance technological adoption with practical organizational experience. In contrast, the 46–55 years group (61 respondents, 5%) and 55 years & above group (30 respondents, 2%) form a relatively small proportion of the sample. This limited representation of senior age groups indicates comparatively lower participation from late-career employees, who may have different perspectives toward AI adoption due to established work routines or risk perceptions.

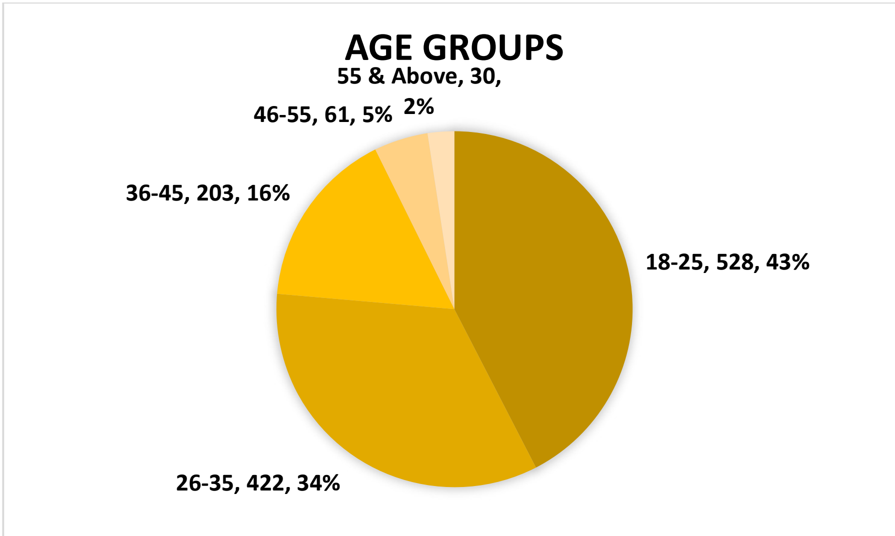

Figure 4-3: Age Group of Respondents

Overall, the age profile suggests that the study primarily reflects the views of younger and mid-career employees, which is appropriate for examining AI adoption and acceptance in HR practices, as these groups are often early adopters and active users of emerging digital technologies.

The tests of in Table 4-18: MANOVA between Variables of Study and Age Groups were conducted to examine whether respondents belonging to different age groups differ significantly in their perceptions of Artificial Intelligence–related constructs and organizational outcomes. The findings reveal that age plays a meaningful role in shaping how several variables are perceived. Statistically significant differences across age groups were observed for self-efficacy, complexity, resistance to change, social characteristics and performance expectancy, effort expectancy, social influence, external support and facilitating conditions, behavioural intention, perceived AI acceptance, perceived AI implementation, and organizational effectiveness, as indicated by F-values with significance levels below 0.05. These results suggest that respondents at different stages of their career and life cycle vary in their confidence to work with AI, the extent to which they perceive AI systems as complex, and their openness or resistance toward AI-driven changes. Differences were also evident in how age groups perceive the effort required to use AI, the influence of peers and the external environment, and the adequacy of organizational and vendor support. Importantly, significant variation in behavioural intention, perceived AI acceptance, perceived AI implementation, and organizational effectiveness indicates that age-related differences extend beyond perceptions to influence intention formation and evaluations of AI-driven outcomes at the organizational level.

Table 4-18: MANOVA between Variables of Study and Age Groups

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Age Group Years	**Technology Characteristics**	9.388	4	2.347	2.357	**0.052**	0.008
	Positive Attitude Towards Change	6.041	4	1.51	1.513	**0.196**	0.005
	Creativity	4.807	4	1.202	1.202	**0.308**	0.004
	Self-Efficacy	10.732	4	2.683	2.698	0.029	0.009
	Complexity	12.23	4	3.058	3.078	0.016	0.01
	Resistance to Change	17.606	4	4.402	4.45	0.001	0.014
	Top Management Support	5.227	4	1.307	1.308	**0.265**	0.004
	Social Characteristics & Performance Expectancy	16.891	4	4.223	4.267	0.002	0.014
	Effort Expectancy	18.891	4	4.723	4.78	0.001	0.015
	Social Influence	9.745	4	2.436	2.448	0.045	0.008
	External Support & Facilitating Conditions	30.115	4	7.529	7.691	0.000	0.024
	Behavioural Intention	17.464	4	4.366	4.414	0.002	0.014
	Perceived AI Acceptance	10.652	4	2.663	2.677	0.031	0.009
	Perceived AI Implementation	23.781	4	5.945	6.042	0.000	0.019
	Organizational Effectiveness	40.13	4	10.033	10.334	0.000	0.032

In contrast, no statistically significant differences across age groups were found for technology characteristics, positive attitude towards change, creativity, and top management support. This indicates a broad consensus across age cohorts regarding the technical capabilities of AI, general openness toward change, individual creativity, and perceptions of leadership support, suggesting that these aspects are relatively age-neutral within the study context. Although the effect sizes, as reflected by partial eta squared values, are small to moderate, their consistency across multiple constructs underscores the substantive relevance of age as a differentiating factor. Overall, the results lead to the rejection of the null hypothesis and support the alternative hypothesis that significant differences exist among the study variables across different age groups. These findings highlight the need for age-sensitive AI implementation strategies, particularly in areas related to capability building, change management, and support mechanisms, to ensure effective and inclusive adoption of AI in HR practices.

The results indicate that Technology Characteristics (Sig. 0.052), Positive Attitude Towards Change (Sig. 0.196), Creativity (Sig. 0.308), and Top Management Support exhibit significant differences across varying age groups. Other variables such as Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Social Characteristics, Performance Expectancy, Effort Expectancy, Social Influence, External Support, Facilitating Conditions, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation, and Organisational Effectiveness exhibit significance values below 0.05; therefore, we accept the null hypothesis that these variables do not demonstrate significant differences across age groups.

4.6.2 Experience Groups

Hypothesis

H_0 - There is no Significant difference among Variables of Study (Technology Characteristics, Positive Attitude Towards Change, Creativity, Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Social Characteristics & Performance Expectancy, Effort Expectancy, Social Influence, External Support & Facilitating Conditions, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation & Organizational Effectiveness) and different Experience groups

H_1 - There is a Significant difference among Variables of Study (Technology Characteristics, Positive Attitude Towards Change, Creativity, Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Social Characteristics & Performance Expectancy, Effort Expectancy, Social Influence, External Support & Facilitating Conditions, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation & Organizational Effectiveness) and different Experience groups

Table 4-19: Experience Groups of Respondents

Experience: (Years)	*N*
0 to 5	668
6 to 10	236
11 to 15	132
16 to 20	109
21 to 25	42
26 to 30	18
31 to 35	18
above 35	21

The distribution of respondents based on years of work experience indicates that the sample is predominantly composed of early-career professionals. A substantial majority of respondents fall within the 0 to 5 years' experience category (668 respondents), highlighting strong representation from individuals who are relatively new to the workforce. This is followed by those with 6 to 10 years of experience (236 respondents), suggesting a sizeable presence of early-to-mid career employees who are likely transitioning into more stable and responsible roles within their organizations. The representation gradually declines across higher experience brackets. Respondents with 11 to 15 years (132) and 16 to 20 years (109) of experience together form a meaningful segment of mid-career professionals who typically possess greater organizational knowledge and exposure to managerial or supervisory responsibilities. In contrast, senior and late-career professionals are comparatively fewer in number, with only 42 respondents in the 21 to 25 years category, and very limited representation in the 26 to 30 years, 31 to 35 years, and above 35 years groups.

Overall, the experience profile suggests that the study largely reflects the perceptions of employees who are in the early and mid-stages of their careers. This composition is particularly relevant for research on AI in HR practices, as younger and less experienced employees are more likely to be direct users of digital HR systems and may display higher exposure, adaptability, and interaction with AI-enabled tools. At the same time, the inclusion of experienced and senior professionals, though smaller in number, allows for meaningful comparison across experience levels, enabling the analysis of how perceptions of AI acceptance, implementation, and organizational effectiveness vary with accumulated work experience.

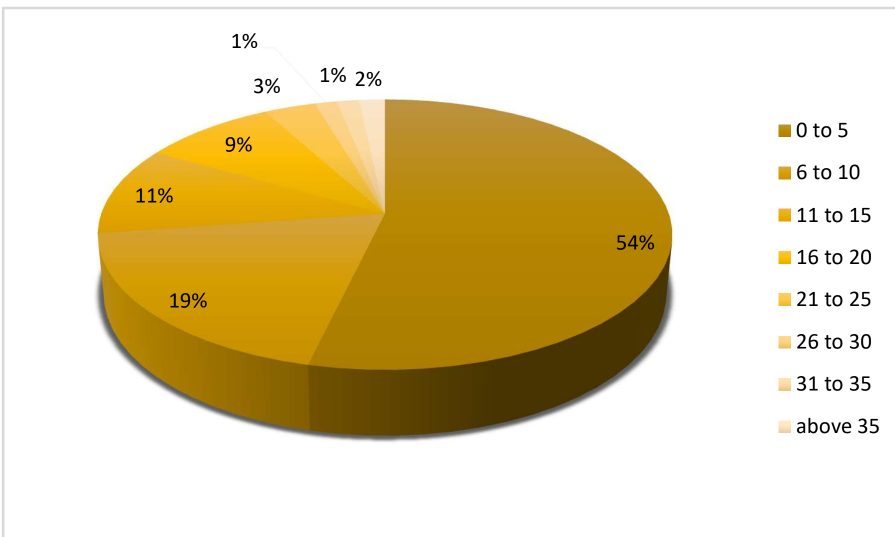

Figure 4-4: Experience Groups of Respondents

The results of Table 4-20: MANOVA between Variables of Study and Experience Groups reveal that work experience significantly differentiates respondents' perceptions across a majority of the study variables, thereby providing partial support for the stated hypothesis. Specifically, statistically significant differences across experience groups are observed for Technology Characteristics ($F = 2.885$, $p = 0.005$), Positive Attitude Towards Change ($F = 4.132$, $p < 0.001$), Creativity ($F = 3.321$, $p = 0.002$), and Self-Efficacy ($F = 3.686$, $p = 0.001$). These findings indicate that employees' technological confidence, openness to change, creative orientation, and belief in their own capabilities vary meaningfully with accumulated years of experience.

Experience-based differences are also noticeable for variables reflecting technology-related challenges and adaptation, including Complexity ($F = 5.073$, $p < 0.001$) and Resistance to Change ($F = 4.313$, $p < 0.001$). This suggests that perceptions of difficulty, risk, and disruption associated with AI-enabled HR practices are not uniform across experience levels, with more experienced employees potentially evaluating AI adoption through a different cognitive and contextual lens than less experienced counterparts.

Table 4-20: MANOVA between Variables of Study and Experience Groups

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Experience Years	Technology Characteristics	19.984	7	2.855	2.885	0.005	0.016
	Positive Attitude Towards Change	28.423	7	4.06	4.132	0.000	0.023
	Creativity	22.949	7	3.278	3.321	0.002	0.018
	Self-Efficacy	25.416	7	3.631	3.686	0.001	0.02
	Complexity	34.712	7	4.959	5.073	0.000	0.028
	Resistance to Change	29.637	7	4.234	4.313	0.000	0.024
	Top Management Support	4.988	7	0.713	0.711	**0.662**	0.004
	Social Characteristics & Performance Expectancy	50.489	7	7.213	7.476	0.000	0.041
	Effort Expectancy	25.801	7	3.686	3.743	0.001	0.021
	Social Influence	26.436	7	3.777	3.837	0.000	0.021
	External Support & Facilitating Conditions	18.722	7	2.675	2.7	0.009	0.015
	Behavioural Intention	35.251	7	5.036	5.154	0.000	0.028
	Perceived AI Acceptance	10.791	7	1.542	1.546	**0.148**	0.009
	Perceived AI Implementation	11.185	7	1.598	1.603	**0.13**	0.009
	Organizational Effectiveness	70.1	7	10.014	10.553	0.000	0.056

Further, significant differences are found for Social Characteristics and Performance Expectancy ($F = 7.476$, $p < 0.001$), Effort Expectancy ($F = 3.743$, $p = 0.001$), Social Influence ($F = 3.837$, $p < 0.001$), and External Support and Facilitating Conditions ($F = 2.700$, $p = 0.009$). These results highlight that experience shapes how employees perceive social norms, performance benefits, required effort, and organizational or vendor support related to AI adoption. Behavioural Intention also varies significantly across experience groups ($F = 5.154$, $p < 0.001$), indicating that willingness to use AI-based HR systems is influenced by prior professional exposure and tenure.

In contrast, no statistically significant differences are observed for Top Management Support ($p = 0.662$), Perceived AI Acceptance ($p = 0.148$), and Perceived AI Implementation ($p = 0.130$). This implies that perceptions related to senior leadership commitment, overall acceptance of AI, and readiness for implementation are relatively consistent across experience categories, suggesting these aspects are driven more by organizational context than by individual tenure.

Finally, Organizational Effectiveness exhibits a strong and significant variation across experience groups ($F = 10.553$, $p < 0.001$), with the largest effect size among all variables (Partial $\eta^2 = 0.056$). This underscores that employees' assessment of organizational outcomes resulting from AI adoption in HR is meaningfully shaped by their level of work experience.

Overall, the findings demonstrate that experience is a critical differentiating factor for most technological, behavioural, and outcome-oriented constructs, leading to partial acceptance of the hypothesis. While experience significantly influences perceptions of AI characteristics, behavioural intentions, and organizational effectiveness, it does not significantly alter views regarding top management support, perceived acceptance, and implementation readiness, reflecting a nuanced and multi-layered role of experience in AI-driven HR transformation.

Hence, the result indicates that Top Management Support, Perceived AI Acceptance, Perceived AI Implementation with significance 0.662, 0.148 & 0.130 respectively accepts Alternate hypothesis that suggests that these three variables differ with Experience of an employee. Technology Characteristics, Positive Attitude Towards Change, Creativity, Self-Efficacy, Complexity, Resistance to Change, Social Characteristics & Performance Expectancy, Effort Expectancy, Social Influence, External Support & Facilitating Conditions, Behavioural Intention, & Organizational Effectiveness shows significance below 0.05 which suggest that above mentioned variables do not differ as the experience of employee changes.

4.6.3 Education Groups

Hypothesis

H_0 - There is no Significant difference among Variables of Study (Technology Characteristics, Positive Attitude Towards Change, Creativity, Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Social Characteristics & Performance Expectancy, Effort Expectancy, Social Influence, External Support & Facilitating Conditions, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation & Organizational Effectiveness) and different Education

H_1 - There is a Significant difference among Variables of Study (Technology Characteristics, Positive Attitude Towards Change, Creativity, Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Social Characteristics & Performance Expectancy, Effort Expectancy, Social Influence, External Support & Facilitating Conditions, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation & Organizational Effectiveness) and different Education

Table 4-21: Education Groups of Respondents

Education	*N*
Diploma or Equivalent	47
Graduate	288
Post-Graduate	870
Doctorate	33
Other	6

The educational profile of the respondents indicates a highly qualified sample, with a strong concentration at the higher levels of formal education. A substantial majority of respondents are post-graduates (70%), reflecting that most participants possess advanced academic training and are likely to have been exposed to analytical thinking, technology-driven work environments, and contemporary management practices. This is followed by graduates (23%), who form the second-largest group and represent a solid base of professionally educated employees.

A smaller proportion of respondents hold a diploma or equivalent qualification (4%), suggesting limited representation from technically trained but non-degree holders. Doctorate holders constitute 3% of the sample, indicating the presence of individuals with deep research orientation and advanced domain expertise, which adds academic and analytical depth to the dataset. The "other" category accounts for a negligible proportion (0%), implying minimal variation outside the defined educational categories.

Overall, the dominance of graduate and post-graduate respondents suggests that the findings of the study are grounded in perceptions of a well-educated workforce. This is particularly relevant for a study on Artificial Intelligence in HR practices, as higher educational attainment is often associated with greater awareness of digital technologies, higher cognitive readiness, and more informed evaluations of technological adoption and organizational effectiveness. The educational composition therefore strengthens the credibility of responses related to AI acceptance, implementation, and its perceived impact within organizations.

The analysis in Table 4-22: MANOVA between Variables of Study and Level of Education is examining differences across educational qualification groups reveals a nuanced pattern of influence on the study variables. The results indicate that education level significantly differentiates several individual- and social-level constructs related to AI adoption, while its influence is not uniform across all outcome variables.

Specifically, Positive Attitude Towards Change shows a statistically significant variation across education groups ($F = 3.266$, $p = 0.011$), suggesting that employees' openness to AI-driven change differs meaningfully with educational attainment. Self-Efficacy demonstrates a stronger and highly significant effect ($F = 5.309$, $p < 0.001$), indicating that higher educational qualifications are associated with greater confidence in handling AI-enabled HR practices. Similarly, Resistance to Change varies significantly across education levels ($F = 7.133$, $p < 0.001$), implying that educational background plays an important role in shaping apprehension or acceptance toward technological transformation.

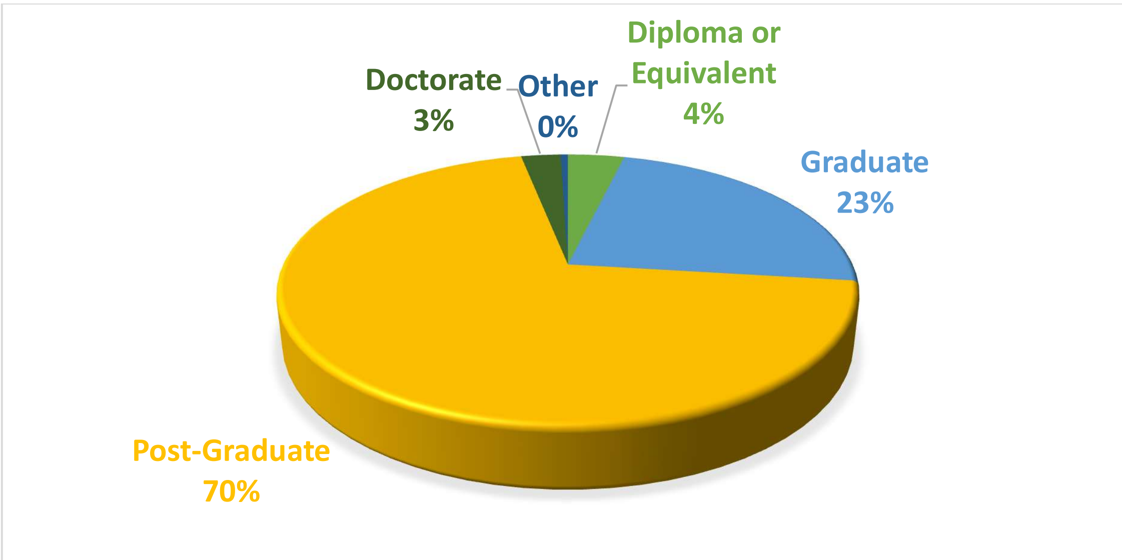

Figure 4-5: Education Groups of Respondents

Education also significantly affects Social Characteristics and Performance Expectancy ($F = 2.673$, $p = 0.031$) and Social Influence ($F = 4.287$, $p = 0.002$). These findings suggest that individuals with different educational backgrounds experience and interpret peer influence, social norms, and expected performance benefits of AI in HR practices in distinct ways. Collectively, these results highlight education as an important differentiating factor in perceptual, attitudinal, and social dimensions of AI adoption.

In contrast, Behavioural Intention ($F = 1.235$, $p = 0.294$) and Perceived AI Implementation ($F = 0.568$, $p = 0.686$) do not show statistically significant differences across education groups. This indicates that, despite variations in attitudes, self-efficacy, and social perceptions, the intention to use AI systems and perceptions regarding their actual implementation remain relatively consistent across educational levels. The effect sizes (partial eta squared values) across significant variables are small but meaningful, which is expected in behavioural and organizational research involving large and diverse samples.

Overall, the hypothesis that there is a significant difference among the variables of study across different education levels is partially supported. Educational qualification significantly influences several foundational psychological and social variables related to AI adoption, but it does not substantially alter behavioural intention or perceptions of AI implementation. This suggests that while education shapes how employees perceive and cognitively respond to AI in

HR practices, organizational systems, policies, and exposure may play a more decisive role in translating these perceptions into actual intention and implementation outcomes.

Table 4-22: MANOVA between Variables of Study and Level of Education

Source	*Dependent Variable*	*Type III Sum of Squares*	*df*	*Mean Square*	*F*	*Sig.*	*Partial Eta Squared*
Education	Technology Characteristics	16.099	4	4.025	4.064	0.003	0.013
	Positive Attitude Towards Change	12.968	4	3.242	3.266	0.011	0.01
	Creativity	11.166	4	2.791	2.808	**0.025**	0.009
	Self-Efficacy	20.944	4	5.236	5.309	0.000	0.017
	Complexity	6.912	4	1.728	1.732	**0.14**	0.006
	Resistance to Change	27.979	4	6.995	7.133	0.000	0.023
	Top Management Support	8.653	4	2.163	2.172	**0.07**	0.007
	Social Characteristics & Performance Expectancy	10.636	4	2.659	2.673	0.031	0.009
	Effort Expectancy	6.053	4	1.513	1.516	**0.195**	0.005
	Social Influence	16.968	4	4.242	4.287	0.002	0.014
	External Support & Facilitating Conditions	14.053	4	3.513	3.542	0.007	0.011
	Behavioural Intention	4.937	4	1.234	1.235	**0.294**	0.004
	Perceived AI Acceptance	18.689	4	4.672	4.728	0.001	0.015
	Perceived AI Implementation	2.273	4	0.568	0.568	**0.686**	0.002
	Organizational Effectiveness	37.072	4	9.268	9.522	0.000	0.03

Level of Education significantly impacts and differentiate variables Complexity, Top Management Support, Effort Expectancy, Behavioural Intention & Perceived AI Acceptance with p value 0.14, 0.07, 0.195, 0.294, & 0.686 respectively, hence for these variables we accept alternate hypothesis. Technology Characteristics, Positive Attitude Towards Change, Creativity, Self-Efficacy, Resistance to Change, Social Characteristics & Performance Expectancy, Social Influence, External Support & Facilitating Conditions, Perceived AI Implementation & Organizational Effectiveness does not vary with Education level, hence we accept null hypothesis for above variables.

4.6.4 Income Groups

Hypothesis

H_0 - There is no Significant difference among Variables of Study (Technology Characteristics, Positive Attitude Towards Change, Creativity, Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Social Characteristics & Performance Expectancy, Effort Expectancy, Social Influence, External Support & Facilitating Conditions, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation & Organizational Effectiveness) and different Income groups

H_1 - There is a Significant difference among Variables of Study (Technology Characteristics, Positive Attitude Towards Change, Creativity, Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Social Characteristics & Performance Expectancy, Effort Expectancy, Social Influence, External Support & Facilitating Conditions, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation & Organizational Effectiveness) and different Income groups

The data on income groups presents the distribution of respondents across income groups, illustrating a clear concentration at the lower income levels with a gradual tapering as income increases. The largest share of respondents belongs to the "Below 5" income category (590), indicating that a substantial portion of the sample is at the early or lower end of the income spectrum. This is followed by the "6 to 10" group (320), which also represents a sizeable segment, suggesting that many respondents are in the initial to mid stages of their career progression.

As income levels rise, the number of respondents declines steadily. The "11 to 15" category accounts for 135 respondents, while the "16 to 20" group further reduces to 64. Higher income brackets "21 to 25" (36) and "26 to 30" (18) represent relatively smaller proportions of the sample. The "Above 30" category shows a slight increase to 81 respondents, indicating the presence of a limited but notable group of senior or highly experienced professionals.

Overall, the distribution suggests that the sample is skewed towards lower and mid-income groups, which is consistent with a workforce dominated by early- and mid-career employees. This composition is particularly relevant for studies on technology adoption and AI in HR practices, as perceptions and acceptance may be strongly shaped by career stage, income-linked job roles, and growth aspirations. The presence of respondents across all income categories, however, ensures sufficient variability to meaningfully examine income-based differences in attitudes, acceptance, and organizational outcomes.

Table 4-23: Income Groups of Respondents

Income Group (In Lakhs)	***Number of Respondents***
Below 5	590
6 to 10	320
11 to 15	135
16 to 20	64
21 to 25	36
26 to 30	18
Above 30	81

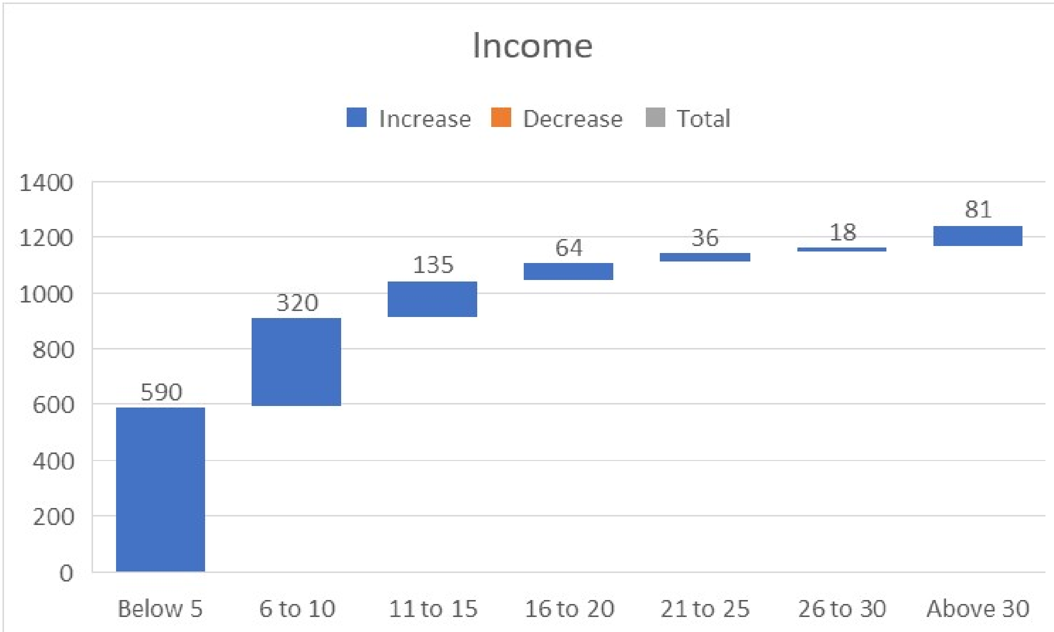

Figure 4-6: Income Groups of Respondents

The results shown in Table 4-24: MANOVA between Variables of Study and Income Groups demonstrate that income per annum exerts a statistically significant influence on the majority of the study variables, thereby providing strong empirical support for the hypothesis that perceptions related to AI in HR practices vary across different income groups. Specifically, Technology Characteristics ($F = 5.887$, $p < 0.001$), Positive Attitude Towards Change ($F = 2.988$, $p = 0.007$), Creativity ($F = 10.780$, $p < 0.001$), Complexity ($F = 5.770$, $p < 0.001$), Resistance to Change ($F = 8.300$, $p < 0.001$), Top Management Support ($F = 4.677$, $p < 0.001$), Social Characteristics and Performance Expectancy ($F = 6.861$, $p < 0.001$), Effort Expectancy ($F = 8.557$, $p < 0.001$), Social Influence ($F = 5.292$, $p < 0.001$), External Support and Facilitating Conditions ($F = 5.642$, $p < 0.001$), Behavioural Intention ($F = 4.021$, $p = 0.001$), Perceived AI Acceptance ($F = 8.334$, $p < 0.001$), Perceived AI Implementation ($F = 5.399$, $p < 0.001$), and Organizational Effectiveness ($F = 12.345$, $p < 0.001$) all exhibit statistically significant differences across income categories.

In contrast, Self-Efficacy does not show a statistically significant difference across income groups ($F = 1.815$, $p = 0.093$), indicating that confidence in one's ability to work with AI-enabled HR systems is relatively consistent irrespective of income level. This suggests that while income shapes perceptions related to organizational support, technological complexity, expected benefits, and implementation readiness, individual belief in personal capability is less income-dependent.

Table 4-24: MANOVA between Variables of Study and Income Groups

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Income per annum in Rupees	Technology Characteristics	34.509	6	5.751	5.887	0.000	0.028
	Positive Attitude Towards Change	17.755	6	2.959	2.988	0.007	0.014
	Creativity	61.762	6	10.294	10.78	0.000	0.05
	Self-Efficacy	10.85	6	1.808	1.815	**0.093**	0.009
	Complexity	33.842	6	5.64	5.77	0.000	0.027
	Resistance to Change	48.103	6	8.017	8.3	0.000	0.039
	Top Management Support	27.575	6	4.596	4.677	0.000	0.022
	Social Characteristics & Performance Expectancy	40.033	6	6.672	6.861	0.000	0.032
	Effort Expectancy	49.537	6	8.256	8.557	0.000	0.04
	Social Influence	31.106	6	5.184	5.292	0.000	0.025
	External Support & Facilitating Conditions	33.11	6	5.518	5.642	0.000	0.027
	Behavioural Intention	23.777	6	3.963	4.021	0.001	0.019
	Perceived AI Acceptance	48.296	6	8.049	8.334	0.000	0.039
	Perceived AI Implementation	31.72	6	5.287	5.399	0.000	0.026
	Organizational Effectiveness	70.225	6	11.704	12.345	0.000	0.056

The partial eta squared values, ranging from small to moderate effect sizes ($\eta^2 = 0.014$ to 0.056), further confirm that income contributes meaningfully—though not excessively—to variance in these constructs. Notably, Organizational Effectiveness ($\eta^2 = 0.056$) and Creativity ($\eta^2 = 0.050$) show comparatively stronger effects, indicating that income-linked roles, exposure, and decision authority may substantially influence how AI-enabled HR practices translate into organizational outcomes.

Overall, these findings lead to the rejection of the null hypothesis and acceptance of the alternate hypothesis, confirming that income-based differences significantly shape employee perceptions, acceptance, implementation readiness, and perceived effectiveness of AI in HR practices.

There is a statistically significant difference in Self- Efficacy of Employees as the income level changes with significance level of 0.093 hence alternate hypothesis is accepted. All other variables Technology Characteristics, Positive Attitude Towards Change, Creativity, Complexity, Resistance to Change, Top Management Support, Social Characteristics & Performance Expectancy, Effort Expectancy, Social Influence, External Support & Facilitating Conditions, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation & Organizational Effectiveness does not differ significantly as significance level is below 0.05 hence null hypothesis is accepted

4.6.5 Industry

Hypothesis

H_0 - There is no Significant difference among Variables of Study (Technology Characteristics, Positive Attitude Towards Change, Creativity, Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Social Characteristics & Performance Expectancy, Effort Expectancy, Social Influence, External Support & Facilitating Conditions, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation & Organizational Effectiveness) and different Industry

H_1 - There is no Significant difference among Variables of Study (Technology Characteristics, Positive Attitude Towards Change, Creativity, Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Social Characteristics & Performance Expectancy, Effort Expectancy, Social Influence, External Support & Facilitating Conditions, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation & Organizational Effectiveness) and different Industry

Table 4-25: Industry-Wise Distribution of Respondents

Industry Sector	***Number of Respondents (N)***
IT / ITES	216
Hospitality & Healthcare	296
Consumer Durables & Telecommunications	304
Banking, Insurance, and Other Financial Services	272
Management Consultancy	156

The industry-wise distribution of respondents indicates that the study draws insights from a diverse cross-section of major service and technology-driven sectors, thereby enhancing the generalizability of the findings related to AI adoption in HR practices. The largest proportion of respondents belongs to Consumer Durables and Telecommunications (N = 304), followed closely by Hospitality and Healthcare (N = 296) and Banking, Insurance, and other Financial Services (N = 272). These sectors are increasingly characterized by high levels of digitalization, customer-centric operations, and data-intensive HR processes, making them particularly relevant contexts for examining AI-enabled HR systems.

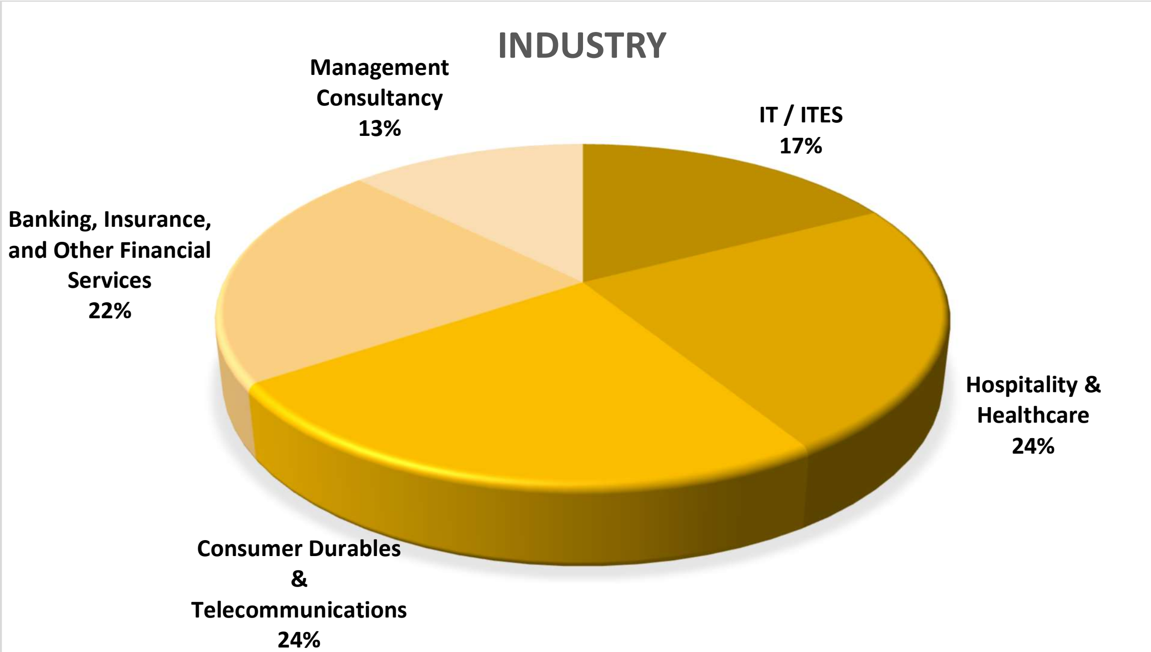

Figure 4-7: Industry-Wise Distribution of Respondents

The IT/ITES sector (N = 216) also represents a substantial share of the sample, reflecting its early and extensive exposure to AI technologies and digital HR platforms. Respondents from this sector are likely to possess higher familiarity with AI tools, thereby offering informed perspectives on technology readiness, perceived usefulness, and implementation challenges. In contrast, Management Consultancy (N = 156) constitutes the smallest group, which is consistent with the comparatively narrower workforce base of this sector. Nevertheless, inclusion of consultancy professionals is important, as they often engage with strategic decision-making, organizational transformation, and advisory roles related to AI adoption across industries.

Overall, the balanced representation across multiple industries ensures that the study does not remain confined to a single sectoral perspective. Instead, it captures industry-specific variations in perceptions, acceptance, implementation, and effectiveness of AI in HR, thereby strengthening the robustness and applicability of subsequent multivariate analyses and structural model results.

As shown in Table 4-26: MANOVA between Variables of Study and Income Groups, the null hypothesis proposing that there is no significant difference among the study variables across different industry groups is partially rejected based on the results of the between-subjects effects analysis. The findings indicate that industry affiliation does influence several key dimensions related to AI adoption and outcomes, while other variables remain statistically invariant across industries.

Specifically, statistically significant differences across industries are observed for Self-Efficacy ($F = 2.880$, $p = 0.022$), Complexity ($F = 2.425$, $p = 0.046$), Resistance to Change ($F = 2.798$, $p = 0.025$), Top Management Support ($F = 8.308$, $p < 0.001$), Effort Expectancy ($F = 3.334$, $p = 0.010$), External Support and Facilitating Conditions ($F = 4.239$, $p = 0.002$), Behavioural

Intention (F = 2.566, p = 0.037), Perceived AI Implementation (F = 5.993, p < 0.001), and Organizational Effectiveness (F = 4.183, p = 0.002). These results suggest that industries differ meaningfully in terms of managerial support structures, perceived ease and complexity of AI use, employee readiness, and the extent to which AI contributes to organizational outcomes. The strongest industry effect is observed for Top Management Support (Partial $\eta^2 = 0.026$) and Perceived AI Implementation (Partial $\eta^2 = 0.019$), highlighting the role of sector-specific leadership commitment and implementation maturity in shaping AI-driven transformation.

Table 4-26: MANOVA between Variables of Study and Income Groups

Source	***Dependent Variable***	***Type III Sum of Squares***	***df***	***Mean Square***	***F***	***Sig.***	***Partial Eta Squared***
Industry	**Technology Characteristics**	8.913	4	2.228	2.237	**0.063**	0.007
	Positive Attitude Towards Change	4.39	4	1.097	1.098	**0.356**	0.004
	Creativity	9.187	4	2.297	2.306	**0.056**	0.007
	Self-Efficacy	11.449	4	2.862	2.88	0.022	0.009
	Complexity	9.656	4	2.414	2.425	**0.046**	0.008
	Resistance to Change	11.127	4	2.782	2.798	0.025	0.009
	Top Management Support	32.47	4	8.117	8.308	0.000	0.026
	Social Characteristics & Performance Expectancy	7.685	4	1.921	1.927	**0.104**	0.006
	Effort Expectancy	13.237	4	3.309	3.334	0.01	0.011
	Social Influence	6.08	4	1.52	1.522	**0.193**	0.005
	External Support & Facilitating Conditions	16.78	4	4.195	4.239	0.002	0.013
	Behavioural Intention	10.211	4	2.553	2.566	0.037	0.008
	Perceived AI Acceptance	2.874	4	0.719	0.718	**0.58**	0.002
	Perceived AI Implementation	23.591	4	5.898	5.993	0.000	0.019
	Organizational Effectiveness	16.563	4	4.141	4.183	0.002	0.013

In contrast, no statistically significant differences are found across industries for Technology Characteristics (p = 0.063), Positive Attitude Towards Change (p = 0.356), Creativity (p = 0.056), Social Characteristics and Performance Expectancy (p = 0.104), Social Influence (p = 0.193), and Perceived AI Acceptance (p = 0.580). This indicates that core perceptions regarding AI functionality, general openness to change, peer influence, and acceptance tendencies are relatively consistent across industry contexts, possibly reflecting the widespread diffusion and normalization of AI technologies across sectors.

Overall, the results demonstrate that while fundamental attitudinal and perceptual dimensions of AI adoption remain stable across industries, organizational and implementation-related factors vary significantly, driven by differences in industry structure, regulatory environments, operational complexity, and leadership practices. Consequently, the null hypothesis of no industry-wise differences is rejected for several organizational and behavioural variables, but retained for basic attitudinal and perceptual constructs, underscoring the nuanced role of industry context in AI-enabled organizational transformation.

Technology Characteristics, Positive Attitude Towards Change, Creativity, Social Characteristics & Performance Expectancy, Social Influence, Perceived AI Acceptance differs with Industry with significance level 0.063, 0.356, 0.056, 0.104, 0.193, & 0.580 Respectively and hence we accept alternate hypothesis.

Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Effort Expectancy, External Support & Facilitating Conditions, Behavioural Intention, Perceived AI Implementation & Organizational Effectiveness does not differ with the industry and hence for these variables the we accept null hypothesis.

4.6.5.1 MANOVA – Post-Hoc Turkey HSD

Hypothesis

I. H0 - There is no Significant difference among Variables of Study (Technology Characteristics, Positive Attitude Towards Change, Creativity, Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Social Characteristics & Performance Expectancy, Effort Expectancy, Social Influence, External Support & Facilitating Conditions, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation) and different Industry Groups

   H_1 - There is a Significant difference among Variables of Study (Technology Characteristics, Positive Attitude Towards Change, Creativity, Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Social Characteristics & Performance Expectancy, Effort Expectancy, Social Influence, External Support & Facilitating Conditions, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation) and different Industry Groups

II. H_0 - There is no Significant difference among Organisational Effectiveness and different Industry Groups
   H_1 - There is a Significant difference among Organisational Effectiveness and different Industry Groups

To further examine the industry-wise differences identified in the overall ANOVA, Tukey's Honestly Significant Difference (HSD) post-hoc test was conducted to locate specific pairwise group differences across industries. The results as shown in Table 4-27: MANOVA – Post-Hoc Turkey HSD provide a nuanced understanding of how particular industry groups differ with respect to the study variables.

Table 4-27: MANOVA – Post-Hoc Turkey HSD

Dependent Variable			Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
ARTIFICIAL INTELLIGENCE	IT/ITES	HEALTHCARE	-.2481671*	.08911389	.043	-.4916080	-.0047263
		CONSUMER DURABLES	-.2556277*	.08868085	.033	-.4978856	-.0133699
		BANKING, INSURANCE & FINANCIAL SERVICES	-.1433817	.09082187	.511	-.3914884	.1047250
		MANAGEMENT CONSULTANCY	-.2997715*	.10470662	.035	-.5858084	-.0137345
	HEALTHCARE	IT/ITES	.2481671*	.08911389	.043	.0047263	.4916080
		CONSUMER DURABLES	-.0074606	.08130440	1.000	-.2295675	.2146463
		BANKING, INSURANCE & FINANCIAL SERVICES	.1047854	.08363447	.720	-.1236867	.3332576
		MANAGEMENT CONSULTANCY	-.0516043	.09853725	.985	-.3207878	.2175792
	CONSUMER DURABLES	IT/ITES	.2556277*	.08868085	.033	.0133699	.4978856
		HEALTHCARE	.0074606	.08130440	1.000	-.2146463	.2295675
		BANKING, INSURANCE & FINANCIAL SERVICES	.1122460	.08317290	.660	-.1149652	.3394573
		MANAGEMENT CONSULTANCY	-.0441437	.09814579	.992	-.3122578	.2239704
	BANKING, INSURANCE & FINANCIAL SERVICES	IT/ITES	.1433817	.09082187	.511	-.1047250	.3914884
		HEALTHCARE	-.1047854	.08363447	.720	-.3332576	.1236867
		CONSUMER DURABLES	-.1122460	.08317290	.660	-.3394573	.1149652
		MANAGEMENT CONSULTANCY	-.1563898	.10008453	.522	-.4298001	.1170206
	MANAGEMENT CONSULTANCY	IT/ITES	.2997715*	.10470662	.035	.0137345	.5858084
		HEALTHCARE	.0516043	.09853725	.985	-.2175792	.3207878
		CONSUMER DURABLES	.0441437	.09814579	.992	-.2239704	.3122578

Multiple Comparisons — Tukey HSD

		BANKING, INSURANCE & FINANCIAL SERVICES	.1563898	.10008453	.522	-.1170206	.4298001
BEHAVIOURAL INTENTION	IT/ITES	HEALTHCARE	.0815666	.08943682	.892	-.1627564	.3258896
		CONSUMER DURABLES	.1681859	.08900220	.323	-.0749498	.4113217
		BANKING, INSURANCE & FINANCIAL SERVICES	.0883512	.09115098	.869	-.1606545	.3373570
		MANAGEMENT CONSULTANCY	.0813179	.10508605	.938	-.2057556	.3683914
	HEALTHCARE	IT/ITES	-.0815666	.08943682	.892	-.3258896	.1627564
		CONSUMER DURABLES	.0866194	.08159903	.826	-.1362924	.3095312
		BANKING, INSURANCE & FINANCIAL SERVICES	.0067847	.08393754	1.000	-.2225154	.2360848
		MANAGEMENT CONSULTANCY	-.0002486	.09889432	1.000	-.2704076	.2699103
	CONSUMER DURABLES	IT/ITES	-.1681859	.08900220	.323	-.4113217	.0749498
		HEALTHCARE	-.0866194	.08159903	.826	-.3095312	.1362924
		BANKING, INSURANCE & FINANCIAL SERVICES	-.0798347	.08347429	.874	-.3078693	.1481999
		MANAGEMENT CONSULTANCY	-.0868680	.09850144	.904	-.3559537	.1822177
	BANKING, INSURANCE & FINANCIAL SERVICES	IT/ITES	-.0883512	.09115098	.869	-.3373570	.1606545
		HEALTHCARE	-.0067847	.08393754	1.000	-.2360848	.2225154
		CONSUMER DURABLES	.0798347	.08347429	.874	-.1481999	.3078693
		MANAGEMENT CONSULTANCY	-.0070333	.10044721	1.000	-.2814344	.2673679
	MANAGEMENT CONSULTANCY	IT/ITES	-.0813179	.10508605	.938	-.3683914	.2057556
		HEALTHCARE	.0002486	.09889432	1.000	-.2699103	.2704076
		CONSUMER DURABLES	.0868680	.09850144	.904	-.1822177	.3559537
		BANKING, INSURANCE & FINANCIAL SERVICES	.0070333	.10044721	1.000	-.2673679	.2814344
PERCEIVED AI ACCEPTANCE	IT/ITES	HEALTHCARE	-.1091781	.08920411	.737	-.3528654	.1345092
		CONSUMER DURABLES	.0416566	.08877063	.990	-.2008465	.2841597

		BANKING, INSURANCE & FINANCIAL SERVICES	-.1510601	.09091381	.458	-.3994179	.0972978
		MANAGEMENT CONSULTANCY	-.2093369	.10481262	.268	-.4956635	.0769896
	HEALTHCARE	IT/ITES	.1091781	.08920411	.737	-.1345092	.3528654
		CONSUMER DURABLES	.1508347	.08138671	.343	-.0714971	.3731665
		BANKING, INSURANCE & FINANCIAL SERVICES	-.0418820	.08371914	.987	-.2705854	.1868215
		MANAGEMENT CONSULTANCY	-.1001588	.09863700	.848	-.3696148	.1692972
	CONSUMER DURABLES	IT/ITES	-.0416566	.08877063	.990	-.2841597	.2008465
		HEALTHCARE	-.1508347	.08138671	.343	-.3731665	.0714971
		BANKING, INSURANCE & FINANCIAL SERVICES	-.1927166	.08325710	.141	-.4201579	.0347246
		MANAGEMENT CONSULTANCY	-.2509935	.09824515	.080	-.5193791	.0173921
	BANKING, INSURANCE & FINANCIAL SERVICES	IT/ITES	.1510601	.09091381	.458	-.0972978	.3994179
		HEALTHCARE	.0418820	.08371914	.987	-.1868215	.2705854
		CONSUMER DURABLES	.1927166	.08325710	.141	-.0347246	.4201579
		MANAGEMENT CONSULTANCY	-.0582769	.10018586	.978	-.3319640	.2154103
	MANAGEMENT CONSULTANCY	IT/ITES	.2093369	.10481262	.268	-.0769896	.4956635
		HEALTHCARE	.1001588	.09863700	.848	-.1692972	.3696148
		CONSUMER DURABLES	.2509935	.09824515	.080	-.0173921	.5193791
		BANKING, INSURANCE & FINANCIAL SERVICES	.0582769	.10018586	.978	-.2154103	.3319640
PERCEIVED AI IMPLEMENTATION	IT/ITES	HEALTHCARE	.0566287	.08882152	.969	-.1860134	.2992709
		CONSUMER DURABLES	.2019189	.08838990	.151	-.0395442	.4433819
		BANKING, INSURANCE & FINANCIAL SERVICES	-.0180855	.09052389	1.000	-.2653782	.2292071
		MANAGEMENT CONSULTANCY	-.2310437	.10436309	.175	-.5161422	.0540548
	HEALTHCARE	IT/ITES	-.0566287	.08882152	.969	-.2992709	.1860134
		CONSUMER DURABLES	.1452901	.08103765	.378	-.0760881	.3666683

		BANKING, INSURANCE & FINANCIAL SERVICES	-.0747143	.08336007	.898	-.3024368	.1530083
		MANAGEMENT CONSULTANCY	-.2876724*	.09821396	.029	-.5559728	-.0193721
	CONSUMER DURABLES	IT/ITES	-.2019189	.08838990	.151	-.4433819	.0395442
		HEALTHCARE	-.1452901	.08103765	.378	-.3666683	.0760881
		BANKING, INSURANCE & FINANCIAL SERVICES	-.2200044	.08290002	.062	-.4464702	.0064614
		MANAGEMENT CONSULTANCY	-.4329625*	.09782378	.000	-.7001970	-.1657281
	BANKING, INSURANCE & FINANCIAL SERVICES	IT/ITES	.0180855	.09052389	1.000	-.2292071	.2653782
		HEALTHCARE	.0747143	.08336007	.898	-.1530083	.3024368
		CONSUMER DURABLES	.2200044	.08290002	.062	-.0064614	.4464702
		MANAGEMENT CONSULTANCY	-.2129582	.09975617	.206	-.4854715	.0595552
	MANAGEMENT CONSULTANCY	IT/ITES	.2310437	.10436309	.175	-.0540548	.5161422
		HEALTHCARE	.2876724*	.09821396	.029	.0193721	.5559728
		CONSUMER DURABLES	.4329625*	.09782378	.000	.1657281	.7001970
		BANKING, INSURANCE & FINANCIAL SERVICES	.2129582	.09975617	.206	-.0595552	.4854715
ORGANIZATIONAL EFFECTIVENESS	IT/ITES	HEALTHCARE	.0378257	.08928806	.993	-.2060909	.2817424
		CONSUMER DURABLES	.0129341	.08885417	1.000	-.2297972	.2556655
		BANKING, INSURANCE & FINANCIAL SERVICES	.1264180	.09099937	.635	-.1221735	.3750096
		MANAGEMENT CONSULTANCY	-.1496407	.10491126	.611	-.4362367	.1369553
	HEALTHCARE	IT/ITES	-.0378257	.08928806	.993	-.2817424	.2060909
		CONSUMER DURABLES	-.0248916	.08146330	.998	-.2474326	.1976494
		BANKING, INSURANCE & FINANCIAL SERVICES	.0885923	.08379792	.828	-.1403264	.3175110
		MANAGEMENT CONSULTANCY	-.1874664	.09872983	.318	-.4571760	.0822432
	CONSUMER DURABLES	IT/ITES	-.0129341	.08885417	1.000	-.2556655	.2297972
		HEALTHCARE	.0248916	.08146330	.998	-.1976494	.2474326

		BANKING, INSURANCE & FINANCIAL SERVICES	.1134839	.08333545	.652	-.1141714	.3411392
		MANAGEMENT CONSULTANCY	-.1625748	.09833760	.464	-.4312129	.1060633
	BANKING, INSURANCE & FINANCIAL SERVICES	IT/ITES	-.1264180	.09099937	.635	-.3750096	.1221735
		HEALTHCARE	-.0885923	.08379792	.828	-.3175110	.1403264
		CONSUMER DURABLES	-.1134839	.08333545	.652	-.3411392	.1141714
		MANAGEMENT CONSULTANCY	-.2760587*	.10028014	.047	-.5500035	-.0021140
	MANAGEMENT CONSULTANCY	IT/ITES	.1496407	.10491126	.611	-.1369553	.4362367
		HEALTHCARE	.1874664	.09872983	.318	-.0822432	.4571760
		CONSUMER DURABLES	.1625748	.09833760	.464	-.1060633	.4312129
		BANKING, INSURANCE & FINANCIAL SERVICES	.2760587*	.10028014	.047	.0021140	.5500035

Based on observed means.
The error term is Mean Square (Error) = .997.
**. The mean difference is significant at the .05 level.*

For Artificial Intelligence, significant mean differences are observed between IT/ITES and Healthcare, IT/ITES and Consumer Durables, and IT/ITES and Management Consultancy ($p < 0.05$). In each case, IT/ITES professionals report significantly lower AI scores compared to these industries, suggesting that sectors such as Healthcare, Consumer Durables, and Management Consultancy may exhibit relatively stronger AI orientation, maturity, or exposure. No significant differences are found between Banking & Financial Services and other industries, indicating relative homogeneity in AI perceptions within this sector.

In contrast, Behavioural Intention shows no statistically significant pairwise differences across any industry combinations (all $p > 0.05$). This confirms that despite differences in organizational context, employees across industries demonstrate comparable levels of intention to use or engage with AI technologies. Accordingly, the null hypothesis for Behavioural Intention across industries is retained.

Similarly, Perceived AI Acceptance does not exhibit statistically significant differences across industry pairs. Although some comparisons (e.g., Consumer Durables vs. Management Consultancy) approach significance, none cross the 0.05 threshold. This suggests that acceptance-related beliefs toward AI are broadly consistent across industries, reflecting the widespread normalization of AI tools irrespective of sectoral boundaries.

For Perceived AI Implementation, however, significant differences emerge involving Management Consultancy. Specifically, Management Consultancy differs significantly from healthcare ($p = 0.029$) and Consumer Durables ($p < 0.001$), with lower perceived implementation levels. This indicates that while consultancy firms may emphasize strategic advisory roles, they may lag in hands-on AI implementation compared to more operationally intensive industries. Other industry comparisons remain statistically non-significant, highlighting that implementation disparities are concentrated around specific sectors rather than widespread.

Regarding Organizational Effectiveness, a significant mean difference is identified between Banking & Financial Services and Management Consultancy ($p = 0.047$). Banking & Financial Services report higher organizational effectiveness outcomes compared to Management Consultancy, suggesting that AI-enabled efficiencies, scalability, and performance gains may be more pronounced in transaction-driven and data-intensive industries. All other pairwise comparisons remain non-significant.

Overall, the post-hoc analysis reveals that industry-wise differences are selective rather than universal. Significant differences are primarily concentrated in AI orientation, perceived implementation, and organizational effectiveness, particularly involving IT/ITES and Management Consultancy. In contrast, Behavioural Intention and Perceived AI Acceptance remain stable across industries, reinforcing the earlier ANOVA conclusion that core acceptance and intention constructs are largely industry-invariant, while organizational capability and implementation outcomes are industry-specific.

IT/ITES has markedly inferior AI relative to healthcare ($p = .043$), Consumer Durables ($p = .033$), and Management Consultancy ($p = .035$). Although the overall ANOVA indicates significance ($p = .039$), no specific industry pair demonstrates a statistically significant difference in Behavioural Intention towards AI ($p > .05$ for all pairwise comparisons).

Despite broad variability, particular industry objectives exhibit statistical similarity. Although the aggregate ANOVA indicates significance ($p < .001$), no individual industry pair demonstrates a statistically significant difference in Perceived AI Acceptance ($p > .05$ for all pairwise comparisons). A uniform level of AI acceptance is noted, without major differences among industry pairs. Management Consultancy exhibits a markedly greater Perceived AI Implementation relative to healthcare ($p = .029$) and Consumer Durables ($p < .001$). Management Consultancy exhibits greater AI implementation compared to Healthcare and Consumer Durables.

Management Consultancy demonstrates markedly superior Organisational Effectiveness relative to Banking, Insurance & Financial Services ($p = .047$). Management Consultancy exhibits superior Organisational Effectiveness relative to the Banking, Insurance, and Financial Services sector. The other industries exhibit no substantial pairwise differences among one another. A statistically significant difference in Organisational Effectiveness exists across the five studied industries ($F(4, 1240) = 5.233$, $p < .001$).

4.6.6 Size of Organization

Hypothesis

H_0 - There is no Significant difference among Variables of Study (Technology Characteristics, Positive Attitude Towards Change, Creativity, Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Social Characteristics & Performance Expectancy, Effort Expectancy, Social Influence, External Support & Facilitating Conditions, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation & Organizational Effectiveness) and different Size of Organization

H_1 - There is a Significant difference among Variables of Study (Technology Characteristics, Positive Attitude Towards Change, Creativity, Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Social Characteristics & Performance Expectancy, Effort Expectancy, Social Influence, External Support & Facilitating Conditions, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation & Organizational Effectiveness) and different Size of Organization

Table 4-28: Size of the organization of Respondents

Size of the organization you work at (Approximate number of employees)	
Below 100	448
100 - 300	267
300 - 500	64
Above 500	465

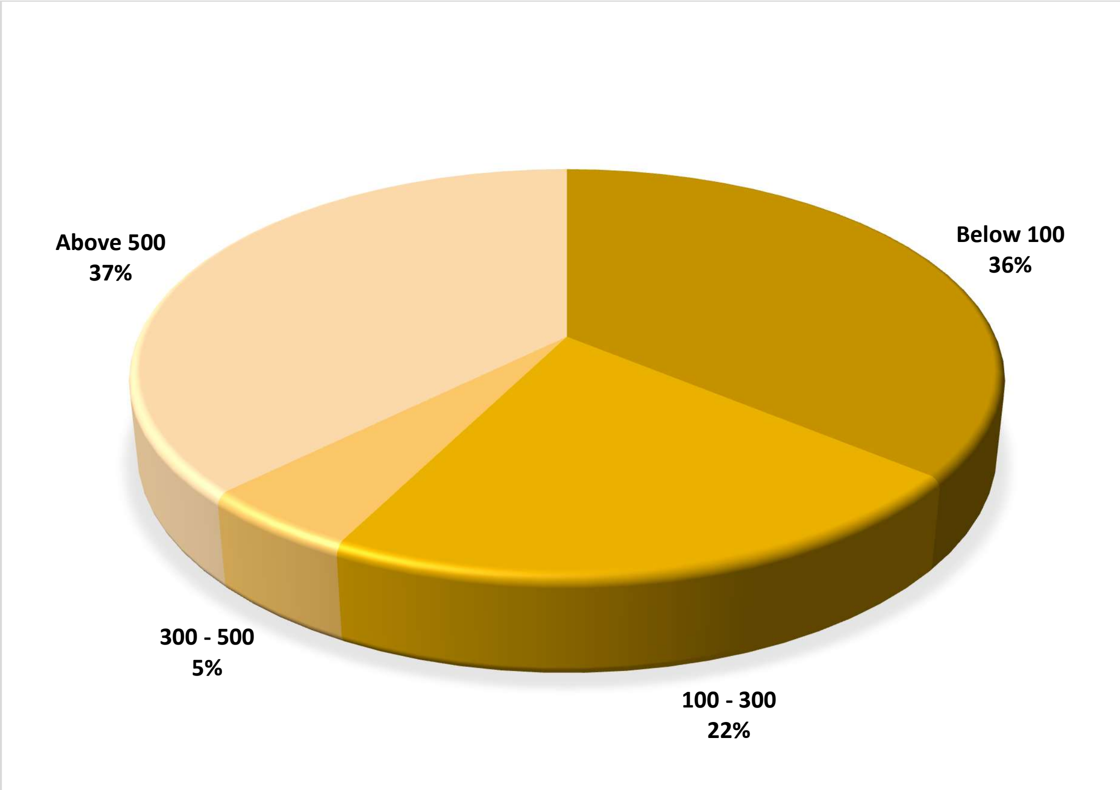

Figure 4-8: Size of the organization of Respondents

The distribution of respondents by organizational size indicates a well-balanced representation across small and large enterprises**,** with relatively fewer respondents from medium-sized organizations. A substantial proportion of participants are employed in large organizations with more than 500 employees (465 respondents; approximately **37%**), closely followed by those working in small organizations with fewer than 100 employees (448 respondents; approximately **36%**). Together, these two categories account for nearly three-quarters of the sample, suggesting that perspectives from both ends of the organizational size spectrum are strongly captured in the study. Respondents from medium-sized organizations employing 100–300 employees constitute 267 individuals (about 22%)**,** reflecting a moderate level of representation. In contrast, organizations with 300–500 employees are comparatively underrepresented, with only 64 respondents (around 5%). This skew suggests that transitional, mid-sized firms form a smaller segment of the sampled population.

Overall, the composition highlights that the empirical findings are informed predominantly by experiences drawn from small and very large organizations, which is particularly relevant for studies on technology adoption and AI-related practices. Smaller firms often face resource and capability constraints, while larger organizations typically possess greater structural readiness and strategic capacity for AI implementation. The inclusion of both groups enhances the robustness and external validity of the analysis, allowing for meaningful comparison across organizational scales while acknowledging the relatively limited input from mid-sized enterprises.

Table 4-29: MANOVA between Variables of study & Size of Organization

Source	*Dependent Variable*	*Type III Sum of Squares*	*df*	*Mean Square*	*F*	*Sig.*	*Partial Eta Squared*
Size	Technology Characteristics	9.884	3	3.295	3.313	0.019	0.008
	Positive Attitude Towards Change	5.883	3	1.961	1.965	**0.117**	0.005
	Creativity	3.616	3	1.205	1.206	**0.306**	0.003
	Self-Efficacy	7.002	3	2.334	2.341	**0.072**	0.006
	Complexity	5.954	3	1.985	1.989	**0.114**	0.005
	Resistance to Change	11.283	3	3.761	3.786	0.01	0.009
	Top Management Support	11.516	3	3.839	3.865	0.009	0.009
	Social Characteristics & Performance Expectancy	5.534	3	1.845	1.849	**0.137**	0.004
	Effort Expectancy	17.393	3	5.798	5.866	0.001	0.014
	Social Influence	1.828	3	0.609	0.609	**0.609**	0.001
	External Support & Facilitating Conditions	8.36	3	2.787	2.799	0.039	0.007
	Behavioural Intention	5.051	3	1.684	1.686	**0.168**	0.004
	Perceived AI Acceptance	6.761	3	2.254	2.261	**0.08**	0.005
	Perceived AI Implementation	0.562	3	0.187	0.187	**0.905**	0
	Organizational Effectiveness	10.894	3	3.631	3.655	0.012	0.009

The analysis as shown in table 4-29 reveals that organizational size exerts a selective yet statistically meaningful influence on several key variables related to AI adoption and outcomes, thereby providing partial support for the stated hypothesis that differences exist among study variables across different sizes of organizations. Specifically, Technology Characteristics show a significant variation across organizational sizes ($F = 3.313$, $p = 0.019$, $\eta^2 = 0.008$), indicating that perceptions of AI-related technological features differ depending on whether respondents belong to small, medium, or large organizations. Similarly, Resistance to Change ($F = 3.786$, $p = 0.010$, $\eta^2 = 0.009$) and Top Management Support ($F = 3.865$, $p = 0.009$, $\eta^2 = 0.009$) exhibit statistically significant differences, suggesting that organizational scale plays a role in shaping both managerial backing and employees' openness toward AI-driven change. These findings align with organizational theory, which posits that larger firms often have more formalized leadership structures and change-management mechanisms, while smaller firms may experience resistance due to limited slack resources. Further, Effort Expectancy demonstrates a strong and significant difference across organization sizes ($F = 5.866$, $p = 0.001$, $\eta^2 = 0.014$), implying that the perceived ease of using AI systems varies meaningfully with organizational scale. External Support and Facilitating Conditions ($F = 2.799$, $p = 0.039$, $\eta^2 = 0.007$) also differ significantly, highlighting that access to infrastructure, vendor support, and enabling resources is not uniform across organizations of different sizes. Importantly, Organizational Effectiveness shows a significant size-based difference ($F = 3.655$, $p = 0.012$, $\eta^2 = 0.009$), indicating that the performance outcomes associated with AI adoption are contingent on organizational scale.

In contrast, several variables including Positive Attitude Towards Change, Creativity, Self-Efficacy, Complexity, Social Characteristics & Performance Expectancy, Social Influence, Behavioural Intention, Perceived AI Acceptance, and Perceived AI Implementation do not exhibit statistically significant differences across organizational size ($p > 0.05$). This suggests that individual-level perceptions and intentions toward AI are relatively stable regardless of organizational scale, whereas structural, managerial, and resource-dependent factors are more sensitive to size-related differences. Overall, the results indicate that the hypothesis of significant differences across organizational size is partially accepted. While not all variables vary by size, the statistically significant effects observed for core technological, managerial, effort-related, and outcome-oriented constructs underscore the importance of organizational scale in shaping the AI adoption environment. The effect sizes, though small to moderate, are meaningful in large-sample organizational research and collectively affirm that size of organization functions as an important contextual factor rather than a universal differentiator across all AI-related perceptions and outcomes.

There is a significant difference between size of organization and variables Positive Attitude Towards Change, Creativity, Self-Efficacy, Complexity, Social Characteristics & Performance Expectancy, Behavioural Intention, Perceived AI Acceptance & Perceived AI Implementation, hence for these variables we accept the alternate hypothesis. There is no significant difference between size of organization and Technology Characteristics, Resistance to Change, Top Management Support, Effort Expectancy, External Support & Facilitating Conditions, Organizational Effectiveness, hence for these variables null hypothesis is accepted.

4.6.7 Level of Management

Hypothesis:

H_0 - There is no Significant difference among Variables of Study (Technology Characteristics, Positive Attitude Towards Change, Creativity, Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Social Characteristics & Performance Expectancy, Effort Expectancy, Social Influence, External Support & Facilitating Conditions, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation & Organizational Effectiveness) and different Level of Management

H_1 - There is no Significant difference among Variables of Study (Technology Characteristics, Positive Attitude Towards Change, Creativity, Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Social Characteristics & Performance Expectancy, Effort

Expectancy, Social Influence, External Support & Facilitating Conditions, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation & Organizational Effectiveness) and different Level of Management

Table 4-30: Level of Management of Respondents

Level of Management	***Count (N)***	***Percentage (%)***
Bottom-level Management	237	19.0%
Middle-level Management	735	59.0%
Top-level Management	273	22.0%

The distribution of respondents across levels of management indicates a predominant representation of middle-level managers, who constitute 59% of the total sample. This substantial proportion suggests that the study largely captures perspectives from individuals who typically act as key intermediaries between strategic decision-makers and operational staff. Middle-level managers are often directly involved in translating organizational strategies—such as AI adoption initiatives—into actionable processes, making their insights particularly relevant for understanding implementation dynamics.

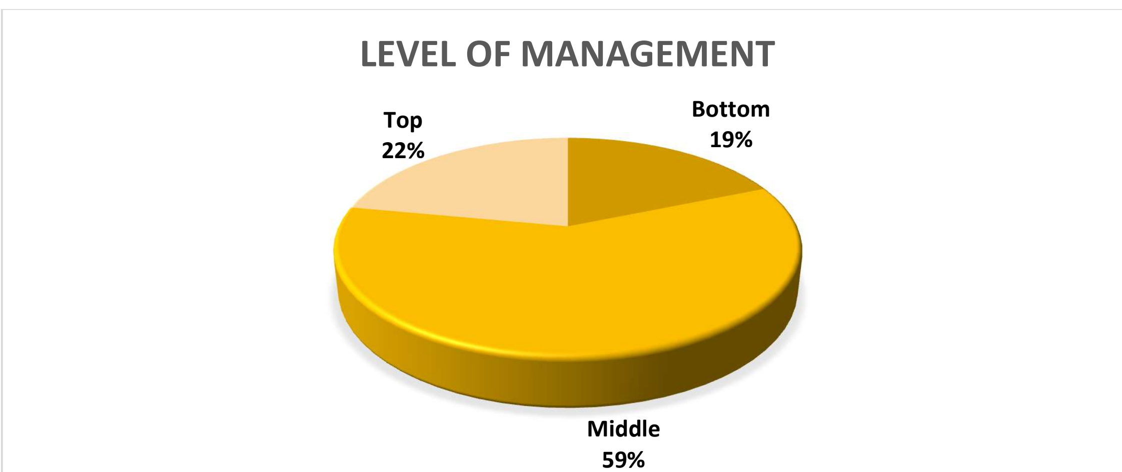

Figure 4-9: Level of Management of Respondents

Top-level management accounts for 22% of the respondents, reflecting a meaningful presence of senior leaders responsible for strategic vision, policy formulation, and resource allocation. Their inclusion strengthens the study by incorporating strategic and governance-oriented viewpoints related to AI adoption and organizational effectiveness. Meanwhile, 19% of respondents belong to bottom-level management, representing operational employees who interact most closely with AI-enabled systems in day-to-day work. Their participation provides valuable insights into practical usability, effort expectancy, and resistance or acceptance at the execution level.

Overall, the managerial composition of the sample is well-balanced and analytically robust, with adequate representation from all three hierarchical levels. This spread supports a comprehensive examination of AI-related perceptions and outcomes across organizational hierarchies, while the dominance of middle management aligns with their central role in driving and sustaining organizational change initiatives.

Table 4-31: MANOVA between Variables of study & Level of Management

Source	*Dependent Variable*	*Type III Sum of Squares*	*df*	*Mean Square*	*F*	*Sig.*	*Partial Eta Squared*
Level of management	**Technology Characteristics**	1.389	2	0.694	0.694	**0.5**	0.001
	Positive Attitude Towards Change	5.538	2	2.769	2.777	**0.063**	0.004
	Creativity	0.513	2	0.257	0.256	**0.774**	0
	Self-Efficacy	5.321	2	2.66	2.668	**0.07**	0.004
	Complexity	8.05	2	4.025	4.045	0.018	0.006
	Resistance to Change	10.739	2	5.37	5.408	0.005	0.009
	Top Management Support	5.413	2	2.706	2.714	**0.067**	0.004
	Social Characteristics & Performance Expectancy	7.742	2	3.871	3.889	0.021	0.006
	Effort Expectancy	1.922	2	0.961	0.961	**0.383**	0.002
	Social Influence	5.43	2	2.715	2.722	**0.066**	0.004
	External Support & Facilitating Conditions	10.189	2	5.095	5.128	0.006	0.008
	Behavioural Intention	13.292	2	6.646	6.707	0.001	0.011
	Perceived AI Acceptance	0.047	2	0.023	0.023	**0.977**	0.000
	Perceived AI Implementation	6.988	2	3.494	3.508	0.03	0.006
	Organizational Effectiveness	20.183	2	10.091	10.242	0.000	0.016

To examine whether perceptions related to AI adoption and its outcomes differ across hierarchical positions, a one-way analysis of variance was conducted with level of management (bottom, middle, and top) as the grouping variable. The results indicate that the null hypothesis of *no significant difference across levels of management* is only partially supported. For several core constructs—namely Technology Characteristics, Creativity, Effort Expectancy, and Perceived AI Acceptance—the differences across management levels were not statistically significant ($p > 0.05$), with negligible effect sizes (partial $\eta^2 \leq 0.002$). This suggests a broadly shared understanding of AI's technological attributes, effort requirements, and acceptance perceptions across hierarchical tiers.

However, statistically significant differences were observed for Complexity ($F = 4.045$, $p = 0.018$), Resistance to Change ($F = 5.408$, $p = 0.005$), Social Characteristics & Performance Expectancy ($F = 3.889$, $p = 0.021$), External Support & Facilitating Conditions ($F = 5.128$, $p = 0.006$), Behavioural Intention ($F = 6.707$, $p = 0.001$), Perceived AI Implementation ($F = 3.508$, $p = 0.030$), and Organizational Effectiveness ($F = 10.242$, $p < 0.001$). Although these effects are statistically significant, the associated partial eta squared values ($\eta^2 = 0.006$–0.016) indicate small effect sizes, implying that while managerial level does influence these perceptions, the magnitude of difference is modest.

Substantively, these findings suggest that hierarchical position shapes how individuals perceive organizational readiness, implementation effectiveness, resistance dynamics, and strategic outcomes of AI, with higher-level managers likely engaging more directly with implementation and performance implications, while lower and middle levels may experience AI more through operational complexity and change-related pressures. Consequently, the hypothesis stating that *there is no significant difference among study variables across levels of management* is rejected for selected organizational and behavioural constructs, but retained for technology-focused and acceptance-related variables. Overall, the evidence points to partial invariance across management levels, highlighting the importance of role-sensitive change management and communication strategies during AI adoption initiatives.

Technology Characteristics, Positive Attitude Towards Change, Creativity, Self-Efficacy, Top Management Support, Effort Expectancy, Social Influence & Perceived AI Acceptance have significance higher than 0.05 which is 0.5, 0.063, 0.774, 0.07, 0.067, 0.383, 0.066, & 0.977 respectively, hence the researcher accepted alternate hypothesis that there is a significant difference between above variables and level of management.

Null hypothesis is accepted for Complexity, Resistance to Change, Social Characteristics & Performance Expectancy, External Support & Facilitating Conditions, Behavioural Intention, Perceived AI Implementation & Organizational Effectiveness, and level of management.

4.6.8 Location

Hypothesis:

H_0 - There is no Significant difference among Variables of Study (Technology Characteristics, Positive Attitude Towards Change, Creativity, Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Social Characteristics & Performance Expectancy, Effort Expectancy, Social Influence, External Support & Facilitating Conditions, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation & Organizational Effectiveness) and different Location

H_1 - There is a Significant difference among Variables of Study (Technology Characteristics, Positive Attitude Towards Change, Creativity, Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Social Characteristics & Performance Expectancy, Effort Expectancy, Social Influence, External Support & Facilitating Conditions, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation & Organizational Effectiveness) and different Location

Table 4-32: Location of Respondents

Location	*Percentage (%)*	*Approx. Count*
Central Gujarat	67%	834
North Gujarat	16%	199
South Gujarat	7%	87
Saurashtra	10%	125

The geographic distribution of respondents indicates a strong regional concentration, with Central Gujarat accounting for the majority of the sample (67%, n ≈ 834). This dominance reflects the higher density of industrial activity, corporate offices, and service-sector organizations in Central Gujarat, which are more likely to be exposed to and engaged in AI-enabled HR practices. North Gujarat represents the second-largest group (16%, n ≈ 199), suggesting moderate participation from semi-urban and emerging industrial regions. Saurashtra contributes about 10% of the respondents (n ≈ 125), while South Gujarat accounts for the smallest share (7%, n ≈ 87), indicating comparatively lower representation.

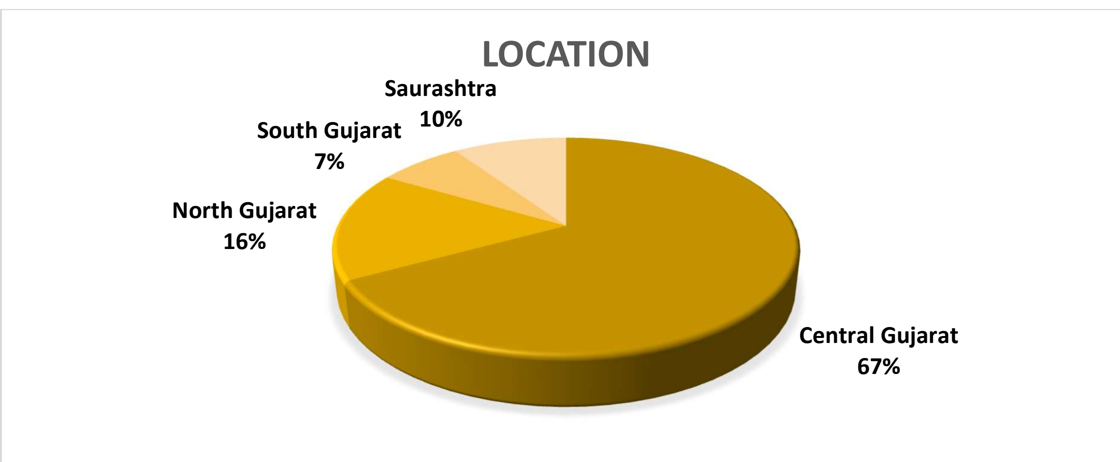

Figure 4-10: Location of Respondents

Overall, the sample demonstrates adequate regional diversity, while remaining realistically aligned with the economic and organizational landscape of Gujarat, where Central Gujarat functions as the primary hub for technology adoption and organizational innovation. This regional composition supports the external validity of the study, particularly for interpreting AI adoption and organizational effectiveness in economically dominant regions, while still allowing comparative insights across less urbanized zones.

To examine whether perceptions related to AI adoption in HR practices differ across geographic locations, an analysis of variance was conducted with location (Central Gujarat, North Gujarat, South Gujarat, and Saurashtra) as the grouping variable and the study constructs as dependent variables. The results as shown in Table 4-33: MANOVA between Variables of study and Location reveal that location exerts a statistically significant influence on several key dimensions**,** thereby providing partial support for the hypothesis that perceptions differ across locations.

Significant differences across locations were observed for Technology Characteristics *($F = 12.975$, $p < 0.001$, $\eta^2 = 0.030$)*, indicating that respondents' evaluation of AI-related technological attributes varies meaningfully by region. Similarly, Complexity *($F = 5.471$, $p = 0.001$, $\eta^2 = 0.013$)* and Effort Expectancy *($F = 8.642$, $p < 0.001$, $\eta^2 = 0.020$)* differed significantly across locations, suggesting that the perceived ease or difficulty of using AI-enabled HR systems is shaped by regional exposure, infrastructure maturity, and technological familiarity. Social Influence *($F = 5.957$, $p < 0.001$, $\eta^2 = 0.014$)* and Behavioural Intention *($F = 3.931$, $p = 0.008$, $\eta^2 = 0.009$)* were also significantly affected, implying that peer influence and intent to use AI in HR practices are geographically contingent. Furthermore, Top Management Support *($F = 3.294$, $p = 0.020$, $\eta^2 = 0.008$)* and Social Characteristics & Performance Expectancy *($F = 2.881$, $p = 0.035$, $\eta^2 = 0.007$)* showed statistically significant variation across locations, highlighting regional differences in leadership commitment and expectations regarding AI-driven performance gains. Importantly, Perceived AI Implementation *($F = 8.241$, $p < 0.001$, $\eta^2 = 0.020$)* and Organizational Effectiveness *($F = 2.929$, $p = 0.033$, $\eta^2 = 0.007$)* also differed significantly, indicating that respondents' assessments of implementation readiness and organizational outcomes are influenced by geographic context.

In contrast, Positive Attitude Towards Change**,** Creativity**,** Self-Efficacy**,** Resistance to Change**,** External Support & Facilitating Conditions**,** and Perceived AI Acceptance did not show statistically significant differences across locations ($p > 0.05$). This suggests that intrinsic psychological orientations and personal capability beliefs toward AI are relatively stable across regions, irrespective of geographic variation.

Overall, the findings demonstrate that location plays a meaningful role in shaping structurally and contextually driven perceptions of AI adoption, particularly those related to technology characteristics, effort expectations, social influence, implementation readiness, and organizational outcomes. However, since not all constructs vary significantly by location, the hypothesis that *there is a significant difference among all variables of study across different locations* is partially accepted. The results underscore the importance of considering regional context when formulating AI adoption strategies, especially in geographically diverse settings where infrastructural and organizational ecosystems differ.

Table 4-33: MANOVA between Variables of study and Location

Source	*Dependent Variable*	*Type III Sum of Squares*	*df*	*Mean Square*	*F*	*Sig.*	*Partial Eta Squared*
Location	**Technology Characteristics**	37.832	3	12.611	12.975	0	0.03
	Positive Attitude Towards Change	1.451	3	0.484	0.483	**0.694**	0.001
	Creativity	5.184	3	1.728	1.731	**0.159**	0.004
	Self-Efficacy	5.649	3	1.883	1.887	**0.13**	0.005
	Complexity	16.237	3	5.412	5.471	0.001	0.013
	Resistance to Change	1.679	3	0.56	0.559	**0.642**	0.001
	Top Management Support	9.829	3	3.276	3.294	0.02	0.008
	Social Characteristics & Performance Expectancy	8.603	3	2.868	2.881	0.035	0.007
	Effort Expectancy	25.456	3	8.485	8.642	0.000	0.02
	Social Influence	17.66	3	5.887	5.957	0.000	0.014
	External Support & Facilitating Conditions	4.243	3	1.414	1.416	**0.237**	0.003
	Behavioural Intention	11.711	3	3.904	3.931	0.008	0.009
	Perceived AI Acceptance	6.065	3	2.022	2.027	**0.108**	0.005
	Perceived AI Implementation	24.298	3	8.099	8.241	0.000	0.02
	Organizational Effectiveness	8.747	3	2.916	2.929	0.033	0.007

There is a significant difference between Technology Characteristics, Positive Attitude Towards Change, Creativity, Resistance to Change, External Support & Facilitating Conditions, Perceived AI Acceptance depending on location of the employee.

There is no significant difference between Self-Efficacy, Complexity, Top Management Support, Social Characteristics & Performance Expectancy, Effort Expectancy, Social

Influence, Behavioural Intention, Perceived AI Implementation & Organizational Effectiveness as per location.

4.6.9 Gender

Hypothesis:

H_0 - There is no Significant difference among Variables of Study (Technology Characteristics, Positive Attitude Towards Change, Creativity, Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Social Characteristics & Performance Expectancy, Effort Expectancy, Social Influence, External Support & Facilitating Conditions, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation & Organizational Effectiveness) and different Gender groups

H_1 - There is a Significant difference among Variables of Study (Technology Characteristics, Positive Attitude Towards Change, Creativity, Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Social Characteristics & Performance Expectancy, Effort Expectancy, Social Influence, External Support & Facilitating Conditions, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation & Organizational Effectiveness) and different Gender groups

Table 4-34: Gender Groups of Respondent

Gender	*Count*
Male	849
Female	395

The gender-wise distribution of respondents indicates that male participants constitute the majority of the sample (849 respondents; 68%), while female participants account for 395 respondents (32%). This distribution reflects a clear gender imbalance in the respondent pool.

From an interpretative point of view, the dominance of male respondents can be reasonably attributed to the current workforce composition in technology-intensive, AI-adopting, and managerial roles, particularly within sectors such as IT/ITES, consumer durables, & telecommunications, healthcare & hospitality, financial services, and consulting, where male representation has traditionally been higher. In many organizational contexts—especially in emerging economies—men continue to be overrepresented in decision-making, technical, and senior operational roles, which are more directly exposed to AI implementation and digital transformation initiatives. Consequently, male employees are more likely to be targeted for, or voluntarily participate in, studies related to advanced technologies such as AI in organizational settings.

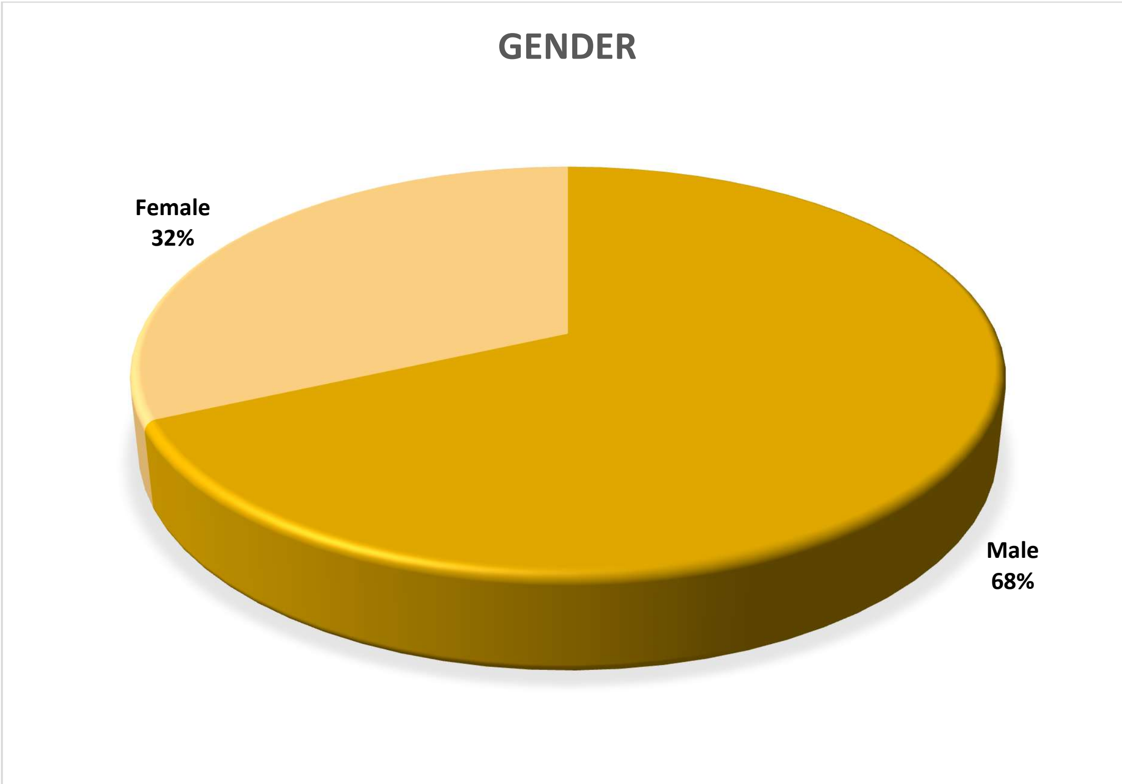

Figure 4-11: Gender Groups of Respondent

The presence of a substantial proportion of female respondents (nearly one-third of the sample) is nevertheless noteworthy and indicates increasing female participation in professional, managerial, and technology-enabled roles. This suggests a gradual narrowing of the gender gap and enhances the inclusiveness and analytical robustness of the study by ensuring that female perspectives on AI adoption, acceptance, and organizational outcomes are meaningfully represented.

Importantly, the observed gender difference is descriptive rather than inferential in nature. The unequal proportions do not imply bias but rather mirror real-world employment patterns and accessibility to AI-related roles at the time of data collection. From a methodological perspective, the sample size for both genders remains sufficiently large to support reliable statistical analysis, thereby ensuring that subsequent inferential tests involving gender comparisons, if conducted, retain adequate statistical power.

Overall, the gender distribution strengthens the external validity of the study by aligning the sample characteristics with prevailing organizational demographics, while simultaneously capturing evolving trends toward greater gender diversity in AI-influenced work environments.

Table 4-35: Mann-Whitney U between Variables of Study and Gender

Test Statistics [a]

	Technology Characteristics	Positive Attitude Towards Change	Creativity	Self-Efficacy	Complexity	Resistance to Change	Top Management Support	Social Characteristics & Performance Expectancy	Effort Expectancy	Social Influence	External Support & Facilitating Conditions	Behavioural Intention	Perceived AI Acceptance	Perceived AI Implementation	Organizational Effectiveness
Mann-Whitney U	164738.500	148601.500	167305.500	162711.500	161113.500	160576.500	166714.500	159944.500	147926.500	162249.500	156829.500	145845.500	148142.500	166046.500	166067.500
Wilcoxon W	525563.500	509426.500	245515.500	240921.500	521938.500	521401.500	527539.500	520769.500	508751.500	523074.500	235039.500	506670.500	508967.500	526871.500	526892.500
Z	-.498	-3.234	-.063	-.842	-1.113	-1.204	-.163	-1.311	-3.348	-.920	-1.839	-3.701	-3.312	-.277	-.273
Asymp. Sig. (2-tailed)	**.618**	.001	**.950**	**.400**	**.266**	**.229**	**.870**	**.190**	.001	**.357**	**.066**	.000	.001	**.782**	**.785**

The Mann–Whitney U test was employed to examine whether statistically significant differences exist between male and female respondents across the study variables, given the non-parametric nature of the data. The results indicate that gender-based differences are selective rather than uniform across all constructs. Specifically, Positive Attitude Towards Change ($Z = -3.234$, $p = 0.001$), Effort Expectancy ($Z = -3.348$, $p = 0.001$), Behavioural Intention ($Z = -3.701$, $p < 0.001$), and Perceived AI Acceptance ($Z = -3.312$, $p = 0.001$) exhibit statistically significant differences between gender groups at the 5% significance level. These findings suggest that male and female respondents differ meaningfully in their attitudinal orientation toward change, perceptions of effort associated with AI use, intention to engage with AI-driven systems, and overall acceptance of AI. Such differences may be attributed to variations in role exposure, prior technological experience, confidence in using advanced systems, and organizational expectations, which have been widely noted in technology adoption literature.

In contrast, Technology Characteristics, Creativity, Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Social Characteristics & Performance Expectancy, Social Influence, External Support & Facilitating Conditions, Perceived AI Implementation, and Organizational Effectiveness do not show statistically significant gender differences ($p > 0.05$). This indicates that, for these constructs, male and female respondents hold broadly comparable perceptions, implying a convergence in how core organizational and technological factors are experienced across genders.

Overall, the hypothesis that there is a significant difference among the variables of study across different gender groups is partially supported. Gender emerges as a differentiating factor primarily for attitudinal, effort-related, and intention-based constructs, while perceptions of structural, organizational, and implementation-related dimensions of AI remain largely gender-neutral. This nuanced pattern underscores the importance of considering gender-sensitive strategies particularly when addressing AI acceptance and behavioural intention, while suggesting that organizational and technological enablers may be designed in a largely gender-inclusive manner.

There is a significant difference between Technology Characteristics, Creativity, Self-Efficacy, Complexity, Resistance to Change, Top Management Support, Social Characteristics & Performance Expectancy, Social Influence, External Support & Facilitating Conditions, Perceived AI Implementation & Organizational Effectiveness with significance value of 0.616, 0.950, 0.400, 0.266, 0.229, 0.870, 0.190, 0.375, 0.066, 0.782 & 0.785 and Gender of Employee. There is no significant difference between Positive Attitude Towards Change, Effort Expectancy, Behavioural Intention & Perceived AI Acceptance, and gender of employee as significance level is below 0.05.

4.7 Conclusion of Data Analysis

This chapter set out to profile the respondents and to empirically examine the relationships and group differences relevant to the adoption and impact of artificial intelligence within organizations. The demographic analysis demonstrates that the sample is broad and heterogeneous, encompassing respondents across age groups, experience levels, educational qualifications, income categories, industries, organizational sizes, managerial levels, locations, and gender. The dominance of working-age professionals, a high proportion of post-graduates, and substantial representation from middle-level management and large organizations indicate that the data are drawn from respondents who are actively engaged in organizational decision-making and technology use. Such diversity strengthens the representativeness of the sample and enhances the external validity of the findings.

The data analysis provides robust statistical evidence on both measurement adequacy and substantive relationships. Exploratory Factor Analysis (EFA) confirmed the underlying factor structure of the study variables, while Confirmatory Factor Analysis (CFA) and measurement model assessments established satisfactory reliability, convergent validity, and discriminant validity. Structural Equation Modelling (SEM) further validated the hypothesized relationships among key constructs, with significant path coefficients and acceptable model fit indices indicating that the proposed framework offers a coherent explanation of AI acceptance, implementation, and organizational effectiveness.

Group-wise comparisons using MANOVA and non-parametric tests reveal that demographic variables exert differential influence across constructs rather than producing uniform effects. Age, experience, income, organizational size, location, and, to a limited extent, education, and level of management show statistically significant differences for several attitudinal, behavioural, and outcome-oriented variables. In contrast, industry and certain demographic categories demonstrate largely homogeneous perceptions, suggesting that some organizational and technological factors are experienced consistently across contexts. Gender-based analysis using the Mann–Whitney U test indicates selective differences, particularly in behavioural intention, effort expectancy, and AI acceptance, while core structural and organizational variables remain largely invariant across gender groups.

Taken together, the findings suggest that AI adoption and its perceived organizational impact are shaped by a complex interplay of individual, organizational, and contextual factors. While foundational technological and organizational conditions tend to be shared across groups, individual characteristics and contextual positioning influence attitudes, intentions, and acceptance levels. This chapter therefore provides a strong empirical foundation for the subsequent discussion chapter, where these results are interpreted in light of existing theory and prior research, and where their practical and theoretical implications for AI-enabled organizational transformation are articulated.

CHAPTER - 5 FINDINGS AND DISCUSSIONS

5.1 Introduction

This chapter presents an integrated discussion of the empirical findings derived from the analysis undertaken to address the research objectives of the study. The discussion is structured around the stated objectives and corresponding hypotheses, drawing upon results from Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), Structural Equation Modelling (SEM), and demographic-based inferential analyses. The findings are interpreted in light of established theoretical frameworks—Technology–Organization–Environment (TOE), Technology Acceptance Model (TAM), and Unified Theory of Acceptance and Use of Technology (UTAUT) to explain the acceptance, implementation, and organizational outcomes of Artificial Intelligence (AI) in Human Resource (HR) practices.

5.2 Findings and Discussions

5.2.1 Objective 1: To analyse the factors influencing the Acceptance and Perceived Implementation of Artificial Intelligence (AI) in Human Resources (HR) practices across selected industries.

The study identified five major variables and sixteen sub-variables influencing AI acceptance and perceived implementation in HR practices through a comprehensive review of extant literature. These variables were systematically anchored in established technology adoption frameworks, namely the Technology–Organization–Environment (TOE) framework, Technology Acceptance Model (TAM), and the Unified Theory of Acceptance and Use of Technology (UTAUT).

The measurement model empirically validated six higher-order constructs: Technology Readiness, Organizational Readiness, Environmental Readiness, Behavioural Intention, Perceived AI Acceptance, and Perceived AI Implementation. All constructs demonstrated exceptional internal consistency, with Cronbach's Alpha and Composite Reliability values exceeding 0.90, indicating a high degree of measurement stability.

Convergent validity was strongly established, as reflected by Average Variance Extracted (AVE) values above 0.50, confirming that the indicators shared substantial variance with their respective constructs. Discriminant validity, assessed using the Fornell–Larcker criterion, further confirmed that each construct was empirically distinct.

Exploratory Factor Analysis revealed a clear and theoretically coherent factor structure, with all 110 items loading strongly (above 0.40) on their intended factors. Variance Inflation Factor (VIF) values were well below the critical threshold of 5, confirming the absence of multicollinearity. Additionally, bootstrapping results showed that confidence intervals for inter-construct paths did not include zero, establishing the robust statistical significance of the relationships.

These findings confirm that AI acceptance and implementation in HR practices are multi-dimensional and interdependent phenomena, shaped by technological attributes, organizational preparedness, environmental pressures, and individual behavioural mechanisms. The strong psychometric properties of the constructs reinforce the theoretical relevance of integrating TOE, TAM, and UTAUT rather than relying on a single adoption lens. Importantly, the robustness of factor structure and path significance suggests that AI adoption in HR cannot be reduced to technology alone, but must be understood as a socio-technical transformation.

Preliminary data diagnostics were conducted to ensure the appropriateness of advanced multivariate techniques. The assessment of data normality indicated significant deviations from a normal distribution, thereby supporting Hypothesis 1. This justified the application of variance-based SEM techniques and non-parametric tests where required.

Bartlett's Test of Sphericity was found to be statistically significant, rejecting the null assumption that the correlation matrix is an identity matrix. This confirms the presence of meaningful correlations among variables, thereby supporting Hypothesis 2 and establishing factorability of the data.

Exploratory Factor Analysis further demonstrated that all observed variables loaded significantly on their theoretically expected latent constructs, with factor loadings exceeding the minimum acceptable threshold. This empirical evidence supports Hypothesis 3, confirming that the observed indicators align with the conceptual domains identified through literature.

5.2.2 Objective 2: To develop conceptual framework for Acceptance and Implementation of Artificial Intelligence in HR Practices and organisational Effectiveness.

A comprehensive conceptual framework was developed and empirically validated using EFA, CFA, and SEM**.** The framework was theoretically grounded in TOE, TAM, and UTAUT, enabling the integration of organizational-level readiness factors with individual-level acceptance mechanisms**.**

Core constructs—Artificial Intelligence, Behavioural Intention, Perceived AI Acceptance, Perceived AI Implementation, and Organisational Effectiveness—demonstrated strong reliability, convergent validity, and discriminant validity. Structural paths were statistically significant, and bias-corrected bootstrapping confirmed the stability and strength of the hypothesised relationships.

Confirmatory Factor Analysis results provided strong evidence that all observed indicators significantly represented their latent constructs, as reflected by high standardized loadings and statistical significance. Thus, Hypothesis 4 is accepted.

The overall measurement model demonstrated acceptable to good model fit indices, indicating that the hypothesised structure adequately reproduces the observed covariance matrix. Accordingly, Hypothesis 5 is supported.

Reliability analysis revealed Cronbach's Alpha and Composite Reliability values well above recommended thresholds, while AVE values exceeded 0.50 for all constructs, confirming strong convergent validity. These results support Hypothesis 6.

Discriminant validity was established using both the Fornell–Larcker criterion and HTMT ratios. In all cases, constructs were empirically distinct from one another, leading to the acceptance of Hypotheses 7 and 8. Together, these findings confirm the robustness and psychometric soundness of the measurement model.

The validated framework provides a holistic and empirically supported explanation of how AI progresses from technological readiness to organizational outcomes through acceptance and implementation mechanisms. By combining three major technology adoption theories, the framework advances existing research that often treats acceptance, implementation, and outcomes as isolated stages. This integrated perspective offers a more realistic depiction of AI adoption in HR contexts.

5.2.3 Objective 3: To measure the impact of AI in HR Practices on Organisational Effectiveness

Structural Equation Modelling results revealed a strong and statistically significant effect of Artificial Intelligence on Behavioural Intention, supporting Hypothesis 9. Behavioural Intention, in turn, exerted a significant positive influence on Perceived AI Acceptance, confirming Hypothesis 10. Perceived AI Implementation emerged as a strong, positive, and highly significant predictor of Organisational Effectiveness, with a path coefficient of 0.815 ($p < 0.001$) and a bias-corrected confidence interval of [0.788, 0.839], robustly excluding zero. Organisational Effectiveness also demonstrated excellent reliability (Cronbach's Alpha = 0.931). The structural model exhibited acceptable fit indices, including GFI, NFI, CFI, and TLI. Perceived AI Acceptance demonstrated a substantial and significant effect on Perceived AI Implementation, leading to the acceptance of Hypothesis 11. Most critically, Perceived AI Implementation exhibited a large, positive, and highly significant impact on Organizational Effectiveness, thereby strongly supporting Hypothesis 12. This establishes AI implementation as a key driver of organisational outcomes. Collinearity diagnostics indicated that all VIF values were well below critical thresholds, confirming the absence of multicollinearity and supporting Hypothesis 13. Finally, the structural model demonstrated acceptable global fit indices, validating the adequacy of the proposed structural framework and supporting Hypothesis 14.

The findings clearly indicate that organizational effectiveness is driven by the depth and quality of AI implementation rather than mere acceptance. While acceptance reflects favourable attitudes, it is the operationalisation of AI within HR systems that translates into enhanced efficiency, adaptability, and strategic performance. This reinforces the argument that AI must be institutionally embedded within HR processes to generate sustained organizational value.

5.2.4 Objective 4: To study the difference between Selected Industries and Variables of Artificial Intelligence

Inferential analyses revealed statistically significant differences across most AI-related variables when grouped by age, experience, and income, thereby supporting Hypotheses 15, 16, and 18. These findings indicate that demographic maturity and economic positioning meaningfully influence perceptions of AI complexity, acceptance, and implementation. Education showed selective influence on variables such as creativity, self-efficacy, and complexity, while behavioural intention and implementation remained unaffected. Hence, Hypothesis 17 is partially supported. Organization size and location were found to significantly differentiate several AI-related variables, including effort expectancy, resistance to change, and perceived implementation, leading to the acceptance of Hypotheses 22 and 24. Level of management and gender demonstrated mixed effects some variables showed significant differences while others did not. This nuanced pattern indicates partial support for Hypotheses 23 and 25, suggesting that hierarchical position and gender influence specific dimensions of AI perception rather than exerting a uniform effect.

Industry-wise analysis revealed statistically significant differences in AI-related variables. Post-hoc Tukey HSD tests showed that IT/ITES reported significantly lower AI scores compared to Healthcare, Consumer Durables, and Management Consultancy. Although Behavioural Intention showed overall ANOVA significance, no specific industry pairs differed significantly. Similarly, Perceived AI Acceptance showed general acceptance across industries without clear pairwise distinctions. However, Perceived AI Implementation differed significantly across industries, with Management Consultancy reporting higher implementation levels than Healthcare and Consumer Durables.

These findings suggest that industry context influences the execution of AI more than its acceptance. Consulting-oriented industries appear better positioned to operationalise AI due to client-driven innovation, project-based work structures, and higher analytical maturity. In contrast, IT/ITES organizations may face legacy system constraints and change fatigue, limiting perceived AI advancement.

5.2.5 Objective 5: To study difference between Selected Industries and Organizational Effectiveness.

MANOVA Test result showcase that there is a highly statistically significant difference in Organizational Effectiveness across the five selected industries ($F(4, 1240) = 5.233$, $p < .001$). Post-Hoc Tukey HSD test on Organizational Effectiveness and selected industries shows Significant Difference where Management Consultancy has significantly higher Organizational Effectiveness compared to Banking, Insurance & Financial Services ($p = .047$). Management Consultancy stands out with higher Organizational Effectiveness compared to the Banking, Insurance & Financial Services sector. The other industries do not show significant pairwise differences among themselves.

MANOVA and post-hoc analyses revealed selective industry-wise differences. While overall MANOVA results indicated variation in certain AI dimensions, many pairwise comparisons did not reach statistical significance, particularly for behavioural intention and acceptance. Thus, Hypotheses 19 and 20 are partially supported.

However, Organizational Effectiveness showed statistically significant differences across industry groups, particularly highlighting superior outcomes in management consultancy relative to more regulated sectors. Consequently, Hypothesis 21 is rejected, and the alternative proposition of industry-based variation in organisational effectiveness is supported.

This outcome highlights that organizational effectiveness is context-dependent, shaped by regulatory flexibility, strategic agility, and innovation orientation. Knowledge-intensive industries appear better equipped to convert AI-enabled HR practices into measurable organizational outcomes.

5.2.6 Objective 6: To study the difference Between variable of Artificial Intelligence and demographic factors

The Demographic Profile of the sample showcase that it comprises of primarily young (18-35: 77%), highly educated (PG: 70%), early-career (0-10 yrs: 73%), from Middle Management (59%), largely belonging to Central Gujarat. Age, Experience, Income Groups showed significant differences across most variables like Technology Characteristics, Complexity, Resistance to Change, Behavioral Intention, Perceived AI Acceptance, Perceived AI Implementation. Education has Influence on factors like Creativity, Self-Efficacy, Complexity, and Perceived AI Acceptance, but not affect Behavioral Intention or Perceived AI Implementation. Management Level, Organization Size, Location, Gender showed significant differences for various factors like Technology Characteristics, Complexity, Resistance to Change, Behavioral Intention, Perceived AI Acceptance, Perceived AI Implementation, with some specific non-significant relationships like Perceived AI Acceptance not differing by Management Level.

The demographic profile indicates a workforce that is predominantly young, highly educated, early-career, and positioned in middle management**,** largely from Central Gujarat. Age, experience, and income showed significant differences across most AI variables, including Technology Characteristics, Complexity, Resistance to Change, Behavioural Intention, Perceived AI Acceptance, and Perceived AI Implementation. Education influenced creativity, self-efficacy, complexity perception, and AI acceptance, but did not significantly affect behavioural intention or implementation. Management level, organization size, location, and gender showed selective significance across AI variables.

These results demonstrate that demographic characteristics condition how AI is perceived, evaluated, and implemented. Younger and early-career employees tend to exhibit higher acceptance and lower resistance, while senior or higher-income groups display more nuanced evaluations of risk and complexity. The findings emphasize the importance of demographically sensitive AI strategies in HR transformation initiatives.

5.2.7 Objective 7: To study the difference Between Organisational Effectiveness and demographic factors.

All tested demographic variables Age, Experience, Education, Income, Management Level, Org. Size, Location, Gender had showed statistically significant differences in respondents' perceptions of Organizational Effectiveness. This indicates that Organisational Effectiveness is not perceived uniformly across workforce segments. Variations in role expectations, decision authority, exposure to AI-enabled systems, and career stage shape how employees evaluate organizational performance. These findings underscore the need for inclusive AI governance and differentiated change-management approaches.

Collectively, the findings demonstrate that AI acceptance and implementation in HR practices are theoretically grounded, empirically robust, and contextually sensitive. While the structural relationships among AI, acceptance, implementation, and organizational effectiveness are strong and consistent, demographic and industry factors introduce meaningful variations. The study therefore advances existing literature by offering an integrated, evidence-based explanation of AI-driven HR transformation and its organizational consequences.

CHAPTER - 6 CONCLUSIONS, RECOMMENDATIONS, & IMPLICATIONS

6.1 Introduction

This chapter presents the concluding observations of the study titled "Acceptance and Implementation of Artificial Intelligence in HR Practices for Organisational Effectiveness." It synthesizes the key empirical findings, draws overarching conclusions in relation to the research objectives, and discusses the theoretical, managerial, policy, and practical implications of the study. The chapter also outlines the limitations of the research and provides directions for future research, thereby offering closure while opening avenues for continued scholarly inquiry.

6.2 Objective-wise Conclusions

6.2.1 Objective 1: To analyse the factors influencing the Acceptance and Perceived Implementation of Artificial Intelligence (AI) in Human Resources (HR) practices across selected industries.

The study identifies five major variables and sixteen sub-variables influencing AI acceptance and perceived implementation in HR practices. These constructs—Technology Readiness, Organizational Readiness, Environmental Readiness, Behavioural Intention, Perceived AI Acceptance, and Perceived AI Implementation—demonstrate excellent internal consistency and reliability, with Cronbach's Alpha and Composite Reliability values exceeding 0.90.

Convergent validity (AVE > 0.50) and discriminant validity (Fornell–Larcker and HTMT criteria) confirm that the constructs are conceptually sound and empirically distinct. The absence of multicollinearity (VIF < 5) and statistically significant bootstrapped paths further validate the stability and robustness of the measurement model.

The findings conclusively demonstrate that the acceptance and perceived implementation of AI in HR practices are influenced by a well-defined set of technological, organizational, environmental, and behavioural factors. Drawing upon an extensive literature review, the study successfully identified five major variables and sixteen sub-variables that collectively explain AI adoption dynamics in HR. The measurement model confirmed that Technology Readiness, Organizational Readiness, Environmental Readiness, Behavioural Intention, Perceived AI Acceptance, and Perceived AI Implementation are robust determinants of AI adoption in HR contexts. All constructs exhibited exceptionally high internal consistency and reliability, with Cronbach's Alpha and Composite Reliability values exceeding recommended thresholds. Strong convergent and discriminant validity further established that the identified factors are theoretically sound and empirically distinct. Overall, this objective is fully achieved, providing a comprehensive and validated understanding of the factors shaping AI acceptance and implementation in HR practices.

6.2.2 Objective 2: To develop conceptual framework for Acceptance and Implementation of Artificial Intelligence in HR Practices and organisational Effectiveness.

The study successfully developed and empirically validated a comprehensive conceptual framework linking AI acceptance and implementation in HR practices to organizational effectiveness. Grounded firmly in established theories such as TOE, TAM, and UTAUT, the framework integrates technological, organizational, environmental, and behavioural dimensions into a coherent structural model. The application of EFA, CFA, and SEM confirmed that the proposed framework demonstrates strong psychometric properties, including high reliability, convergent validity, and discriminant validity. The statistically significant and bias-corrected structural paths provide strong empirical support for the hypothesized relationships among constructs. Thus, the objective of developing a theoretically grounded and empirically validated framework is conclusively met.

6.2.3 Objective 3: To measure the impact of Artificial Intelligence in HR Practices on Organisational Effectiveness.

One of the most significant contributions of this research is the empirical confirmation that Perceived AI Implementation exerts a strong, positive, and highly significant influence on Organizational Effectiveness**.** The findings suggest that organizations benefit from AI in HR only when AI systems are fully embedded into HR workflows, supported by training, leadership commitment, and process alignment. The Organizational Effectiveness construct itself exhibits excellent reliability (Cronbach's Alpha = 0.931), and the structural model demonstrates acceptable goodness-of-fit indices (GFI, NFI, CFI, TLI), reinforcing the credibility of the findings.

The results provide compelling empirical evidence that Artificial Intelligence in HR practices significantly enhances organizational effectiveness. Specifically, Perceived AI Implementation exhibits a strong, positive, and highly significant impact on Organizational Effectiveness, with a large standardized path coefficient and narrow confidence intervals that robustly exclude zero. This confirms that effective implementation rather than mere acceptance of AI tools in HR functions leads to measurable organizational benefits. The Organizational Effectiveness construct itself demonstrated excellent reliability and validity, further strengthening the credibility of this relationship. The structural model fit indices indicate that the model adequately explains the observed data. Therefore, this objective is fully achieved, firmly establishing AI-driven HR implementation as a strategic contributor to organizational performance.

6.2.4 Objective 4: To study the difference between Selected Industries and Variables of Artificial Intelligence.

The analysis reveals that significant differences exist across industries with respect to several AI-related variables. Post-hoc comparisons indicate that industries differ meaningfully in their levels of Artificial Intelligence adoption and perceived implementation. In particular, IT/ITES exhibits significantly lower levels of AI compared to healthcare, consumer durables, and management consultancy, while management consultancy demonstrates higher levels of perceived AI implementation than certain other sectors. However, despite overall differences, behavioural intention and perceived AI acceptance remain relatively uniform across industries, suggesting a broadly shared openness toward AI adoption. This objective is thus achieved by demonstrating that industry context shapes AI-related perceptions and implementation patterns, while also highlighting areas of convergence across sectors.

6.2.5 Objective 5: To study the difference between Selected Industries and Organizational Effectiveness

The findings confirm that organizational effectiveness varies significantly across selected industries. The ANOVA results reveal statistically significant differences, with post-hoc analysis identifying management consultancy as exhibiting higher organizational effectiveness compared to the banking, insurance, and financial services sector. These results suggest that industry-specific operational structures, strategic orientations, and levels of AI integration contribute to differential organizational outcomes. Consequently, this objective is successfully fulfilled by empirically establishing industry-based variation in organizational effectiveness.

6.2.6 Objective 6: To study the difference Between variable of Artificial Intelligence and demographic factors

The study conclusively demonstrates that demographic factors play a critical role in shaping perceptions of AI-related variables. Age, experience, income, education, management level, organizational size, location, and gender significantly influence multiple dimensions such as technology characteristics, complexity, resistance to change, behavioural intention, perceived AI acceptance, and perceived AI implementation. While some demographic variables show selective non-significant effects on certain constructs, the overall pattern confirms substantial heterogeneity in AI perceptions across demographic groups. This objective is therefore fully achieved, underscoring the necessity for demographic-sensitive AI adoption and change management strategies.

6.2.7 Objective 7: To study the difference Between Organisational Effectiveness and demographic factors

The results clearly establish that organizational effectiveness differs significantly across demographic categories. All examined demographic variables—including age, experience, education, income, management level, organizational size, location, and gender—show statistically significant variations in respondents' assessments of organizational effectiveness. These findings indicate that demographic characteristics shape not only AI-related perceptions but also broader evaluations of organizational performance. Hence, this objective is conclusively met, highlighting the importance of aligning organizational strategies with workforce demographics to enhance effectiveness.

6.3 Conclusions

This research provides comprehensive empirical evidence on the acceptance, perceived implementation, and organizational outcomes of Artificial Intelligence (AI) in Human Resource (HR) practices across selected industries. Drawing on responses from 1,245 employees, the study rigorously examines how technological, organizational, environmental, and behavioural factors interact to shape AI adoption and its subsequent impact on Organizational Effectiveness**.**

The study successfully establishes a robust, reliable, and valid measurement and structural model, grounded in well-established theoretical frameworks Technology–Organization–Environment (TOE)**,** Technology Acceptance Model (TAM)**,** and Unified Theory of Acceptance and Use of Technology (UTAUT)**.** (Woolley et al., n.d.)Through Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), and Structural Equation Modelling (SEM), the research confirms that AI adoption in HR is not a purely technological phenomenon but a socio-technical transformation influenced by human perceptions, organizational readiness, leadership support, and environmental enablers. (Chowdhury et al., 2023; Jarrahi, 2018)

A central conclusion of this study is that Perceived AI Implementation, rather than mere acceptance, plays a decisive role in enhancing Organizational Effectiveness. The exceptionally strong path coefficient ($\beta = 0.815$, $p < 0.001$) demonstrates that tangible, effective deployment of AI-enabled HR systems leads to measurable improvements in efficiency, decision quality, and organizational performance. This finding advances the discourse beyond intention-based adoption models and emphasizes the importance of execution and integration in realizing AI's strategic value. (Fosso Wamba et al., 2023; M. Malik et al., 2024; Mikalef et al., 2025)

The research also highlights the critical moderating role of demographic characteristics, including age, experience, education, income, management level, organizational size, location, and gender. These factors significantly shape employees' perceptions of AI-related constructs such as technology characteristics, complexity, resistance to change, behavioural intention, acceptance, implementation, and organizational effectiveness. This underscores the need for context-sensitive and people-centric AI strategies within HR functions. (Stahl & Eke, 2024)

Alignment of study with Global Studies

The findings of the present study align closely with recent global research, which emphasizes that the value of Artificial Intelligence (AI) lies not merely in acceptance but in its effective implementation and integration into organizational processes. Consistent with contemporary scholarship, the study confirms that AI adoption in HR is a socio-technical phenomenon, shaped by technological capabilities, organizational readiness, leadership support, and employee perceptions. (Duan et al., 2019; Erik Brynjolfsson and Andrew McAfee, 2017; Jarrahi, 2018; Leonardi, 2015; Y. D.-I. E. and Management & 2025, 2025; Murugesan et al., 2023)

The observation that AI acceptance is relatively uniform across industries, while implementation varies significantly, supports global evidence that AI is increasingly normalized, but organizations differ in their ability to translate acceptance into actual use. (CROITORU et al., 2025; Kraus et al., 2023; Mikalef et al., 2025; Stahl & Eke, 2024; Vasant Tambe, 2025) This highlights the importance of organizational context and readiness, as emphasized in the TOE framework. (Roberts et al., 2024)

Further, the study establishes that Perceived AI Implementation is the primary driver of Organizational Effectiveness, aligning with recent research that underscores the role of process integration, capability development, and routinization in achieving performance gains. (Davenport, 2018; Erik Brynjolfsson and Andrew McAfee, 2017; Fosso Wamba et al., 2023; M. Malik et al., 2024; Mikalef et al., 2025) This also supports critiques of TAM and UTAUT for their limited focus on post-adoption outcomes. (Venkatesh et al., 2023).

The influence of demographic and contextual factors is consistent with literature highlighting the role of human diversity, trust, and workforce readiness in AI adoption, (Dwivedi et al., 2023; Huang et al., n.d.; Murugesan et al., 2023; Stahl & Eke, 2024; Woolley et al., n.d.), while also aligning with DOI theory, which emphasizes assimilation and routinization over initial adoption. (BİLİMLER & 2025, 2025; Li, 2020a; Research & 2025, 2025; Venkatesh et al., 2023)

This emphasizes the need for organizations to move beyond intention-based adoption and focus on execution, integration, and continuous utilization of AI in HR practices to achieve meaningful and sustainable outcomes.

6.4 Recommendations

Based on the empirical findings and validated structural relationships established in this research, the following recommendations are proposed for organizations, HR practitioners, policymakers, and researchers to enhance the effective acceptance and implementation of Artificial Intelligence in HR practices and to improve organizational effectiveness.

6.4.1 Industry Recommendations

6.4.1.1 Strategic Emphasis on AI Implementation Rather Than Mere Adoption

Organizations should move beyond symbolic or pilot-level adoption of AI and focus on deep, organization-wide implementation within HR functions. The study clearly establishes that Perceived AI Implementation, rather than acceptance alone, has a strong and direct impact on Organizational Effectiveness. Therefore, AI initiatives should be aligned with HR workflows, decision-making processes, and performance management systems to ensure tangible organizational outcomes.

6.4.1.2 Strengthening Organizational Readiness Through Leadership Commitment

Top Management Support emerged as a critical enabler across multiple AI-related variables. Senior leadership should actively champion AI initiatives by clearly communicating the strategic purpose of AI in HR, allocating adequate financial and human resources, Demonstrating visible involvement in AI-driven transformation. Such leadership commitment can reduce resistance to change and foster a culture that is conducive to innovation and learning.

6.4.1.3 Focused Change Management and Resistance Mitigation Strategies

Given the significant influence of Resistance to Change and Complexity, organizations should adopt structured change management practices. These include early involvement of employees in AI-related decisions, transparent communication about AI's role and limitations, addressing fears related to job displacement and skill obsolescence. Change readiness assessments should precede AI implementation to identify and address psychological and cultural barriers.

6.4.1.4 Customized AI Training and Skill Development Programs

The study highlights the importance of Self-Efficacy, Effort Expectancy, and Technological Characteristics in shaping AI acceptance. Organizations should invest in continuous training programs that enhance digital and AI literacy among HR professionals, provide hands-on exposure to AI tools, build confidence in using AI for HR analytics, recruitment, performance appraisal, and workforce planning. Training initiatives should be tailored according to employee experience levels, educational backgrounds, and management hierarchies.

6.4.1.5 Demographic-Sensitive AI Implementation Approaches

Significant differences across age, experience, education, income, management level, organizational size, location, and gender suggest that a one-size-fits-all AI strategy is ineffective. Organizations should customize communication and training strategies for different demographic groups, design inclusive AI policies that address diverse workforce expectations, use demographic insights to predict acceptance challenges and implementation readiness. Such targeted strategies can enhance both AI acceptance and organizational effectiveness.

6.4.1.6 Ethical, Transparent, and Responsible Use of AI in HR

Concerns related to Complexity, Uncertainty/Risk, Bias, and Privacy underline the need for ethical AI governance. Organizations should ensure transparency in AI-driven HR decisions, regularly audit AI algorithms for bias and fairness, comply strictly with data protection and privacy regulations. Embedding ethical guidelines into AI governance frameworks will enhance trust among employees and stakeholders.

6.4.1.7 Industry-Specific AI Roadmaps

The observed differences across industries indicate that AI adoption in HR is context-dependent. Industry bodies and organizations should develop sector-specific AI implementation frameworks, share best practices across industries, benchmark AI maturity levels within their sectors. This will help organizations align AI strategies with industry realities and competitive dynamics.

6.4.1.8 Continuous Monitoring and Evaluation of AI Implementation

Organizations should establish mechanisms to regularly assess the impact of AI on HR outcomes and organizational effectiveness. This includes periodic employee feedback on AI systems, performance audits of AI-driven HR processes, continuous refinement of AI strategies based on empirical evidence. This ensures sustained value creation and long-term organizational benefits.

Overall, the recommendations emphasize that AI in HR should be viewed as a strategic, human-centric, and context-sensitive transformation initiative, rather than a purely technological intervention. Effective implementation, supported by leadership, ethical governance, demographic awareness, and continuous learning, is essential for translating AI potential into organizational effectiveness.

6.4.2 Academic Recommendations

Drawing from the empirical evidence and validated theoretical framework developed in this study, several academic recommendations are proposed to advance future research on Artificial Intelligence adoption in Human Resource Management and organizational effectiveness.

6.4.2.1 Extension and Integration of Technology Adoption Theories in HR Contexts

Future research should continue extending established technology adoption theories such as Technology–Organization–Environment (TOE)**,** Technology Acceptance Model (TAM)**,** and

Unified Theory of Acceptance and Use of Technology (UTAUT) within the HR domain. This study demonstrates that combining these frameworks offers a more comprehensive explanation of AI acceptance and implementation in HR than relying on any single theory. Scholars are encouraged to further refine this integrated approach by incorporating emerging constructs such as algorithmic trust, explainability, and human–AI collaboration.

6.4.2.2 Distinguishing Between AI Acceptance and AI Implementation

Researchers should explicitly conceptualize and empirically differentiate Perceived AI Acceptance and Perceived AI Implementation as distinct constructs. The findings of this study confirm that acceptance alone does not guarantee effective implementation or organizational impact. Future studies may explore additional mediating or moderating mechanisms that explain how acceptance translates into sustained AI usage and value creation within organizations.

6.4.2.3 Emphasis on Human and Behavioural Dimensions of AI Adoption

The significant roles of Self-Efficacy, Resistance to Change, Social Influence, and Top Management Support highlight the importance of human-centric perspectives in AI research. Scholars are encouraged to move beyond techno-centric models and investigate psychological, social, and cultural dimensions that shape AI adoption in HR settings. Qualitative or mixed-method approaches could provide deeper insights into employee sense-making, emotional responses, and identity-related concerns associated with AI.

6.4.2.4 Expanding the Role of Organizational Effectiveness in AI Studies

Organizational Effectiveness emerged as a critical outcome variable influenced by AI implementation. Future academic work should further decompose this construct into dimensions such as operational efficiency, employee engagement, strategic agility, and decision quality. This would enhance theoretical clarity and allow for more nuanced understanding of AI's organizational impact.

6.4.2.5 Cross-Cultural and Comparative Research Opportunities

As this study focuses on selected Indian industries based at state of Gujarat, future research should undertake cross-cultural and cross-national comparisons to examine how institutional, regulatory, and cultural contexts influence AI adoption in HR. Comparative studies between developed and developing economies would be particularly valuable in enriching global AI-HR literature.

6.4.2.6 Incorporation of Ethical and Governance Perspectives

The influence of Complexity and Uncertainty/Risk underscores the need to integrate ethical considerations into AI adoption models. Academics are encouraged to explore constructs related to fairness, transparency, accountability, data privacy, and algorithmic bias. Embedding ethical governance frameworks within AI acceptance models would significantly advance both theory and practice.

6.4.2.7 Demographic Sensitivity in AI Adoption Research

The study establishes that demographic factors such as age, experience, education, income, management level, gender, and location significantly shape AI perceptions. Future research should examine these variables not merely as control variables, but as substantive moderators that influence AI adoption pathways and organizational outcomes.

6.4.2.8 Encouraging Interdisciplinary Research Approaches

Researchers are encouraged to adopt interdisciplinary perspectives by integrating insights from human resource management, information systems, organizational psychology, ethics, and data science**.** Such integrative research can generate richer theoretical models and provide more actionable insights into AI-driven HR transformation.

In summary, this study opens multiple avenues for advancing AI-HR scholarship by advocating for theoretically integrated models, human-centric perspectives, robust methodologies, ethical considerations, and context-sensitive research designs. These academic directions can collectively contribute to a more mature, nuanced, and impactful body of knowledge on Artificial Intelligence in Human Resource Management.

6.5 Implications of the study

6.5.1 Academic Implications

The present research makes several meaningful academic contributions to the interdisciplinary domains of Human Resource Management (HRM), Information Systems (IS), and Organizational Studies by advancing theory, methodology, and contextual understanding of Artificial Intelligence (AI) adoption in HR practices and its linkage to organizational effectiveness.

Advancement of Technology Adoption Theory

A key academic implication of this study lies in its integrative theoretical approach**.** While prior research has predominantly relied on individual models such as the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), or the Technology–Organization–Environment (TOE) framework in isolation, this study empirically demonstrates the value of combining these frameworks into a unified conceptual model**.** By doing so, it captures technological perceptions, organizational readiness, environmental pressures, and behavioural responses within a single analytical structure.

This integrated approach extends the explanatory power of technology adoption theories by demonstrating that AI acceptance alone is insufficient to generate organizational outcomes unless it translates into effective implementation**.** The empirical distinction between Perceived AI Acceptance *and* Perceived AI Implementation offers a refined theoretical lens that moves beyond intention-based adoption models and contributes to more process-oriented theorization. (Venkatesh et al., 2003; Tornatzky & Fleischer, 1990; Wamba et al., 2021).

Conceptual Clarification Between Acceptance and Implementation

From an academic standpoint, one of the most significant contributions of this research is the conceptual and empirical separation of AI acceptance and AI implementation**.** Existing literature often treats adoption as a binary outcome—adopted or not adopted—without adequately examining how technologies are operationalized and embedded within organizational routines (Rogers, 2003).

By empirically validating acceptance and implementation as distinct yet sequential constructs**,** this study enriches adoption scholarship and responds to calls for deeper theorization of post-adoption behaviour in technology research. This distinction is particularly relevant for AI in HR, where ethical concerns, governance mechanisms, and human–algorithm interaction significantly shape implementation outcomes (Kellogg et al., 2020; Sony et al., 2025).

Extension of Organizational Effectiveness Theory

The study also contributes to organizational theory by reinforcing the view that organizational effectiveness is a multidimensional construct that cannot be reduced to productivity or efficiency alone. By adopting the D. M. Pestonjee framework—rooted in Indian organizational psychology—the research integrates goal clarity, autonomy, initiative, commitment, value alignment, and pride into the assessment of effectiveness.

Academically, this reinforces the argument that technological interventions such as AI must be evaluated not only through performance metrics but also through human and social outcomes, particularly in HR contexts where employee perceptions play a critical role (Pestonjee, 1988; Daft, 2016). This human-centric framing strengthens the bridge between HRM scholarship and digital transformation research.

Contribution to HRM and AI Literature in Emerging Economies

Another important academic implication is the study's contextual contribution to AI–HRM literature in emerging economies**,** particularly India. Much of the existing empirical evidence on AI adoption originates from developed economies and technology-intensive firms, limiting the contextual relevance of findings (Prikshat, Malik & Budhwar, 2021).

By focusing on multiple service-sector industries within the Indian context, the study enriches comparative HRM literature and highlights how demographic, institutional, and sectoral factors shape AI acceptance and implementation differently. This contributes to the growing body of scholarship advocating **context-sensitive theorization** rather than universal adoption models (Budhwar & Sparrow, 2002; Amankwah-Amoah et al., 2021).

Methodological Contributions to Measurement and Validation

From a methodological perspective, the study contributes by developing and validating a robust, multi-construct measurement model using EFA, CFA, and SEM. The use of rigorous psychometric validation—high reliability, convergent validity, discriminant validity (Fornell–Larcker and HTMT), and multicollinearity diagnostics—enhances the credibility and replicability of the model.

Academically, this offers future researchers a validated instrument for studying AI acceptance and implementation in HR contexts (Hair et al., 2017). The methodological rigor also responds to critiques regarding weak measurement practices in technology adoption studies and strengthens empirical standards in the field.

Emphasis on Demographic and Individual Differences

The findings further underscore the academic importance of demographic heterogeneity in technology adoption research. By demonstrating that age, experience, education, income, management level, organizational size, location, and gender significantly influence perceptions of AI and organizational effectiveness, the study challenges overly homogenized models of technology acceptance.

This aligns with emerging scholarship emphasizing the role of individual differences, power dynamics, and social positioning in shaping technology outcomes (Ajzen, 2011; Orlikowski, 2007). The study thus encourages future academic work to integrate demographic and socio-structural variables more systematically into AI and HRM research.

Opening New Research Pathways in Ethical and Human-Centric AI

Finally, the study’s findings highlight the academic necessity of incorporating ethical governance, trust, and transparency into AI adoption models. While not explicitly modelled as independent constructs, the observed influence of resistance, complexity, and uncertainty signals the growing relevance of ethical AI scholarship in HRM.

This contributes to the emerging academic discourse on human-centric and responsible AI, encouraging future theorization that integrates ethics, explainability, and legitimacy into mainstream HR and technology adoption frameworks (Raghavan et al., 2020; Floridi et al., 2018).

6.5.2 Managerial and Industry Implications

To justify investing in AI technology, business leaders and HR executives can give real-world evidence from the study of how perceived acceptance of artificial intelligence increases Organisational effectiveness. This shifts it from a mere technological trend to a strategic decision.

The study shows that implementing AI entails more than merely installing the latest software. Organisational readiness (top management support and employee knowledge), technological readiness (usability and ease of use), and environmental readiness (social impact and external support) are all critical. Change management, training, and strategic collaborations must be funded by the industry. The significant impact of "Resistance to Change" and "Complexity" highlights the need for robust change management strategies, transparent communication, and involving employees in the AI adoption process from the outset.

The "Complexity" and "Uncertainty/Risk" criterion (which deal with User Acceptance) raise ethical concerns such as data privacy and algorithmic bias. When utilising AI, businesses must prioritize fairness, transparency, and data protection in order to gain the trust of their employees and HR professionals.

Because of significant demographic variations like as age, experience, education, income, management level, region, and gender, HR departments should not utilise the same approach to AI communication, training, and implementation for everyone.

The consistent significance of Top Management Support across various factors (though not always significant across all demographics for every factor) indicates that active championship from senior leadership is vital for fostering an AI-ready culture.

From a policy perspective, the study highlights the need for frameworks that promote ethical, transparent, and inclusive AI deployment in HR. Addressing concerns related to complexity, bias, privacy, and uncertainty is essential for sustaining employee trust and long-term organizational value.

Industry wise AI implementation strategies

The results of the current study provide important practical insights for industries that seek to leverage Artificial Intelligence (AI) in Human Resource (HR) practices to improve organisational effectiveness. The research found that while acceptance of AI is relatively consistent across industries, the scope and quality of AI implementation vary widely, and that impacts organisational outcomes. This provides an important managerial insight: value from AI is not in the acceptance stage but through effective and sustained implementation.

The study suggests that in the case of IT/ITES sector with strong technological capabilities, the biggest challenge lies in human-centric factors like self-efficacy and resistance to change. For this reason, organisations in this sector should focus on continuous skill development, especially on improving employees' ability to interact with AI systems. Structured training programs, practical exposure and change management initiatives can bridge the gap between technical readiness and behavioural adoption. This will help ensure that AI tools are available and effectively used in HR processes.

The use of AI in hospitality and healthcare, where operational consistency and service quality are critical, requires standardisation and ethical integration. The study indicates that there is acceptance, but the implementation might not be uniform. Managers should think about applying AI to everyday HR practices such as planning the workforce, hiring, and evaluating performance, but with openness and fairness. To achieve consistent results, it will be important to strengthen enabling conditions, including infrastructure and employee support systems.

The consumer durables and telecommunications sector can scale AI beyond pilot initiatives. The study underscores the need for deep integration of AI in core HR processes such as talent analytics and performance management. Organisations should plan their AI initiatives with a strategy that is aligned with business objectives and that can be tracked through measurable performance indicators. This will allow a shift from piece-meal application to enterprise-wide deployment and therefore increase effectiveness and agility.

In the banking, insurance, and financial services (BFSI) sector, which is known for structured processes and regulatory oversight, the application of AI should move beyond compliance-driven use to strategic value creation. Findings indicate that innovation is potentially limited, but preparedness is fairly stable. AI can be applied by managers for more advanced HR analytics, predictive workforce planning and employee engagement. Leadership should actively champion experimentation and innovation, within the bounds of regulation.

The study shows that the diffusion of AI practices varies among management consultancy firms, suggesting room for increasing the diffusion of AI practices. The research findings can be used by firms to incorporate AI into consulting approaches and internal HR processes. Promoting knowledge sharing, building AI skills within consultants and encouraging leadership-led adoption will allow AI to be seen as a core strategic asset, not an add-on.

The results indicate the importance of aligning technological readiness (TOE framework), individual perceptions (TAM/UTAUT), and innovation diffusion processes (DOI theory) in all industries. Organisations thus need to embrace a holistic approach to combine these dimensions to achieve successful AI adoption. Ultimately, the application of this research is to help managers move from the acceptance of AI to the effective implementation of AI, resulting in sustainable improvements in organisational effectiveness.

CHAPTER - 7 LIMITATIONS AND POTENTIAL FUTURE SCOPE

7.1 Limitations of Study

Despite its strong methodological rigor and substantial empirical contribution, the present study is subject to certain limitations that should be acknowledged while interpreting the findings. Recognizing these limitations not only strengthens the credibility of the research but also provides direction for future scholarly inquiry.

7.1.1 Contextual and Sectoral Boundaries

The study is confined to selected service-sector industries in India, namely IT/ITES, Healthcare & Hospitality, Consumer Durables & Telecommunications, Banking and Financial Services, and Management Consultancy. While this focus allows for meaningful sectoral comparison and contextual depth, it limits the direct generalizability of the findings to other industries such as manufacturing, public administration, education, or agriculture. Variations in technological maturity, regulatory frameworks, organizational culture, and workforce composition across sectors may influence AI acceptance and implementation differently.

7.1.2 Geographic Concentration

Data were collected primarily from organizations located in Gujarat, with a higher representation from Central Gujarat. Although Gujarat is a major industrial and economic hub, regional disparities in infrastructure, digital readiness, and exposure to AI technologies across other Indian states may lead to different adoption patterns. Consequently, the findings should be interpreted as regionally grounded rather than nationally exhaustive.

7.1.3 Cross-Sectional Research Design

The study adopts a cross-sectional design, capturing employee perceptions at a single point in time. While this design is suitable for examining relationships among constructs and testing theoretical models, it restricts the ability to observe changes in AI acceptance, learning effects, and organizational outcomes over time. AI implementation is an evolutionary process, and longitudinal studies could provide deeper insights into post-implementation dynamics and sustained effectiveness.

7.1.4 Self-Reported Data and Common Method Bias

The research relies on self-reported survey data, particularly for constructs related to perceptions of AI, behavioural intention, acceptance, implementation, and organizational effectiveness. Although methodological precautions such as scale validation, reliability checks, and SEM were employed, responses may still be influenced by social desirability bias, perceptual errors, or individual optimism or scepticism toward AI. Future research may triangulate survey data with objective performance metrics or managerial assessments.

7.1.5 Non-Normal Distribution of Data

The data were found to deviate from normality, necessitating the use of robust analytical techniques such as bootstrapping, PLS-SEM, and non-parametric tests. While these methods are statistically appropriate and widely accepted, results may differ if replicated using normally distributed data or alternative estimation techniques. This limitation underscores the importance of cautious interpretation, particularly when comparing findings with studies using traditional parametric approaches.

7.1.6 Focus on Perceived Implementation Rather Than Actual Use

The construct of Perceived AI Implementation captures employees' beliefs of organizational readiness and implementation effectiveness rather than direct measurement of actual AI system usage or maturity levels. While perception-based measures are valuable in understanding acceptance and behavioural responses, they may not fully reflect technical depth, system performance, or integration quality of AI tools within HR processes.

7.1.7 Limited Exploration of Technical and Algorithmic Dimensions

The study intentionally adopts a managerial and behavioural perspective and does not delve into the technical architecture, algorithmic design, or computational performance of AI systems used in HR. As a result, issues such as model accuracy, algorithmic bias, explainability, and system interoperability are addressed only at a perceptual level. Future interdisciplinary research combining HRM and data science perspectives could offer deeper technical insights.

7.1.8 Ethical and Regulatory Dimensions Not Exhaustively Modelled

Although constructs such as uncertainty, risk, and complexity indirectly capture ethical concerns, the study does not explicitly model AI ethics, data governance frameworks, or legal compliance variables. Given the increasing importance of responsible AI and regulatory oversight, future research could benefit from explicitly incorporating ethical governance constructs into AI acceptance and effectiveness models.

7.1.9 Demographic Representation Imbalance

The sample comprises a higher proportion of younger, early-career, and postgraduate-qualified respondents. While reflective of the current service-sector workforce, this demographic skew may underrepresent perspectives of senior professionals or late-career employees who may experience AI differently. This limitation suggests caution in generalizing findings across all age and experience groups.

7.1.10 Absence of Qualitative Insights

The exclusively quantitative approach limits the ability to capture nuanced employee narratives, emotional responses, and contextual meanings associated with AI adoption in HR. Qualitative interviews or case studies could have enriched the understanding of resistance, trust, and adoption processes, particularly during AI implementation phases.

In summary, while the study offers robust empirical evidence and a validated conceptual framework, its findings should be interpreted within the boundaries of sectoral focus, geographic scope, cross-sectional design, perceptual data, and methodological constraints. These limitations do not diminish the study's contribution; rather, they provide a transparent foundation for future research aimed at deepening and broadening understanding of AI implementation in HR and its impact on organizational effectiveness.

7.2 Potential Future Scope of the Study

Building upon the findings and limitations of the present research, several promising avenues emerge for future scholarly exploration.

First, future studies can expand the conceptual framework across industries and institutional contexts, including public sector organizations, MSMEs, and global enterprises. This would enable comparative analysis of how organizational structure and governance influence AI acceptance and effectiveness.

Second, longitudinal research designs can provide deeper understanding of how AI acceptance transitions into habitual use, governance maturity, and long-term organizational effectiveness. Such studies would be particularly valuable in capturing post-implementation learning curves and change fatigue.

Third, future research may integrate ethical AI governance frameworks into HR adoption models by explicitly examining fairness perceptions, transparency mechanisms, explainable AI, and employee trust. This is especially relevant given increasing regulatory scrutiny and ethical expectations around AI use.

Fourth, scholars may explore moderating and mediating mechanisms, such as organizational culture, leadership style, psychological safety, and learning orientation, to better understand the pathways linking AI implementation to organizational effectiveness.

Fifth, mixed-method and qualitative approaches can deepen insight into employee narratives, resistance dynamics, emotional responses, and identity shifts caused by AI-driven HR systems—dimensions that quantitative models alone cannot fully capture.

Sixth, future studies may examine AI maturity stages in HR, moving beyond adoption to assess optimization, innovation capability, and strategic transformation enabled by AI.

Finally, cross-cultural, and international comparative studies can help establish whether the observed relationships hold across different socio-economic, regulatory, and cultural environments, thereby contributing to the global AI-HRM literature.

References

Abbas, S. K., Hassan, H. A., Iftikhar, S., & Waris, A. (2018a). Assimilation of TTF and UTAUT for Mobile Banking Usage. *International Journal of Advanced Engineering, Management and Science*, *4*(4), 305–308. https://doi.org/10.22161/IJAEMS.4.4.12

Abbas, S. K., Hassan, H. A., Iftikhar, S., & Waris, A. (2018b). Assimilation of TTF and UTAUT for Mobile Banking Usage. *International Journal of Advanced Engineering, Management and Science*, *4*(4), 305–308. https://doi.org/10.22161/IJAEMS.4.4.12

Abdekhoda, M., Dehnad, A., & Zarei, J. (2018a). *Determinant factors in applying electronic medical records in health-*. (January). https://doi.org/10.26719/emhj.18.007

Abdekhoda, M., Dehnad, A., & Zarei, J. (2018b). *Determinant factors in applying electronic medical records in health-*. (January). https://doi.org/10.26719/emhj.18.007

Agarwal, A. (2022a). AI adoption by human resource management: a study of its antecedents and impact on HR system effectiveness. *Foresight*, *25*(1), 67–81. https://doi.org/10.1108/FS-10-2021-0199/FULL/XML

Agarwal, A. (2022b). AI adoption by human resource management: a study of its antecedents and impact on HR system effectiveness. *Foresight*, *25*(1), 67–81. https://doi.org/10.1108/FS-10-2021-0199/FULL/XML

Agarwal, M. (2024). *India Employment Report 2024 : Job & Employment opportunities for Youth through Education and Skills 1 1 Sharma, Alakh and Michiko Miyamoto; Indian Employment Report; Book Review*.

Ahmed, Dr. O. (2018). ARTIFICIAL INTELLIGENCE. *IJRAR*, *5*(4), 2349–5138. https://doi.org/10.1049/ep.1976.0108

AI for HR: The future of Human Resources | SAP. (n.d.). Retrieved January 6, 2026, from https://www.sap.com/resources/ai-for-hr

AI in HR: How is Artificial Intelligence transforming human resources? (n.d.). Retrieved January 6, 2026, from https://www.imd.org/blog/digital-transformation/ai-in-hr/

Ajzen, I. (2011). The theory of planned behaviour: Reactions and reflections. *Psychology and Health*, *26*(9), 1113–1127. https://doi.org/10.1080/08870446.2011.613995

Al Mamun, A., Kumar, N., Ibrahim, M. D., & Bin Yusoff, M. N. H. (2025). The Wired Workplace: Analyzing IoT's Role in Shaping the Future of Human Resource Management. *Interdisciplinary Research Review*, *20*(2), 51–66. https://doi.org/10.14254/2071-789X.2017/10-4/5

Alam, M. S., Khan, T.-U.-Z., Dhar, S. S., & Munira, K. S. (2020). HR Professionals' Intention to Adopt and Use of Artificial Intelligence in Recruiting Talents. *Business Perspective Review*, *2*(2), 15–30. https://doi.org/10.38157/business-perspective-review.v2i2.122

Alami, H., Lehoux, P., Denis, J., Motulsky, A., Petitgand, C., Savoldelli, M., Rouquet, R., Gagnon, M., Roy, D., & Fortin, J. (2021). *Organizational readiness for artificial intelligence in health care : insights for decision-making and practice*. (January). https://doi.org/10.1108/JHOM-03-2020-0074

Alan Bryman. (2016). *Social Research Methods* (5th ed.). Oxford University Press. https://www.scirp.org/reference/referencespapers?referenceid=1948986

Alekseeva, L., Gine, M., Samila, S., & Taska, B. (2020). AI Adoption and Firm Performance: Management versus IT. *SSRN Electronic Journal*. https://doi.org/10.2139/SSRN.3677237

Alfons, A. K., & Alfons Kodiyan, A. (2019). *An overview of ethical issues in using AI systems in hiring with a case study of Amazon's AI based hiring tool*.

Alsheibani, S., & Messom, C. (2018). *Artificial Intelligence Adoption : AI-readiness at Artificial Intelligence Adoption : AI-readiness at*.

Al-Suqri, F. D.-, MN, undefined, Al-Aufi, undefined, Seeking, A. I., & 1989, undefined. (n.d.). Technology acceptance model: TAM. *Quod.Lib.Umich.Edu*. Retrieved December 22, 2025, from https://quod.lib.umich.edu/b/busadwp/images/b/1/4/b1409190.0001.001.pdf

Álvarez-Gutiérrez, F. J., Stone, D. L., Castaño, A. M., & García-Izquierdo, A. L. (2022). Human Resources Analytics: A systematic Review from a Sustainable Management Approach. *Https://Journals.Copmadrid.Org/Jwop*, *38*(3), 129–147. https://doi.org/10.5093/JWOP2022A18

Amankwah-Amoah, J., Debrah, Y. A., Yu, W., Lin, Z., Danso, A., & Adomako, S. (2021a). Technology strategies in emerging economies: Emerging issues, challenges and new research agenda. *Technological Forecasting and Social Change*, *170*. https://doi.org/10.1016/j.techfore.2021.120881

Amankwah-Amoah, J., Debrah, Y. A., Yu, W., Lin, Z., Danso, A., & Adomako, S. (2021b). Technology strategies in emerging economies: Emerging issues, challenges and new research agenda. *Technological Forecasting and Social Change*, *170*. https://doi.org/10.1016/j.techfore.2021.120881

Angrave, D., Charlwood, A., Kirkpatrick, I., Lawrence, M., & Stuart, M. (2016). *HR and analytics: why HR is set to fail the big data challenge*. *26*(1), 1–11. https://doi.org/10.1111/1748-8583.12090

Arabia, S., Colleges, O., & Arabia, S. (2021). *DEVELOPMENT OF ARTIFICIAL INTELLIGENCE TECHNIQUES IN SAUDI ARABIA : THE IMPACT ON COVID-19 PANDEMIC . LITERATURE REVIEW*. *16*(6), 4530–4547.

Ashraf, G., & Abd Kadir, S. bte. (2012). A review on the models of organizational effectiveness: A look at Cameron's model in higher education. *International Education Studies*, *5*(2), 80–87. https://doi.org/10.5539/ies.v5n2p80

Bagheri Rad, M., Valmohammadi, C., & Shayan, A. (2020). An Empirical Investigation of the Factors Affecting the Use of Social Networks in Human Resources Recruitment. *International Journal of Public Administration*, *43*(6), 517–526. https://doi.org/10.1080/01900692.2019.1636396

Baharuden, A. F., Isaac, O., & Ameen, A. (2019). Factors Influencing Big Data & Analytics (BD&A) Learning Intentions with Transformational Leadership as Moderator Variable: Malaysian SME Perspective. *International Journal of Management and Human Science (IJMHS)*, *3*(1), 10–20.

Baker, J. (2012). *The Technology–Organization–Environment Framework*. 231–245. https://doi.org/10.1007/978-1-4419-6108-2_12

Balakrishnan, J., Dwivedi, Y. K., Hughes, L., & Boy, F. (2021a). Enablers and Inhibitors of AI-Powered Voice Assistants: A Dual-Factor Approach by Integrating the Status Quo Bias and Technology Acceptance Model. *Information Systems Frontiers*. https://doi.org/10.1007/s10796-021-10203-y

Balakrishnan, J., Dwivedi, Y. K., Hughes, L., & Boy, F. (2021b). Enablers and Inhibitors of AI-Powered Voice Assistants: A Dual-Factor Approach by Integrating the Status Quo Bias and Technology Acceptance Model. *Information Systems Frontiers*. https://doi.org/10.1007/s10796-021-10203-y

Balas, V. E. (n.d.). *Intelligent Systems Reference Library 193 Further Advances in Internet of Things in Biomedical and Cyber Physical Systems*.

Basu, B., Roy, S. K., & Apostolidis, C. (2025). Unveiling the Charisma of Artificial Intelligence: How Voice Assistants Captivate Users and Emotionally Influence User Experience. *Wiley Online Library*, *42*(9), 2334–2351. https://doi.org/10.1002/MAR.22233

Becker, B. E. , & H. M. A. (1998). High performance work systems and firm performance: A synthesis of research and managerial implications. *Academy of Management Journal*, *41*(1), 8–29. https://cir.nii.ac.jp/crid/1370848664756512129

Bere, A. (2018). Applying an Extended Task-Technology Fit for Establishing Determinants of Mobile Learning: An Instant Messaging Initiative. *Journal of Information Systems Education*, *29*(4), 239–252.

Berhil, S., Benlahmar, H., & Labani, N. (2020). A review paper on artificial intelligence at the service of human resources management. *Indonesian Journal of Electrical Engineering and Computer Science*, *18*(1), 32–40. https://doi.org/10.11591/ijeecs.v18.i1.pp32-40

Best, M. C., Hjort, J., Szakonyi, D., Abowd, J. M., Acemoglu, D., Allcott, H., Besley, T., Bloom, N., Blundell, R., Chetty, R., Collard-Wexler, A., Decarolis, F., Drenik, A., Dupas, P., Faber, B., Finan, F., Gentzkow, M., Gottlieb, J., Hoxby, C., … Carlos Best, M. (2017). *NBER WORKING PAPER SERIES INDIVIDUALS AND ORGANIZATIONS AS SOURCES OF STATE EFFECTIVENESS the AEA meetings*. http://www.nber.org/papers/w23350

Bhatt, M., & Shah, P. (2023). Acceptance of Artificial Intelligence in Human Resource Practices by Employees. *The Adoption and Effect of Artificial Intelligence on Human Resources Management, Part B*, 13–30. https://doi.org/10.1108/978-1-80455-662-720230002

BİLİMLER, N. Z.-S., & 2025, undefined. (2025). BUILDING TRUST BETWEEN HUMANS AND ARTIFICIAL INTELLIGENCE: THE FUTURE OF PERCEIVED JUSTICE IN

HR MANAGEMENT. *Iksadyayinevi.Com*. https://iksadyayinevi.com/wp-content/uploads/2025/12/SOSYAL-BILIMLER-Disiplinlerarasi-Perspektifler-ve-Guncel-Konular-2.pdf#page=30

Bogen, M., & Rieke, A. (2018). *An Examination of Hiring Algorithms, Equity, and Bias HELP WANTED*.

Bondarouk, T., Human, C. B.-T. I. J. of, & 2016, undefined. (2016). Conceptualising the future of HRM and technology research. *Taylor & FrancisT Bondarouk, C BrewsterThe International Journal of Human Resource Management, 2016•Taylor & Francis*, *27*(21), 2652–2671. https://doi.org/10.1080/09585192.2016.1232296

Bose, M., Journal, K. S.-S. U. C., & 2021, undefined. (2021). A study on the application of HR analytics on talent acquisition compensation & benefits and employee turnover in the Indian IT industry. *Researchgate.Net*, *Vol-44 No.-01(XIV)*. https://www.researchgate.net/profile/Subha-Krishnamoorthy-2/publication/353972728_A_STUDY_ON_THE_APPLICATION_OF_HR_ANALYTICS_ON_TALENT_ACQUISITION_COMPENSATION_BENEFITS_AND_EMPLOYEE_TURNOVER_IN_THE_INDIAN_IT_INDUSTRY/links/611cd6631e95fe241adc2dd7/A-STUDY-ON-THE-APPLICATION-OF-HR-ANALYTICS-ON-TALENT-ACQUISITION-COMPENSATION-BENEFITS-AND-EMPLOYEE-TURNOVER-IN-THE-INDIAN-IT-INDUSTRY.pdf

Brougham, D., & Haar, J. (2018). Smart Technology, Artificial Intelligence, Robotics, and Algorithms (STARA): Employees' perceptions of our future workplace. *Journal of Management and Organization*, *24*(2), 239–257. https://doi.org/10.1017/JMO.2016.55

Burgess, J. (2021). *AI and Meaningful work: exploring the challenges for HR Professionals Managing technology, work, and life after Covid-19*. (May).

Cabrera, Á. A., Perer, A., & Hong, J. I. (2023). Improving Human-AI Collaboration With Descriptions of AI Behavior. *Proceedings of the ACM on Human-Computer Interaction*, *7*(CSCW1). https://doi.org/10.1145/3579612;WGROUP:STRING:ACM

Cai, D., Liu, J., Zhao, H., & Li, M. (2020). Could social media help in newcomers' socialization? The moderating effect of newcomers' utilitarian motivation. *Computers in Human Behavior*, *107*, 106273. https://doi.org/10.1016/J.CHB.2020.106273

Cao, G., Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2021a). Understanding managers' attitudes and behavioral intentions towards using artificial intelligence for organizational decision-making. *Technovation*, *106*, 102312. https://doi.org/10.1016/j.technovation.2021.102312

Cao, G., Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2021b). Understanding managers' attitudes and behavioral intentions towards using artificial intelligence for organizational decision-making. *Technovation*, *106*, 102312. https://doi.org/10.1016/j.technovation.2021.102312

Carter, L., Stone-Jovicich, S., Bohensky, E., Coates, R., Douglas, D., Ferrer-Mestres, J., Harwood, B., Islam, M. Z., Kandanaarachchi, S., McGrath, M., Ong, C. S., Paris, C., Reeson, A., Scovell, M., Wissing, K., & Chades, I. (2025). Lessons from the Edges of

Interdisciplinarity-Integrating Artificial Intelligence with the Humanities, Social and Economic Sciences. *Taylor & Francis*, *39*(1), 2584380. https://doi.org/10.1080/08839514.2025.2584380

Chakma, D. (2021). *Merits and Demerits of Realism*. *51*(1), 1–9. https://doi.org/10.17265/2328-2185/2021.05.004

Charlwood, A., & Guenole, N. (2022). Can HR adapt to the paradoxes of artificial intelligence? *Human Resource Management Journal*, *32*(4), 729–742. https://doi.org/10.1111/1748-8583.12433;REQUESTEDJOURNAL:JOURNAL:17488583;WGROUP:STRING:PUBLICATION

Chatterjee, S., Chaudhuri, R., Vrontis, D., & Siachou, E. (2022). Examining the dark side of human resource analytics: an empirical investigation using the privacy calculus approach. *International Journal of Manpower*, *43*(1), 52–74. https://doi.org/10.1108/IJM-02-2021-0087

Chatterjee, S., Rana, N. P., Dwivedi, Y. K., & Baabdullah, A. M. (2021a). Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model. *Technological Forecasting and Social Change*, *170*(November 2020), 120880. https://doi.org/10.1016/j.techfore.2021.120880

Chatterjee, S., Rana, N. P., Dwivedi, Y. K., & Baabdullah, A. M. (2021b). Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model. *Technological Forecasting and Social Change*, *170*(November 2020), 120880. https://doi.org/10.1016/j.techfore.2021.120880

Chen, L. (2022). *Artificial intelligence in training and development: A new paradigm for organizational learning*. 123–140.

Chiu, C.-Y. C. S. C. C.-L. (2017). An integrated perspective of TOE framework and innovation diffusion in broadband mobile applications adoption by enterprises. *International Journal of Management, Economics and Social Sciences (IJMESS)*, *6*(1), 1439.

Chowdhury, S., Dey, P., Joel-Edgar, S., Bhattacharya, S., Rodriguez-Espindola, O., Abadie, A., & Truong, L. (2023). Unlocking the value of artificial intelligence in human resource management through AI capability framework. *Human Resource Management Review*, *33*(1), 100899. https://doi.org/10.1016/J.HRMR.2022.100899

Chuttur, M. (2009a). Overview of the Technology Acceptance Model: Origins , Developments and Future Directions. *Sprouts: Working Papers on Information Systems*, *9*(37), 1–23. https://doi.org/10.1021/jf001443p

Chuttur, M. (2009b). *Overview of the technology acceptance model: Origins, developments and future directions*. https://aisel.aisnet.org/sprouts_all/290/?utm

Claus, L. (2019). HR disruption—Time already to reinvent talent management. *BRQ Business Research Quarterly*, *22*(3), 207–215. https://doi.org/10.1016/j.brq.2019.04.002

Creswell, J. W., & Creswell, J. D. (2018). Research Design Qualitative, Quantitative, and Mixed Methods Approaches. *Scientific Research Publishing*. https://www.scirp.org/reference/referencespapers?referenceid=2895169

CROITORU, I. O., CHIRIȚĂ, S., & STERIOPOL, B. C. (2025). THE FUTURE OF LEADERSHIP: THE CONVERGENCE BETWEEN DIGITALIZATION AND INNOVATION. *Strategic Universe Journal / Univers Strategic*, (1), 55.

Daft, R. L. . (2016). *Organization theory & design*. 667.

D'Ambra, J., Wilson, C. S., & Akter, S. (2013). Application of the task-technology fit model to structure and evaluate the adoption of E-books by academics. *Journal of the American Society for Information Science and Technology*, *64*(1), 48–64. https://doi.org/10.1002/ASI.22757

Damsgaard, J. (2014). *A stage model of intranet technology implementation and management*. (May).

Daniel Bagana, B., Irsad, M., & Santoso, I. H. (2021). Batara Daniel Bagana, Moch. Irsad, Ignatius Hari Santoso / Artificial Intelligence as a Human Substitution? Customer's Perception of the Conversational User Interface in Banking Industry ARTIFICIAL INTELLIGENCE AS A HUMAN SUBSTITUTION? CUSTOMER'S PERCEPTI. *Review of Management and Entrepreneurship*, *05*, 1.

Daniel Norwood. (2025, April 18). *Insights to Impact: Inside Perceptyx's Award-Winning AI Solution*. Https://Blog.Perceptyx.Com/Insights-to-Impact-inside-Perceptyxs-Award-Winning-Ai-Solution. https://blog.perceptyx.com/insights-to-impact-inside-perceptyxs-award-winning-ai-solution

Daradkeh, M. (2019). Visual analytics adoption in business enterprises: An integrated model of technology acceptance and task-technology fit. *International Journal of Information Systems in the Service Sector*, *11*(1), 68–89. https://doi.org/10.4018/IJISSS.2019010105

Dastin, J. (2022). Amazon Scraps Secret AI Recruiting Tool that Showed Bias against Women *. *Ethics of Data and Analytics*, 296–299. https://doi.org/10.1201/9781003278290-44

Davenport, T. H. (2018). From analytics to artificial intelligence. *Https://Doi.Org/10.1080/2573234X.2018.1543535*, *1*(2), 73–80. https://doi.org/10.1080/2573234X.2018.1543535

Davenport, T. H., & Ronanki, R. (2018). *Artificial intelligence for the real world. Harvard Business Review*.

Davis, F. (1985). *A technology acceptance model for empirically testing new end-user information systems: Theory and results*. https://dspace.mit.edu/bitstream/handle/1721.1/15192/14927137-MIT.pdf

Davis, F., Bagozzi, R., science, P. W.-M., & 1989, undefined. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Pubsonline.Informs.Org*, *35*(8), 982–1003. https://doi.org/10.1287/MNSC.35.8.982

Davis, F. D. (1989a). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly: Management Information Systems*, *13*(3), 319–339. https://doi.org/10.2307/249008

Davis, F. D. (1989b). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly: Management Information Systems*, *13*(3), 319–339. https://doi.org/10.2307/249008

Davis, F. D. (1993). User acceptance of information technology: system characteristics, user perceptions and behavioral impacts. *Elsevier - International Journal of Man-Machine Studies*, *38*(3), 475–487. https://doi.org/https://doi.org/10.1006/imms.1993.1022

Del Barone, L., de Gennaro, D., & Buonocore, F. (2025). AI-driven HRM and managerial competencies: strengthening organizational resilience in Public Administration. *Emerald.Com*. https://doi.org/10.1108/MD-06-2024-1252/FULL/HTML

Del Giudice, M., Scuotto, V., Orlando, B., & Mustilli, M. (2021a). Toward the human – Centered approach. A revised model of individual acceptance of AI. *Human Resource Management Review*, (November 2020), 100856. https://doi.org/10.1016/j.hrmr.2021.100856

Del Giudice, M., Scuotto, V., Orlando, B., & Mustilli, M. (2021b). Toward the human – Centered approach. A revised model of individual acceptance of AI. *Human Resource Management Review*, (November 2020), 100856. https://doi.org/10.1016/j.hrmr.2021.100856

Deloitte's Global Human Capital Trends Workday Differentiators. (2024). https://www.deloitte.com/global/en/alliances/workday/analysis/global-human-capital-trends-through-workday-lens.html

DeLone, W. H., & McLean, E. R. (1992). Information systems success: The quest for the dependent variable. *Pubsonline.Informs.Org*, *3*(1), 60–95. https://doi.org/10.1287/ISRE.3.1.60

DeLone, W., systems, E. M. management information, & 2003, undefined. (2003). The DeLone and McLean model of information systems success: a ten-year update. *Taylor & Francis*, *19*(4), 9–30. https://doi.org/10.1080/07421222.2003.11045748

Dickson, D. R., & Nusair, K. (2010). An HR perspective: The global hunt for talent in the digital age. *Worldwide Hospitality and Tourism Themes*, *2*(1), 86–93. https://doi.org/10.1108/17554211011012612

Diffusion of Innovations. (2014). 432–448. https://doi.org/10.4324/9780203887011-36

Digital Personal Data Protection Act 2023 (2023).

DiRomualdo, A., El-Khoury, D., & Girimonte, F. (2018). HR in the digital age: how digital technology will change HR's organization structure, processes and roles. *Strategic HR Review*, *17*(5), 234–242. https://doi.org/10.1108/shr-08-2018-0074

Dodel, M., & Mesch, G. S. (2020). Perceptions about the impact of automation in the workplace. *Https://Doi.Org/10.1080/1369118X.2020.1716043*, *23*(5), 665–680. https://doi.org/10.1080/1369118X.2020.1716043

Dong, L., & Neufeld, D. (2008). *Testing Klein and Sorra 's innovation implementation model : An empirical examination Testing Klein and Sorra 's innovation implementation model :*

An empirical examination §. (December). https://doi.org/10.1016/j.jengtecman.2008.10.006

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda. *International Journal of Information Management*, *48*, 63–71. https://doi.org/10.1016/J.IJINFOMGT.2019.01.021

Dwivedi, Y. K., Hughes, L., Wang, Y., Alalwan, A. A., Ahn, S. J., Balakrishnan, J., Barta, S., Belk, R., Buhalis, D., Dutot, V., Felix, R., Filieri, R., Flavián, C., Gustafsson, A., Hinsch, C., Hollensen, S., Jain, V., Kim, J., Krishen, A. S., … Wirtz, J. (2023). Artificial intelligence (AI) futures: India-UK collaborations emerging from the 4th Royal Society Yusuf Hamied workshop. *Elsevier*, *40*(4), 750–776. https://doi.org/10.1002/MAR.21767

Erik Brynjolfsson and Andrew McAfee. (2017, July 18). *What it can — and cannot — do for your organization - The Business of Artificial Intelligence*. Https://Hbr.Org/2017/07/the-Business-of-Artificial-Intelligence. https://hbr.org/2017/07/the-business-of-artificial-intelligence

Errida, A., & Lotfi, B. (2020). Measuring change readiness for implementing a project management methodology: An action research study. *Academy of Strategic Management Journal*, *19*(1), 1–17.

Esen, M., & Erdoğmuş, N. (2014). EFFECTS OF TECHNOLOGY READINESS ON TECHNOLOGY ACCEPTANCE IN E-HRM: MEDIATING ROLE OF PERCEIVED USEFULNESS Murat ESEN 1 Nihat E RDOĞMUŞ 2. *Bilgi Ekonomisi ve Yonetimi Dergisi*, *9*(1), 7–15. https://pdfs.semanticscholar.org/a37f/dd70fa1ce26f508845982502728833l3ebc1.pdf

Esen, M., & Özbağ, G. K. (2014). An Investigation of the Effects of Organizational Readiness on Technology Acceptance in e-HRM Applications. *International Journal of Human Resource Studies*, *4*(1), 232. https://doi.org/10.5296/ijhrs.v4i1.5643

Eubanks, Ben. (2025). *Artificial Intelligence for HR : Use AI to Support and Develop a Successful Wokforce*. 268.

EVERETT M. ROGERS, A. S. M. M. Q. (2014). Diffusion of innovations. In *An Integrated Approach to Communication Theory and Research* (2nd ed.). taylorfrancis.com. https://doi.org/10.4324/9780203887011-36/DIFFUSION-INNOVATIONS-EVERETT-ROGERS-ARVIND-SINGHAL-MARGARET-QUINLAN

Everett Roge. (1995). *Diffusion of innovations*.

Fermin Diez, M. B. & V. L. (2019). Fundamentals of HR Analytics: A Manual on Becoming HR Analytical. In *emerald.com*. https://doi.org/10.1108/978-1-78973-961-920191009/FULL/HTML

Feroz Alam. (2020). Advanced Compensation in Workday: A Data-Driven Approach to Talent Management and People Analytics. *International Journal of Trend in Research and Development*, *7(5)*. https://www.researchgate.net/profile/Dharmasena-Sd/publication/395657855_Advanced_Compensation_in_Workday_A_Data-Driven_Approach_to_Talent_Management_and_People_Analytics/links/68cd3dda0f14e

901fcd1b750/Advanced-Compensation-in-Workday-A-Data-Driven-Approach-to-Talent-Management-and-People-Analytics.pdf

Filomena Buonocore, Davide de Gennaro, Ludovica Del Barone, & Viviana Colombi Evangelista. (2026). Transforming public-sector HRM through AI: an integrated TAM–TOE framework. *Journal of Managerial Psychology Emerald.Com*. https://doi.org/10.1108/JMP-05-2024-0351/1360252

Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., Luetge, C., Madelin, R., Pagallo, U., Rossi, F., Schafer, B., Valcke, P., & Vayena, E. (2018). AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. *Springer*, *28*(4), 689–707. https://doi.org/10.1007/S11023-018-9482-5

Fosso Wamba, S., Queiroz, M. M., Chiappetta Jabbour, C. J., & Shi, C. (Victor). (2023). Are both generative AI and ChatGPT game changers for 21st-Century operations and supply chain excellence? *International Journal of Production Economics*, *265*, 109015. https://doi.org/10.1016/J.IJPE.2023.109015

Fred D. Davis. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *JSTOR - MIS Quarterly*, *13*(3), 319–340. https://doi.org/https://doi.org/10.2307/249008

Fred Davis. (1987). User Acceptance of Information Systems: Technology acceptance model (TAM). In *quod.lib.umich.edu*. https://quod.lib.umich.edu/b/busadwp/images/b/1/4/b1409190.0001.001.pdf

Fui-Hoon Nah, F., Zheng, R., Cai, J., Siau, K., & Chen, L. (2023). Generative AI and ChatGPT: Applications, challenges, and AI-human collaboration. *Journal of Information Technology Case and Application Research*, *25*(3), 277–304. https://doi.org/10.1080/15228053.2023.2233814

G Revillod. (2025). Trust influence on AI HR tools perceived usefulness in Swiss HRM: the mediating roles of perceived fairness and privacy concerns. *Springer*, *40*(6), 4789–4822. https://doi.org/10.1007/S00146-025-02216-X

Gado, S., Kempen, R., Lingelbach, K., & Bipp, T. (2021). Artificial intelligence in psychology: How can we enable psychology students to accept and use artificial intelligence? *Psychology Learning and Teaching*, (September). https://doi.org/10.1177/14757257211037149

Gangwar, H., Date, H., & Ramaswamy, R. (2015a). Understanding determinants of cloud computing adoption using an integrated TAM-TOE model. *Journal of Enterprise Information Management*, *28*(1), 107–130. https://doi.org/10.1108/JEIM-08-2013-0065

Gangwar, H., Date, H., & Ramaswamy, R. (2015b). Understanding determinants of cloud computing adoption using an integrated TAM-TOE model. *Journal of Enterprise Information Management*, *28*(1), 107–130. https://doi.org/10.1108/JEIM-08-2013-0065

George*, D. G., & Thomas, D. M. R. (2019). Integration of Artificial Intelligence in Human Resource. *International Journal of Innovative Technology and Exploring Engineering*, *9*(2), 5069–5073. https://doi.org/10.35940/ijitee.L3364.129219

Georgopoulos, S. B. (1957). *The Study of Organizational Effectiveness - Price (1972).pdf*.

Gholami, Z., … M. A.-D. J. of, & 2018, undefined. (2018). Determinant Factors in Adopting Mobile Technology-based Services by Academic Librarians. *Researchgate.Net*, *38*(4), 271–277. https://doi.org/10.14429/djlit.38.4.12676

Gianina Lala. (2014). The emergence and development of the technology acceptance model (TAM). *Ceeol.Com*, (7), 149–160. https://www.ceeol.com/search/article-detail?id=48800

Gikopoulos, J. (2019). Alongside, not against: balancing man with machine in the HR function. *Strategic HR Review*, *18*(2), 56–61. https://doi.org/10.1108/shr-12-2018-0103

Go, H., Kang, M., & Suh, S. B. C. (2020a). Machine learning of robots in tourism and hospitality: interactive technology acceptance model (iTAM) – cutting edge. *Tourism Review*, *75*(4), 625–636. https://doi.org/10.1108/TR-02-2019-0062

Go, H., Kang, M., & Suh, S. B. C. (2020b). Machine learning of robots in tourism and hospitality: interactive technology acceptance model (iTAM) – cutting edge. *Tourism Review*, *75*(4), 625–636. https://doi.org/10.1108/TR-02-2019-0062

Goodhue, D. L. (1998). Development and Measurement Validity of a Task-Technology Fit Instrument for User Evaluations of Information System. *Decision Sciences*, *29*(1), 105–138. https://doi.org/10.1111/J.1540-5915.1998.TB01346.X

Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS Quarterly: Management Information Systems*, *19*(2), 213–233. https://doi.org/10.2307/249689

Guenole, N., & Feinzig, S. (2018). The Business Case for AI in HR With Insights and Tips on Getting Started. *IBM Corporation*.

Guest, D. E. (1997). Human resource management and performance: a review and research agenda. *International Journal of Human Resource Management*, *8*(3), 263–276. https://doi.org/10.1080/095851997341630

Guillaume REVILLOD. (24 C.E.). Implementation of AI Recruitment Systems in Swiss HRM: The Importance of Technological and Organizational Factors. *Ceeol.Com*, *XXVII*(2), 95–122. https://doi.org/10.46287/YDNH4362

Guillaume Revillod. (2024). Recruitment Through Ai in Swiss Organizations: The Importance of Organizational, Environmental, and Contextual Factors. *Papers.Ssrn.Com*. https://doi.org/http://dx.doi.org/10.2139/ssrn.4823207

Gulliford, F., & Parker Dixon, A. (2019). AI: the HR revolution. *Strategic HR Review*, *18*(2), 52–55. https://doi.org/10.1108/shr-12-2018-0104

Gutierrez, A., Holloway, R., & Boukrami, E. (2017a). *Technological , organisational and environmental factors influencing managers ' decision to adopt cloud computing in the UK Journal of Enterprise Information Management Article information :* (October 2015). https://doi.org/10.1108/JEIM-01-2015-0001

Gutierrez, A., Holloway, R., & Boukrami, E. (2017b). *Technological , organisational and environmental factors influencing managers ' decision to adopt cloud computing in the*

UK Journal of Enterprise Information Management Article information : (October 2015). https://doi.org/10.1108/JEIM-01-2015-0001

Hair, William, Black, Barry, A. (2010). Multivariate Data Analysis. *Gedrag & Organisatie*, *19*(3), 1–759.

Hashmi, A. U., & Baig, M. M. (2020). Impact of Artificial Intelligence on HR Management – A Review. *Dogo Rangsang Research Journal*, *10*(06), 92–101.

Hermawan, I., & Suharnomo, S. (2020). Information Technology as a Strategic Resource in Encouraging Organizational Change Readiness through the Role of the Human Capital Effectiveness. *Jurnal Dinamika Manajemen*, *11*(2), 242–254. https://doi.org/10.15294/jdm.v11i2.23700

Hidayati, R., Permatasari, R., & Fairy, A. N. (2019). *Factors Affecting E-Commerce Adoption and Their Impact on SMEs' Performance: A Case Study of Jabodetabek Region*. *98*(Icot), 19–23. https://doi.org/10.2991/icot-19.2019.5

Hidayatno, A., Destyanto, A. R., & Hulu, C. A. (2019). Industry 4.0 Technology Implementation Impact to Industrial Sustainable Energy in Indonesia: A Model Conceptualization. *Energy Procedia*, *156*, 227–233. https://doi.org/10.1016/J.EGYPRO.2018.11.133

Hmoud, B. (2021). The adoption of artificial intelligence in human resource management and the role of human resources. *Forum Scientiae Oeconomia*, *9*(1), 105–118.

Hmoud, B., & Várallyai, L. (2021). Artificial Intelligence In Talent Acquisition, Do we Trust It? *Journal of Agricultural Informatics*, *12*(1). https://doi.org/10.17700/jai.2021.12.1.594

Hogg, P. (2019). Artificial intelligence: HR friend or foe? *Strategic HR Review*, *18*(2), 47–51. https://doi.org/10.1108/shr-11-2018-0094

Holt, D. T., Armenakis, A. A., Feild, H. S., & Harris, S. G. (2007). Readiness for organizational change: The systematic development of a scale. *Journal of Applied Behavioral Science*, *43*(2), 232–255. https://doi.org/10.1177/0021886306295295

Hossin, M., Ulfy, M., Ali, I., & Karim, M. (2021). Challenges in Adopting Artificial Intelligence (AI) in HRM Practices: A study on Bangladesh Perspective. *Working Articles*, *1*(1), 66–73. https://doi.org/10.5281/zenodo.4480245

How AI Transforms HR Management in 2025 | HR Automation. (n.d.). Retrieved January 6, 2026, from https://agentiveaiq.com/blog/how-ai-is-transforming-hr-management-in-2025?utm_source=chatgpt.com

HR Tech Trends 2025 — Global Adoption of AI & Predictive Analytics in HR. (n.d.). Retrieved January 6, 2026, from https://blog.darwinbox.com/hr-tech-trends-2025-global-adoption-of-ai-predictive-analytics-in-hr?utm_source=chatgpt.com

Huang, M., Research, R. R.-J. of C., & 2025, undefined. (n.d.). The GenAI future of consumer research. *Academic.Oup.ComMH Huang, RT RustJournal of Consumer Research, 2025•academic.Oup.Com*. Retrieved May 9, 2026, from https://academic.oup.com/jcr/article-abstract/52/1/4/8132289

Im, I., Hong, S., & Kang, M. S. (2011a). An international comparison of technology adoption. *Information & Management*, *48*(1), 1–8. https://doi.org/10.1016/j.im.2010.09.001

Im, I., Hong, S., & Kang, M. S. (2011b). An international comparison of technology adoption. *Information & Management*, *48*(1), 1–8. https://doi.org/10.1016/j.im.2010.09.001

Information, M., & Information, M. (2014a). *The Change : Information Systems Technology Implementation*. *15*(2), 229–242.

Information, M., & Information, M. (2014b). *The Change : Information Systems Technology Implementation*. *15*(2), 229–242.

Iyer, S., Pani, A. K., & Gurunathan, L. (2020a). User Adoption of eHRM - An Empirical Investigation of Individual Adoption Factors Using Technology Acceptance Model. In *IFIP Advances in Information and Communication Technology* (Vol. 617). Springer International Publishing. https://doi.org/10.1007/978-3-030-64849-7_21

Iyer, S., Pani, A. K., & Gurunathan, L. (2020b). User Adoption of eHRM - An Empirical Investigation of Individual Adoption Factors Using Technology Acceptance Model. In *IFIP Advances in Information and Communication Technology* (Vol. 617). Springer International Publishing. https://doi.org/10.1007/978-3-030-64849-7_21

Jaiswal, A., Arun, C. J., & Varma, A. (2021). *Rebooting employees: upskilling for artificial intelligence in multinational corporations*. https://doi.org/10.1080/09585192.2021.1891114

Jarrahi, M. H. (2018). Arti fi cial intelligence and the future of work : Human-AI symbiosis in organizational decision making. *Business Horizons*. https://doi.org/10.1016/j.bushor.2018.03.007

Jatoba, M., Gutierriz, I., Fernandes, P. O., Teixeira, J. P., & Moscon, D. (2019). Artificial Intelligence in the Recruitment \& Selection: Innovation and Impacts for the Human Resources Management. *Economic and Social Development: 43Rd International Scientific Conference on Economic and Social Development Rethinking Management in the Digital Era: Challenges From Industry 4.0 To Retail Management*, (2013), 96–104.

Jatobá, M., Santos, J., Gutierriz, I., Moscon, D., Fernandes, P. O., & Teixeira, J. P. (2019). Evolution of Artificial Intelligence Research in Human Resources. *Procedia Computer Science*, *164*, 137–142. https://doi.org/10.1016/j.procs.2019.12.165

Jha, J., Vishwakarma, A., … A. N.-2023 1st, & 2023, undefined. (2023). Artificial intelligence and applications. *Ieeexplore.Ieee.Org*. https://doi.org/10.37965/jait.2022.0102

Jha, M., Agarwal, S., Engineering, V. K.-I. J. of, & 2025, undefined. (2025). Artificial Intelligence at Work Transforming Industries and Redefining the Workforce Landscape. *Researchgate.Net*. https://www.researchgate.net/profile/Manish-Jha-27/publication/394304902_Artificial_Intelligence_at_Work_Transforming_Industries_and_Redefining_the_Workforce_Landscape/links/6891c3cf6e1ad24f59edb9bc/Artificial-Intelligence-at-Work-Transforming-Industries-and-Redefining-the-Workforce-Landscape.pdf

Johansson, J., Herranen, S., & Mccauley, B. (2019). The application of Artificial Intelligence (AI) in Human Resource Management: Current state of AI and its impact on the traditional recruitment process. *Bachelorarbeit*, (May), 0–60.

Jöhnk, J., Weißert, M., & Wyrtki, K. (2021a). Ready or Not, AI Comes— An Interview Study of Organizational AI Readiness Factors. *Business and Information Systems Engineering*, *63*(1), 5–20. https://doi.org/10.1007/s12599-020-00676-7

Jöhnk, J., Weißert, M., & Wyrtki, K. (2021b). Ready or Not, AI Comes— An Interview Study of Organizational AI Readiness Factors. *Business and Information Systems Engineering*, *63*(1), 5–20. https://doi.org/10.1007/s12599-020-00676-7

Joseph F. Hair, William C. Black, Barry J. Babin, Ralph E. Anderson, S. (2018). Multivariate data analysis. *Journal of Human Resource and Sustainability Studies*, xvii, 813 pages : https://books.google.com/books/about/Multivariate_Data_Analysis.html?id=0R9ZswEACAAJ

Journal, I., Ijmess, S. S., Chiu, C., Chen, S., & Chen, C. (2017). *An integrated perspective of TOE framework and innovation diffusion in broadband mobile applications adoption by enterprises An Integrated Perspective of TOE Framework and Innovation Diffusion in Broadband Mobile*.

Kakulapati, V., Chaitanya, K. K., Chaitanya, K. V. G., & Akshay, P. (2020). Predictive analytics of HR - A machine learning approach. *Journal of Statistics and Management Systems*, *23*(6), 959–969. https://doi.org/10.1080/09720510.2020.1799497

Keegan, D. J., & Farwa, A. (1 C.E.). Human Services 2.0: Navigating Ethics, Innovation, and Applications of AI in Human Services. *Https://Services.Igi-Global.Com/Resolvedoi/Resolve.Aspx?Doi=10.4018/979-8-3693-6507-6.Ch010*, 247–272. https://doi.org/10.4018/979-8-3693-6507-6.CH010

Kelibay, I., Nurmandi, A., & Ajree D Malawani. (2020). e-Government Adoption of Human Resource Management in Sorong City, Indonesia. *Journal of Asian Review of …*, *5*(1), 1–20.

Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Journals.Aom.Org*, *14*(1), 366–410. https://doi.org/10.5465/ANNALS.2018.0174

Khaled, A. S. D., Kakar, A. S., & Khan, A. (2023). Artificial intelligence and performance management systems. *International Journal of Productivity and Performance Management*.

Khan, F., Khan, N., human, A. A.-R. and review:, & 2024, undefined. (n.d.). Adoption of artificial intelligence in human resource management: an application of TOE-TAM model. *Researchgate.Net*, *5*, 22–36. Retrieved April 27, 2026, from https://www.researchgate.net/profile/Fawaz-Ahmad-Khan/publication/380490808_Adoption_of_Artificial_Intelligence_in_Human_Resource_Management_An_Application_of_TOE-TAM_Model/links/663eeab635243041539720e8/Adoption-of-Artificial-Intelligence-in-Human-Resource-Management-An-Application-of-TOE-TAM-Model.pdf

Kim, J., Lee, H., & Cho, Y. H. (2022). Learning design to support student-AI collaboration: Perspectives of leading teachers for AI in education. *SpringerJ Kim, H Lee, YH ChoEducation and Information Technologies, 2022•Springer*, *27*(5), 6069–6104. https://doi.org/10.1007/S10639-021-10831-6

Kim S. Cameron. (1986). Effectiveness as paradox: Consensus and conflict in conceptions of organizational effectiveness. *Pubsonline.Informs.OrgKS CameronManagement Science, 1986•pubsonline.Informs.Org*, *32*(5), 539–553. https://doi.org/10.1287/MNSC.32.5.539

King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information and Management*, *43*(6), 740–755. https://doi.org/10.1016/j.im.2006.05.003

Klopping, I. M. (2004). *Extending the Technology Acceptance Model and the Task - Technology Fit Model to Consumer E - Commerce*. *22*(1), 35–48.

Kothari, C. R. ., & Garg, Gaurav. (2025). *Research methodology : Methods and techniques*. 464.

Kranthi Kumar Routhu. (2020). Strategic Compensation Equity and Rewards Optimization: A Multi-cloud Analytics Blueprint with Oracle Analytics Cloud. *KOS Journal of AIML, Data Science, and Robotics*, *1*(1). https://doi.org/http://dx.doi.org/10.2139/ssrn.5737266

Kraus, S., Ferraris, A., & Bertello, A. (2023). The future of work: How innovation and digitalization re-shape the workplace. *Journal of Innovation & Knowledge*, *8*(4), 100438. https://doi.org/10.1016/J.JIK.2023.100438

Kukafka, R., Johnson, S. B., Linfante, A., & Allegrante, J. P. (2003a). *Grounding a new information technology implementation framework in behavioral science : a systematic analysis of the literature on IT use*. *36*, 218–227. https://doi.org/10.1016/j.jbi.2003.09.002

Kukafka, R., Johnson, S. B., Linfante, A., & Allegrante, J. P. (2003b). Grounding a new information technology implementation framework in behavioral science: a systematic analysis of the literature on IT use. *Journal of Biomedical Informatics*, *36*(3), 218–227. https://doi.org/10.1016/J.JBI.2003.09.002

Kukafka, R., Johnson, S. B., Linfante, A., & Allegrante, J. P. (2003c). Grounding a new information technology implementation framework in behavioral science: a systematic analysis of the literature on IT use. *Journal of Biomedical Informatics*, *36*(3), 218–227. https://doi.org/10.1016/J.JBI.2003.09.002

Kukafka, R., Johnson, S. B., Linfante, A., & Allegrante, J. P. (2003d). Grounding a new information technology implementation framework in behavioral science: a systematic analysis of the literature on IT use. *Journal of Biomedical Informatics*, *36*(3), 218–227. https://doi.org/10.1016/J.JBI.2003.09.002

Kukafka, R., Johnson, S. B., Linfante, A., & Allegrante, J. P. (2003e). Grounding a new information technology implementation framework in behavioral science: a systematic analysis of the literature on IT use. *Journal of Biomedical Informatics*, *36*(3), 218–227. https://doi.org/10.1016/J.JBI.2003.09.002

Kukafka, R., Johnson, S. B., Linfante, A., & Allegrante, J. P. (2003f). *Grounding a new information technology implementation framework in behavioral science : a systematic analysis of the literature on IT use*. *36*, 218–227. https://doi.org/10.1016/j.jbi.2003.09.002

Kwan, F. P., Hermawan, L. R., & Hafizhi, N. (2019). E-Hrm : Pain or Gain for Hrm Effectiveness. *Jurnal TAM*, *10*(1), 22–32.

Lai, V. S., & Mahapatra, R. K. (1997). *Exploring the research in information technology implementation*.

Lavanchy, M. (2006). *AMAZON'S SEXIST HIRING ALGORITHM COULD STILL BE BETTER THAN A HUMAN EXPECTING ALGORITHMS TO PERFORM PERFECTLY MIGHT BE ASKING TOO MUCH OF OURSELVES*. www.imd.org

Lazanyi, K. (2018). *Readiness for Artificial Intelligence*. 235–238.

Lee, D. C., Lin, S. H., Ma, H. L., & Wu, D. B. (2017). Use of a Modified UTAUT Model to Investigate the Perspectives of Internet Access Device Users. *International Journal of Human-Computer Interaction*, *33*(7), 549–564. https://doi.org/10.1080/10447318.2016.1261249

Lee, Y., Kozar, K. A., & Larsen, K. R. T. (2003a). The Technology Acceptance Model: Past, Present, and Future. *Communications of the Association for Information Systems*, *12*. https://doi.org/10.17705/1cais.01250

Lee, Y., Kozar, K. A., & Larsen, K. R. T. (2003b). The Technology Acceptance Model: Past, Present, and Future. *Communications of the Association for Information Systems*, *12*. https://doi.org/10.17705/1cais.01250

Leonardi, P. M. (2015). Ambient Awareness and Knowledge Acquisition: Using Social Media to Learn "Who Knows What" and "Who Knows Whom." *MIS Quarterly*, *39*(4), 747–762. https://misq.umn.edu/ambient-awareness-and-knowledge-acquisition-using-social-media-to-learn-who-knows-what-and-who-knows-whom.html

Leong, C. (2018). Technology & recruiting 101: how it works and where it's going. *Strategic HR Review*, *17*(1), 50–52. https://doi.org/10.1108/shr-12-2017-0083

Leung, D. (2015a). *Applying the Technology-Organization-Environment framework to explore ICT initial and continued adoption : An exploratory study of an independent hotel in Hong Kong Applying the Technology-Organization-Environment framework to explore ICT initial and cont*. (December). https://doi.org/10.1080/02508281.2015.1090152

Leung, D. (2015b). *Applying the Technology-Organization-Environment framework to explore ICT initial and continued adoption : An exploratory study of an independent hotel in Hong Kong Applying the Technology-Organization-Environment framework to explore ICT initial and continued adoption : An exploratory study of an independent hotel in Hong Kong*. (December). https://doi.org/10.1080/02508281.2015.1090152

Levenson, A. (2005). Harnessing the power of HR analytics. *Strategic HR Review*, *4*(3), 28–31. https://doi.org/10.1108/14754390580000607

Li, J. C. F. (2020a). *Roles of Individual Perception in Technology Adoption at Organization Level : Behavioral Model versus TOE Framework*. *10*(3), 97–118. https://doi.org/10.33168/JSMS.2020.0308

Li, J. C. F. (2020b). *Roles of Individual Perception in Technology Adoption at Organization Level : Behavioral Model versus TOE Framework*. *10*(3), 97–118. https://doi.org/10.33168/JSMS.2020.0308

Lim, W. M., Kumar, S., & Ali, F. (2022). Advancing knowledge through literature reviews:'what','why', and "how to contribute." *Taylor & Francis*, *42*(7–8), 481–513. https://doi.org/10.1080/02642069.2022.2047941

LOUIS G TORNATZKY, & MITCHELL FLEISCHER. (1990). *THE PROCESSES OF TECHNOLOGICAL INNOVATION*. LEXINGTON BOOKS.

Luciano Floridi. (2018). Soft ethics, the governance of the digital and the General Data Protection Regulation. *Royalsocietypublishing.Org*, *376*(2133). https://doi.org/10.1098/RSTA.2018.0081

M. PANIMALAR, & K. KANNAN. (2013). A Study on Employee Perception Towards Effectiveness And Impact Of Environment Management System At Tamil Nadu Cooperative Textile Processing Mill Ltd., Erode. *Journal of Business Management & Social Sciences Research (JBM&SSR)*, *2*(1). https://www.academia.edu/5715370/A_Study_on_Employee_Perception_Towards_Effectiveness_And_Impact_Of_Environment_Management_System_At_Tamil_Nadu_Cooperative_Textile_Processing_Mill_Ltd_Erode

Mahendrati, H. A., & Mangundjaya, W. (2020). *Individual Readiness for Change and Affective Commitment to Change: The Mediation Effect of Technology Readiness on Public Sector*. *431*(First 2019), 52–59. https://doi.org/10.2991/assehr.k.200407.010

Mahoney, T. A., & Weitzel, W. (1969). Managerial Models of Organizational Effectiveness. *Administrative Science Quarterly*, *14*(3), 357. https://doi.org/10.2307/2391131

Makarius, E. E., Mukherjee, D., Fox, J. D., & Fox, A. K. (2020). Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization. *Journal of Business Research*, *120*, 262–273. https://doi.org/10.1016/J.JBUSRES.2020.07.045

Malik, M., Andargoli, A., Chavez Clavijo, R., & Mikalef, P. (2024). A relational view of how social capital contributes to effective digital transformation outcomes. *The Journal of Strategic Information Systems*, *33*(2), 101837. https://doi.org/10.1016/J.JSIS.2024.101837

Malik, P., & Garg, P. (2017). The relationship between learning culture, inquiry and dialogue, knowledge sharing structure and affective commitment to change. *Journal of Organizational Change Management*, *30*(4), 610–631. https://doi.org/10.1108/JOCM-09-2016-0176

Management, G. R.-I. J. of E. and, & 2024, undefined. (2024). What Drives The Diffusion of AI Recruitment Systems in Swiss HRM? The Importance of Technological Expertise, Innovative Climate, Competitive Pressure. *Ojs.Lib.Unideb.Hu*, *9*(4). https://doi.org/10.21791/IJEMS.2024.029

Management, Y. D.-I. E. and, & 2025, undefined. (2025). Generative Artificial Intelligence (GenAI) in entrepreneurial education and practice: emerging insights, the GAIN Framework, and research agenda. *Springer*, *21*(1). https://doi.org/10.1007/S11365-025-01089-2

Marler, J. H., & Boudreau, J. W. (2017). An evidence-based review of HR analytics. *The International Journal of Human Resource Management*, 3–26.

Marler, J., Human, J. B.-T. I. J. of, & 2017, undefined. (2017). An evidence-based review of HR Analytics. *Taylor & FrancisJH Marler, JW BoudreauThe International Journal of Human Resource Management, 2017•Taylor & Francis*, *28*(1), 3–26. https://doi.org/10.1080/09585192.2016.1244699

Martin, K. (2022). Discrimination and Data Analytics. *Ethics of Data and Analytics*, 291–295. https://doi.org/10.1201/9781003278290-43/DISCRIMINATION-DATA-ANALYTICS-KIRSTEN-MARTIN

Matias, J. B. (2021a). *Cloud Computing Adoption Intention by MSMEs in the Philippines Cloud Computing Adoption Intention by MSMEs in the Philippines*. (August 2019). https://doi.org/10.1177/0972150918818262

Matias, J. B. (2021b). *Cloud Computing Adoption Intention by MSMEs in the Philippines Cloud Computing Adoption Intention by MSMEs in the Philippines*. (August 2019). https://doi.org/10.1177/0972150918818262

Meet Bhatt & Dr. Priyanka Shah. (2024a). EMPLOYEE PERCEPTION TOWARDS ACCEPTANCE OF HR ANALYTICS. *Annals of the Bhandarkar Oriental Research Institute*, *2024*(1), 115–123.

Meet Bhatt & Dr. Priyanka Shah. (2024b). EMPLOYEE PERCEPTION TOWARDS ACCEPTANCE OF HR ANALYTICS. *Annals of the Bhandarkar Oriental Research Institute*, *2024*(1), 115–123.

Meet Bhatt & Dr. Priyanka Shah. (2025a). Empowering Employees : Embracing Artificial Intelligence (AI) in HR Practices in Retail Sector. *International Journal of Business Analytics and Intelligence*, *13*(1), 23–31. http://publishingindia.com/ijbai/

Meet Bhatt & Dr. Priyanka Shah. (2025b). Empowering Employees : Embracing Artificial Intelligence (AI) in HR Practices in Retail Sector. *International Journal of Business Analytics and Intelligence*, *13*(1), 23–31.

Meijerink, J., Bos-Nehles, A., & de Leede, J. (2020). How employees' pro-activity translates high-commitment HRM systems into work engagement: the mediating role of job crafting. *International Journal of Human Resource Management*, *31*(22), 2893–2918. https://doi.org/10.1080/09585192.2018.1475402;ISSUE:ISSUE:DOI

Meijerink, J., Forrier, A., & Keegan, A. (n.d.). Reframing Organizations in the More-than-Human Society. *Egos.Org*. Retrieved December 24, 2025, from https://www.egos.org/jart/prj3/egos/main.jart?rel=de&reserve-mode=active&content-id=1756645686117&subtheme_id=1733175518787

Mikalef, P., Benlian, A., Conboy, K., & Tarafdar, M. (2025). Responsible AI starts with the artifact: Challenging the concept of responsible AI in IS research. *European Journal of Information Systems*, *34*(3), 407–414. https://doi.org/10.1080/0960085X.2025.2506875

Minbaeva, D. (2021). *Disrupted HR?*

M.M. Abdullah Al Mamun Sony a b, M. B. A. c d e , A. A. f , K. M. A. I. e , N. C. D. g , G. C. D. (2025). Bias in AI-driven HRM systems: Investigating discrimination risks embedded in AI recruitment tools and HR analytics. *Elsevier*. https://doi.org/https://doi.org/10.1016/j.ssaho.2025.102082

Molitor, M. (2020). *Effective Human-Robot Collaboration in the Industry 4 . 0 Context - Implications for Human Resource Management*. 0–54.

Money, W., & Turner, A. (2004a). Application of the technology acceptance model to a knowledge management system. *Proceedings of the Hawaii International Conference on System Sciences*, *37*(C), 3707–3715. https://doi.org/10.1109/hicss.2004.1265573

Money, W., & Turner, A. (2004b). Application of the technology acceptance model to a knowledge management system. *Proceedings of the Hawaii International Conference on System Sciences*, *37*(C), 3707–3715. https://doi.org/10.1109/hicss.2004.1265573

Murugesan, U., Subramanian, P., Srivastava, S., & Dwivedi, A. (2023). A study of Artificial Intelligence impacts on Human Resource Digitalization in Industry 4.0. *Decision Analytics Journal*, *7*, 100249. https://doi.org/10.1016/J.DAJOUR.2023.100249

nasscom Technology & Leadership Forum 2024. (2024). https://www.nasscom.in/ntlf2024/

Nawaz, N., Arunachalam, H., Pathi, B. K., & Gajenderan, V. (2024). The adoption of artificial intelligence in human resources management practices. *International Journal of Information Management Data Insights*, *4*(1). https://doi.org/10.1016/j.jjimei.2023.100208

Nguyen, T. H., & Le, X. C. (2022a). *An Extended Technology-Organization-Environment (TOE) Framework for Online Retailing Utilization in Digital Transformation : Empirical Evidence from Vietnam*.

Nguyen, T. H., & Le, X. C. (2022b). *An Extended Technology-Organization-Environment (TOE) Framework for Online Retailing Utilization in Digital Transformation : Empirical Evidence from Vietnam*.

Nyathani, R. (2023). AI in Performance Management: Redefining Performance Appraisals in the Digital Age. *Journal of Artificial Intelligence & Cloud Computing*, *2023*(December), 1–5. https://doi.org/10.47363/jaicc/2023(2)134

Ochmann, J., & Laumer, S. (2020). AI recruitment: Explaining job seekers' acceptance of automation in human resource management. *Proceedings of the 15th International Conference on Business Information Systems 2020 "Developments, Opportunities and Challenges of Digitization", WIRTSCHAFTSINFORMATIK 2020*. https://doi.org/10.30844/wi_2020_q1

Okoli, C. (2015). A Guide to Conducting a Standalone Systematic Literature Review. *Communications of the Association for Information Systems*, *37*(1), 43. https://doi.org/10.17705/1CAIS.03743

Omar Ashurbayev. (2025). LEADERSHIP'S ROLE IN AI ADOPTION AND DIGITAL TRANSFORMATION: BUILDING TRUST AND TRANSPARENCY FOR SUSTAINABLE INNOVATION. *Lajoe.Org*. https://doi.org/10.5281/zenodo.17634702

P. S Varsha. (2023). How can we manage biases in artificial intelligence systems – A systematic literature review. *International Journal of Information Management Data Insights*, *3*(1). https://doi.org/10.1016/j.jjimei.2023.100165

Pan, Y., Froese, F., Liu, N., Hu, Y., & Ye, M. (2021a). The adoption of artificial intelligence in employee recruitment: The influence of contextual factors. *Https://Doi.Org/10.1080/09585192.2021.1879206*. https://doi.org/10.1080/09585192.2021.1879206

Pan, Y., Froese, F., Liu, N., Hu, Y., & Ye, M. (2021b). The adoption of artificial intelligence in employee recruitment: The influence of contextual factors. *Https://Doi.Org/10.1080/09585192.2021.1879206*. https://doi.org/10.1080/09585192.2021.1879206

Pandey, Anamika., Balusamy, Balamurugan., & Chilamkurti, Naveen. (2023). *Disruptive artificial intelligence and sustainable human resource management : impacts and innovations : the future of HR*. 276. https://books.google.com/books/about/Disruptive_Artificial_Intelligence_and_S.html?id=bh_dEAAAQBAJ

Papageorgiou, D. (2018). Transforming the HR Function Through Robotic Process Automation: EBSCOhost. *Benefits Quarterly*, *34*, 27–30. http://web.b.ebscohost.com/ehost/detail/detail?vid=0&sid=42d055c4-f261-42f9-b02a-cbaabe2718b8%40sessionmgr102&bdata=JnNpdGU9ZWhvc3QtbGl2ZSZzY29wZT1zaXRl#AN=129603839&db=bth

Pareek, U., & Rao, T. (2015). *Designing and managing human resource systems*. https://books.google.com/books?hl=en&lr=&id=cDM1fJBlge4C&oi=fnd&pg=PR5&dq=Pareek,+U.,+%26+Rao,+T.+V.+(2003).+Designing+and+managing+human+resource+systems.+Oxford+%26+IBH.&ots=ByjsFKsUrV&sig=ZQJgfkE_F55WWbNYZnMcSS_dWU8

Park, I., Kim, D., Moon, J., Kim, S., Kang, Y., & Bae, S. (2022a). Searching for New Technology Acceptance Model under Social Context: Analyzing the Determinants of Acceptance of Intelligent Information Technology in Digital Transformation and Implications for the Requisites of Digital Sustainability. *Sustainability 2022, Vol. 14, Page 579*, *14*(1), 579. https://doi.org/10.3390/SU14010579

Park, I., Kim, D., Moon, J., Kim, S., Kang, Y., & Bae, S. (2022b). *Searching for New Technology Acceptance Model under Social Context : Analyzing the Determinants of Acceptance of Intelligent Information Technology in Digital Transformation and Implications for the Requisites of Digital Sustainability*.

Park, I., Kim, D., Moon, J., Kim, S., Kang, Y., & Bae, S. (2022c). *Searching for New Technology Acceptance Model under Social Context : Analyzing the Determinants of Acceptance of Intelligent Information Technology in Digital Transformation and Implications for the Requisites of Digital Sustainability*.

Peisl, T., & Edlmann, R. (2020). Exploring Technology Acceptance and Planned Behaviour by the Adoption of Predictive HR Analytics During Recruitment. *Communications in Computer and Information Science*, *1251 CCIS*, 177–190. https://doi.org/10.1007/978-3-030-56441-4_13/COVER

Pestonjee, D. (1988a). *Second Handbook of Psychological and Social Instruments*.

Pestonjee, D. (1988b). *Second Handbook of Psychological and Social Instruments*.

Phoolka, S. (2018). Effect of demographics on change readiness of executives working in indian mobile service sector. *Journal of Strategic Human Resource Management*, *7*(2), 24–39.

Pillai, R. (2021). *Adoption of artificial intelligence (AI) for talent acquisition in IT / ITeS organizations*. https://doi.org/10.1108/BIJ-04-2020-0186

Pillai, R., & Sivathanu, B. (2020). Adoption of artificial intelligence (AI) for talent acquisition in IT/ITeS organizations. *Benchmarking*, *27*(9), 2599–2629. https://doi.org/10.1108/BIJ-04-2020-0186/FULL/XML

Pina, A., Ferrão, P., Fournier, J., Lacarrière, B., & Corre, O. Le. (2019). ScienceDirect ScienceDirect Industry 4 . 0 Technology Implementation Impact to Industrial Technology Implementation Impact to Industrial Sustainable Energy in Indonesia : A Model Conceptualization Sustainable Energy in Indonesia : A Model Conceptualization Assessing the feasibility of using the heat temperature function for Rahmawan district heat demand forecast. *Energy Procedia*, *156*, 227–233. https://doi.org/10.1016/j.egypro.2018.11.133

Prikshat, V., Malik, A., & Budhwar, P. (2021a). AI-augmented HRM: Antecedents, assimilation and multilevel consequences. *Human Resource Management Review*, (September), 100860. https://doi.org/10.1016/j.hrmr.2021.100860

Prikshat, V., Malik, A., & Budhwar, P. (2021b). AI-augmented HRM: Antecedents, assimilation and multilevel consequences. *Human Resource Management Review*, (September), 100860. https://doi.org/10.1016/j.hrmr.2021.100860

quarterly, F. D.-M., & 1989, undefined. (n.d.). Perceived Usefulness, Perceived Ease of Use and User Acceptance of Information Technology. *Misq.Umn.Edu*. Retrieved December 22, 2025, from https://misq.umn.edu/misq/article-pdf/13/3/319/903/6_davis.pdf

Quddus Mohammed, A. (2019). HR ANALYTICS: A MODERN TOOL IN HR FOR PREDICTIVE DECISION MAKING. *Article in Journal of Management*, *6*(3), 51–63. https://doi.org/10.34218/JOM.6.3.2019.007

'Quiet Cracking' At Work: Empathy, Not AI-Driven Rating, To Fill In Void, Say HR Leaders | Nagpur News - The Times of India. (n.d.). Retrieved January 6, 2026, from https://timesofindia.indiatimes.com/city/nagpur/quiet-cracking-at-work-empathy-not-ai-

driven-rating-to-fill-in-void-say-hr-leaders/articleshow/124818046.cms?utm_source=chatgpt.com

Quinn, R. E., & Rohrbaugh, J. (1983). A spatial model of effectiveness criteria: Towards a competing values approach to organizational analysis. *Pubsonline.Informs.OrgRE Quinn, J RohrbaughManagement Science, 1983•pubsonline.Informs.Org*, *29*(3), 363–377. https://doi.org/10.1287/MNSC.29.3.363

R Jesuthasan, & 2017, undefined. (2017). HR's new role: rethinking and enabling digital engagement. *Emerald.ComR JesuthasanStrategic HR Review, 2017•emerald.Com*, *16*(2), 60–65. https://doi.org/10.1108/SHR-01-2017-0009/FULL/HTML

Rafferty, A. E., Jimmieson, N. L., & Armenakis, A. A. (2013). Change Readiness: A Multilevel Review. *Journal of Management*, *39*(1), 110–135. https://doi.org/10.1177/0149206312457417

Rafferty, A. E., & Minbashian, A. (2019). Cognitive beliefs and positive emotions about change: Relationships with employee change readiness and change-supportive behaviors. *Human Relations*, *72*(10), 1623–1650. https://doi.org/10.1177/0018726718809154

Raghavan, M., Barocas, S., Kleinberg, J., & Levy, K. (2020). Mitigating bias in algorithmic hiring: Evaluating claims and practices. *FAT* 2020 - Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*, 469–481. https://doi.org/10.1145/3351095.3372828;WGROUP:STRING:ACM

Rahman, M. A., Qi, X., & Jinnah, M. S. (2016a). Factors affecting the adoption of HRIS by the Bangladeshi banking and financial sector. *Cogent Business and Management*, *3*(1). https://doi.org/10.1080/23311975.2016.1262107

Rahman, M. A., Qi, X., & Jinnah, M. S. (2016b). Factors affecting the adoption of HRIS by the Bangladeshi banking and financial sector. *Cogent Business and Management*, *3*(1). https://doi.org/10.1080/23311975.2016.1262107

Rahman, M. A., Qi, X., & Jinnah, M. S. (2016c). Factors affecting the adoption of HRIS by the Bangladeshi banking and financial sector. *Cogent Business and Management*, *3*(1), 1–10. https://doi.org/10.1080/23311975.2016.1262107

Raisch, S., & Krakowski, S. (2021a). Artificial intelligence and management: The automation–augmentation paradox. *Journals.Aom.OrgS Raisch, S KrakowskiAcademy of Management Review, 2021•journals.Aom.Org*, *46*(1), 192–210. https://doi.org/10.5465/AMR.2018.0072

Raisch, S., & Krakowski, S. (2021b). Artificial intelligence and management: The automation–augmentation paradox. *Journals.Aom.OrgS Raisch, S KrakowskiAcademy of Management Review, 2021•journals.Aom.Org*, *46*(1), 192–210. https://doi.org/10.5465/AMR.2018.0072

Rajani Meshram, D. R., & Librarian, A. (2023). THE ROLE OF ARTIFICIAL INTELLIGENCE (AI) IN RECRUITMENT AND SELECTION OF EMPLOYEES IN THE ORGANISATION. In *Issue 9s RUSSIAN LAW JOURNAL: XI*.

Ranawaka, R. A. T. K. G., Ranathunga, Y. S., Sudarvannan, N., & Karunathilake, I. M. (2020). Readiness for technology based teaching among undergraduates of faculty of education, University of Colombo. *South-East Asian Journal of Medical Education*, *13*(2), 86. https://doi.org/10.4038/seajme.v13i2.215

Ranjitha S, & Usha K. (2021). *A study on application of Artificial Intelligence and its challenges in HR PJAEE, 18 (9) (2021) Ranjitha S 1 , Usha K 2 , A study on application of Artificial Intelligence and its challenges A study on application of Artificial Intelligence and its challe*. *18*(9), 112–120.

Raza, S. A., Qazi, W., Khan, K. A., & Salam, J. (2021a). Social Isolation and Acceptance of the Learning Management System (LMS) in the time of COVID-19 Pandemic: An Expansion of the UTAUT Model. *Journal of Educational Computing Research*, *59*(2), 183–208. https://doi.org/10.1177/0735633120960421

Raza, S. A., Qazi, W., Khan, K. A., & Salam, J. (2021b). Social Isolation and Acceptance of the Learning Management System (LMS) in the time of COVID-19 Pandemic: An Expansion of the UTAUT Model. *Journal of Educational Computing Research*, *59*(2), 183–208. https://doi.org/10.1177/0735633120960421

Reetu, Yadav, Dr. A., & Redhu, Dr. K. (2019). Relationship between Organizational Effectiveness and Its Predictors among IT Sector. *International Journal of Recent Technology and Engineering (IJRTE)*, *8*(4), 3194–3202. https://doi.org/10.35940/ijrte.d8024.118419

Research, V. V.-I. S., & 2025, undefined. (2025). Leveraging context: Re-thinking research processes to make "contributions to theory." *Pubsonline.Informs.Org*, *36*(3), 1871–1886. https://doi.org/10.1287/ISRE.2021.0048

Roberts, J., Baker, M., & Andrew, J. (2024). Artificial intelligence and qualitative research: The promise and perils of large language model (LLM) 'assistance.' *Critical Perspectives on Accounting*, *99*, 102722. https://doi.org/10.1016/J.CPA.2024.102722

Rogers, E. M. (1962). *DIFFUSION OF INNOVATIONS Third Edition*.

Rusly, F. H., Sun, P. Y.-T., & Corner, J. L. (2015). Change Readiness: Creating Understanding and Capability for the Knowledge Acquisition Process Fariza Hanim Rusly Peter Yih-Tong Sun James L Corner. *Journal of Knowledge Management*, *19*(6), 1204–1223.

Russell, S., & Norvig, P. (2010). Artificial Intelligence A Modern Approach Third Edition. *Pearson*. https://doi.org/10.1017/S0269888900007724

Sakka, F., Bin, H., & Smart, M. (2022). HUMAN RESOURCE MANAGEMENT IN THE ERA OF ARTIFICIAL INTELLIGENCE : FUTURE HR WORK PRACTICES , ANTICIPATED SKILL SET , FINANCIAL. *Academy of Strategic Management Journal*, *21*(1), 1–14.

Samuel Fosso Wamba, Ransome Epie Bawack, Cameron Guthrie, Maciel M. Queiroz, & Kevin Daniel André Carillo. (2021). Are we preparing for a good AI society? A bibliometric review and research agenda. *Elsevier - Technological Forecasting and Social Change*, *164*. https://doi.org/https://doi.org/10.1016/j.techfore.2020.120482

Saxena, M., Bagga, T., Gupta, S., & Mittal, A. (2022). Employees' Experiences of Accepting and Adopting HR Analytics: A Phenomenology Study. *The Open Psychology Journal*, *15*(1). https://doi.org/10.2174/18743501-V15-E2208040

Schafheitle, S., Analytics, J. M.-A. R. A. F. H., & 2024, undefined. (n.d.). Trust and control amidst intelligent technology at work: what we can learn from online labor platforms. *Elgaronline.Com*. Retrieved December 24, 2025, from https://www.elgaronline.com/edcollchap/book/9781035301096/chapter10.xml

Schoville, R. (2015). *Guiding Healthcare Technology Implementation : A New Integrated Guiding Healthcare Technology Implementation*. (March). https://doi.org/10.1097/CIN.0000000000000130

Science, G. R.-S. R. and B., & 2025, undefined. (2025). Exploring the acceptability of artificial intelligence in human resources management: insights from Swiss organizations. *Wiley Online Library*, *42*(4), 1061–1084. https://doi.org/10.1002/SRES.3140

Scott W. O'Connor. (2020, January 2). *Artificial Intelligence in Human Resource Management*. https://www.northeastern.edu/graduate/blog/artificial-intelligence-in-human-resource-management/

Sekaran, U., & Bougie, R. (2016). *Research Methods for Business A Skill-Building Approach.* (7th ed.). Wiley & Sons. https://www.scirp.org/reference/referencespapers?referenceid=2371540

Shakeel, A., & Siddiqui, D. A. (2021a). The effect of Technological, Organizational, Environmental, and Task Technology fit on the Adoption and usage of artificial intelligence (AI) for talent acquisition (TA): Evidence from the Pakistani banking sector. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3943071

Shakeel, A., & Siddiqui, D. A. (2021b). The effect of Technological, Organizational, Environmental, and Task Technology fit on the Adoption and usage of artificial intelligence (AI) for talent acquisition (TA): Evidence from the Pakistani banking sector. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3943071

Singh, G., Bhardwaj, G., Singh, S. V., & Kumar, V. (2020a). *Technology Acceptance Model to Assess Employee ' s Perception and Intention of Integration of Artificial Intelligence and Human Resource Management in IT Industry INTRODUCTION : Research and Methods of collection of Data : 29*(3), 11485–11490.

Singh, G., Bhardwaj, G., Singh, S. V., & Kumar, V. (2020b). *Technology Acceptance Model to Assess Employee ' s Perception and Intention of Integration of Artificial Intelligence and Human Resource Management in IT Industry INTRODUCTION : Research and Methods of collection of Data : 29*(3), 11485–11490.

Sivathanu, B., & Pillai, R. (2018). Smart HR 4.0 – how industry 4.0 is disrupting HR. *Human Resource Management International Digest*, *26*(4), 7–11. https://doi.org/10.1108/HRMID-04-2018-0059

Smith, C. (2019). An employee's best friend? How AI can boost employee engagement and performance. *Strategic HR Review*, *18*(1), 17–20. https://doi.org/10.1108/shr-11-2018-0092

Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of Business Research*, *104*, 333–339. https://doi.org/10.1016/J.JBUSRES.2019.07.039

Sohn, K., & Kwon, O. (2020a). Technology acceptance theories and factors influencing artificial Intelligence-based intelligent products. *Telematics and Informatics*, *47*, 101324. https://doi.org/10.1016/j.tele.2019.101324

Sohn, K., & Kwon, O. (2020b). Technology acceptance theories and factors influencing artificial Intelligence-based intelligent products. *Telematics and Informatics*, *47*, 101324. https://doi.org/10.1016/j.tele.2019.101324

Soleimani, M., Intezari, A., Arrowsmith, J., Pauleen, D. J., & Taskin, N. (2025). *The International Journal of Human Resource Management Reducing AI bias in recruitment and selection: an integrative grounded approach*. https://doi.org/10.1080/09585192.2025.2480617

Soni, J. (2022). A STUDY ON THE IMPACT OF ARTIFICIAL INTELLIGENCE ON HUMAN RESOURCE MANAGEMENT Report submitted in partial fulfilment of the award of the PGDM. *International Journal of Research and Analytical Reviews*. www.ijrar.org

Sony, M. M. A. A. M., Amin, M. Bin, Ashraf, A., Islam, K. M. A., Debnath, N. C., & Debnath, G. C. (2025). Bias in AI-driven HRM systems: Investigating discrimination risks embedded in AI recruitment tools and HR analytics. *Social Sciences & Humanities Open*, *12*, 102082. https://doi.org/10.1016/J.SSAHO.2025.102082

Sony, M. M. A. A. M., Nupur, A. A., Siddiqua, S., Tonny, A. F., Hasan, M. T., & Rashid, M. M. (2025). Empathy meets algorithms: Building human-centric workplaces with emotional and artificial intelligence. *Api.Taylorfrancis.Com*, 104–122. https://doi.org/10.4324/9781003608042-5

Soomro, M. A., Hizam-hanafiah, M., Abdullah, N. L., & Jusoh, M. S. (2021). *LogForum*. *17*(1), 83–96.

Stahl, B. C., & Eke, D. (2024). The ethics of ChatGPT – Exploring the ethical issues of an emerging technology. *International Journal of Information Management*, *74*, 102700. https://doi.org/10.1016/J.IJINFOMGT.2023.102700

Stone, M., Aravopoulou, E., Ekinci, Y., Evans, G., Hobbs, M., Labib, A., Laughlin, P., Machtynger, J., & Machtynger, L. (2020). Artificial intelligence (AI) in strategic marketing decision-making: a research agenda. *Emerald.Com*, *33*(2), 183–200. https://doi.org/10.1108/BL-03-2020-0022/FULL/HTML

Stone, P., Brooks, R., Brynjolfsson, E., … R. C. preprint arXiv, & 2022, undefined. (2016). Artificial intelligence and life in 2030: the one hundred year study on artificial intelligence. *Arxiv.Org*. https://arxiv.org/abs/2211.06318

Straub, E. T. (2009a). *Review of Educational Future Directions for Informal Learning*. https://doi.org/10.3102/0034654308325896

Straub, E. T. (2009b). Understanding technology adoption: Theory and future directions for informal learning. *Review of Educational Research*, *79*(2), 625–649. https://doi.org/10.3102/0034654308325896/ASSET/IMAGES/LARGE/10.3102_0034654308325896-FIG1.JPEG

Suseno, Y., Chang, C., Hudik, M., & Fang, E. S. (2021). Beliefs , anxiety and change readiness for artificial intelligence adoption among human resource managers : the moderating role of high- performance work systems. *The International Journal of Human Resource Management*, *33*(6), 1209–1236. https://doi.org/10.1080/09585192.2021.1931408

Taddeo, M., & Floridi, L. (2018). How AI can be a force for good. *Science.Org*, *361*(6404), 751–752. https://doi.org/10.1126/SCIENCE.AAT5991

Tam, C., & Oliveira, T. (2016a). Performance impact of mobile banking: using the task-technology fit (TTF) approach. *International Journal of Bank Marketing*, *34*(4), 434–457. https://doi.org/10.1108/IJBM-11-2014-0169/FULL/XML

Tam, C., & Oliveira, T. (2016b). Performance impact of mobile banking: using the task-technology fit (TTF) approach. *International Journal of Bank Marketing*, *34*(4), 434–457. https://doi.org/10.1108/IJBM-11-2014-0169/FULL/XML

Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management: Challenges and A path forward. *California Management Review*, *61*(4), 15–42. https://doi.org/10.1177/0008125619867910

Tan, P. J. B. (2013). Applying the UTAUT to understand factors affecting the use of english e-learning websites in Taiwan. *SAGE Open*, *3*(4). https://doi.org/10.1177/2158244013503837/ASSET/IMAGES/LARGE/10.1177_2158244013503837-FIG10.JPEG

Tayal, R., & Upadhyay, R. K. (2019). *The Development and Validation of the Organizational Effectiveness The Development and Validation of the Organizational Effectiveness Scale Using Confirmatory Factor Analysis*. (January). https://doi.org/10.1177/0972150918811720

Technology, S. V.-J. of C. S. and, & 2025, undefined. (2025). Leveraging Predictive Analytics for Strategic Compensation Forecasting. *Al-Kindipublishers.Org*. https://doi.org/10.32996/jcsts

Thakur, R. R., & Srivastava, S. (2017). From resistance to readiness : role of mediating variables Introduction. *Journal of Organizational Change Management*, *Vol. 31*(No. 1), 230–247. https://doi.org/https://doi.org/10.1108/JOCM-06-2017-0237

The Role of AI in HR Continues to Expand. (n.d.). Retrieved January 6, 2026, from https://www.shrm.org/in/topics-tools/research/2025-talent-trends/ai-in-hr?utm_source=chatgpt.com

Tornatzky, L. G., & Fleischer, Mitchell. (1990a). The processes of technological innovation | SpringerLink. *D.C. Heath & Company*, 298.

Tornatzky, L. G., & Fleischer, Mitchell. (1990b). The processes of technological innovation | SpringerLink. *D.C. Heath & Company*, 298.

https://books.google.com/books/about/The_Processes_of_Technological_Innovatio.html?id=EotRAAAAMAAJ

Úbeda-García, M., … B. M.-L.-J. of I. &, & 2025, undefined. (n.d.). Artificial intelligence, knowledge and human resource management: A systematic literature review of theoretical tensions and strategic implications. *Elsevier*. Retrieved December 24, 2025, from https://www.sciencedirect.com/science/article/pii/S2444569X25001544

Upadhyay, A. K., & Khandelwal, K. (2018a). Applying artificial intelligence: implications for recruitment. *Strategic HR Review*, *17*(5), 255–258. https://doi.org/10.1108/SHR-07-2018-0051/FULL/HTML

Upadhyay, A. K., & Khandelwal, K. (2018b). *Applying artificial intelligence: Implications for recruitment.* 255–258.

Vasant Tambe, M. (2025). Reshaping The Labor Landscape: Artificial Intelligence and The Future of Workforce Transformation in The Global Economy the Creative Commons Attribution 4.0 International License (CC BY NC ND). https://creativecommons.org/licenses/by/4.0. *Int. Jr. of Contemp. Res. in Multi. PEER-REVIEWED JOURNAL*, *4*, 39. https://doi.org/10.5281/zenodo.15375253

Vasiljeva, T., Kreituss, I., & Lulle, I. (2021a). Artificial Intelligence: The Attitude of the Public and Representatives of Various Industries. *Journal of Risk and Financial Management*, *14*(8), 339. https://doi.org/10.3390/jrfm14080339

Vasiljeva, T., Kreituss, I., & Lulle, I. (2021b). Artificial Intelligence: The Attitude of the Public and Representatives of Various Industries. *Journal of Risk and Financial Management*, *14*(8), 339. https://doi.org/10.3390/jrfm14080339

Venkatesh, V., & Davis, F. D. (2000a). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Pubsonline.Informs.OrgV Venkatesh, FD DavisManagement Science, 2000•pubsonline.Informs.Org*, *46*(2), 186–204. https://doi.org/10.1287/MNSC.46.2.186.11926

Venkatesh, V., & Davis, F. D. (2000b). Theoretical extension of the Technology Acceptance Model: Four longitudinal field studies. *Management Science*, *46*(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., & Davis, F. D. (2000c). Theoretical extension of the Technology Acceptance Model: Four longitudinal field studies. *Management Science*, *46*(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., & Davis, F. D. (2000d). Theoretical extension of the Technology Acceptance Model: Four longitudinal field studies. *Management Science*, *46*(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., Davis, F. D., & Zhu, Y. (2023). Competing roles of intention and habit in predicting behavior: A comprehensive literature review, synthesis, and longitudinal field study. *International Journal of Information Management*, *71*, 102644. https://doi.org/10.1016/J.IJINFOMGT.2023.102644

Venkatesh, V., Information, J. T.-J. of the association for, & 2016, undefined. (n.d.). Unified theory of acceptance and use of technology: A synthesis and the road ahead. *Academia.Edu*. Retrieved December 24, 2025, from https://www.academia.edu/download/74627454/SSRN_id2800121.pdf

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003a). User acceptance of information technology: Toward a unified view. *MIS Quarterly: Management Information Systems*, *27*(3), 425–478. https://doi.org/10.2307/30036540

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003b). User acceptance of information technology: Toward a unified view. *MIS Quarterly: Management Information Systems*, *27*(3), 425–478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J., quarterly, X. X.-M., & 2012, undefined. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *JSTOR*. https://www.jstor.org/stable/41410412

Venkateswaran, R., Ugalde, B., & T., R. (2019). Impact of Social Media Application in Business Organizations. *International Journal of Computer Applications*, *178*(30), 5–10. https://doi.org/10.5120/IJCA2019919126

Venugopal, M., Madhavan, V., Prasad, R., & Raman, R. (2024). Transformative AI in human resource management: enhancing workforce planning with topic modeling. *Cogent Business and Management*, *11*(1), 2432550. https://doi.org/10.1080/23311975.2024.2432550;JOURNAL:JOURNAL:OABM20;CTYPE:STRING:JOURNAL

Venumuddala, V. R., & Kamath, R. (2020). Emerging Technologies and Emergent Workplaces: Findings from an Ethnographic Study at an Indian IT Organization. *IFIP Advances in Information and Communication Technology*, *617*, 54–66. https://doi.org/10.1007/978-3-030-64849-7_6

Verma, S. (2025). Leveraging Predictive Analytics for Strategic Compensation Forecasting. *Journal of Computer Science and Technology Studies*, *7*(4), 283–288. https://doi.org/10.32996/JCSTS.2025.7.4.32

Virajanand Varma. (2012). *Organizational Chaneg Readiness Sentiments*.

Viswanath Venkatesh, M. G. M. G. B. D. and F. D. D. (2003). User acceptance of information technology: Toward a unified view. *JSTOR - MIS Quarterly*, *27*(3), 425–478. https://doi.org/https://doi.org/10.2307/30036540

Votto, A. M., Valecha, R., Najafirad, P., & Rao, H. R. (2021). Artificial Intelligence in Tactical Human Resource Management: A Systematic Literature Review. *International Journal of Information Management Data Insights*, *1*(2). https://doi.org/10.1016/j.jjimei.2021.100047

Vrontis, D., Christofi, M., Pereira, V., Tarba, S., Makrides, A., & Trichina, E. (2022). Artificial intelligence, robotics, advanced technologies and human resource management: a systematic review. *International Journal of Human Resource Management*, *33*(6), 1237–1266. https://doi.org/10.1080/09585192.2020.1871398

What is Artificial Intelligence (AI) - GeeksforGeeks. (n.d.). Retrieved January 4, 2026, from https://www.geeksforgeeks.org/artificial-intelligence/what-is-artificial-intelligence-ai/

What is Organizational Effectiveness? - SixSigma.us. (n.d.). Retrieved January 16, 2021, from https://www.6sigma.us/six-sigma-articles/what-is-organizational-effectiveness/

Wilkins, L., & Swatman, P. (2007). *' Through A Glass Darkly ': Can Theoretical Models for Technology Adoption Add Value to Enterprise Wide System Implementations ? ' Through A Glass Darkly ': Can Theoretical Models for Technology Adoption Add Value to Enterprise Wide System Implementations ?* (May 2014).

Woolley, A., Gupta, P., work, E. G.-H. of virtual, & 2023, undefined. (n.d.). Using AI to enhance collective intelligence in virtual teams: Augmenting cognition with technology to help teams adapt to complexity. *Elgaronline.ComAW Woolley, P Gupta, E GliksonHandbook of Virtual Work, 2023•elgaronline.Com*. Retrieved May 4, 2026, from https://www.elgaronline.com/edcollchap/book/9781802200508/book-part-9781802200508-11.xml

Wozney, L., & Abrami, P. (2016). *Implementing Computer Technologies : Teachers ' Implementing Computer Technologies : Teachers ' Perceptions and Practices*. (May).

Xu, N., & Wang, K. J. (2021a). Adopting robot lawyer? The extending artificial intelligence robot lawyer technology acceptance model for legal industry by an exploratory study. *Journal of Management and Organization*, *27*(5), 867–885. https://doi.org/10.1017/jmo.2018.81

Xu, N., & Wang, K. J. (2021b). Adopting robot lawyer? The extending artificial intelligence robot lawyer technology acceptance model for legal industry by an exploratory study. *Journal of Management and Organization*, *27*(5), 867–885. https://doi.org/10.1017/jmo.2018.81

Yap, & Ng, X. H. (2018). (2018). 기사 (Article) 와 안내문 (Information) [. *The Eletronic Library*, *34*(1), 1–5.

Zhu, S., Yang, H. H., MacLeod, J., Shi, Y., & Wu, D. (2018). Parents' and students' attitudes toward tablet integration in schools. *International Review of Research in Open and Distance Learning*, *19*(4), 222–241. https://doi.org/10.19173/IRRODL.V19I4.2970

Annexure A – Questionnaire

Acceptance and implementation of Artificial Intelligence (AI) in HR Practices for Organizational Effectiveness

Dear Respondent,
My name is Ms. Meet Bhatt, and I am currently Pursuing my PhD from Gujarat Technological University (GTU). I am reaching out to you as a potential respondent for a research project I am conducting on title "Acceptance and implementation of Artificial Intelligence in HR Practices for Organizational Effectiveness" My study aims to understand more about the potential applications of AI in human resources operations in the future and to determine if the employees are prepared for these changes. Your knowledge and perceptions would be extremely beneficial to the accomplishment of this research. Your input will aid in shaping the outcomes of this research and provide valuable data for analysis. The questionnaire should take no more than ten to fifteen minutes to complete. The response you provide will be confidential and will only be used for research purposes.

Thanks, and regards,
Meet Bhatt

Demographic Factors:

1. Name: ____________________________

2. Gender:
   a. Male b. Female c. Other

3. Age Group (Years):
   a. 18-25 b. 26-35 c. 36-45
   d. 46-55 e. Above 56

4. Experience (Years):
   a. 0-5 b. 6-10 c. 11-15
   d. 16-20 e. 21-25 f. 26-30
   g. 31-35 h. Above 35

5. Income (Annual):
   a. Less Than 5 Lakhs b. 5 to 10 Lakhs c. 11 to 15 Lakhs
   d. 16 to 20 Lakhs e. 21 to 25 lakhs f. 26 to 30 lakhs
   g. Above 30

6. Education:
   a. Diploma or equivalent b. Graduate
   c. Post-Graduate d. Doctorate
   e. Other
   ____

7. Industry you Work at:

a. IT/ITES
b. Pharmaceutical
c. Consumer Durables
d. Banking, Insurance, and other financial services
e. Management Consultancy /HR/Marketing/Digital/Consultancy
f. Retail
g. FMCG
h. Government
i. Healthcare
j. Telecommunications
k. Hospitality
l. Other___________________________

8. Size of the organization you work at (Approximate number of employees):

a. Below 100
b. 100-300
c. 300-500
d. Above 500

9. Level of management you work at:

a. Top Level of Management
b. Middle Level of Management
c. Bottom Level of Management

10. Location:

a. Central Gujarat
b. North Gujarat
c. Saurashtra
d. Kutch
e. South Gujarat
f. Other ___________

Select any one of the following for each question:

1. Strongly Agree (SA)
2. Agree (A)
3. Neutral (N)
4. Disagree (D)
5. Strongly Disagree (SD)

Questions	SD	D	N	A	SA
Artificial Intelligence – Section 1					
• **Technology Readiness**					
○ ***Technology Characteristics -Part 1*** • Artificial Intelligence provides ubiquitous & Reliable HR services • Artificial Intelligence improves the working of HR practices • Artificial Intelligence provides scalable services (add or reduce required features) • To manage HR functions Artificial Intelligence based applications are appropriate					

• AI based applications are compatible with the HR tasks • AI Based applications meets the HR function needs in your organization					
• **Perceived Value (Usefulness)**					
○ ***Relative Advantage – Part 2*** • Artificial Intelligence in HR Practices will provide competitive Advantage to organization • Artificial Intelligence is more beneficial than current system infrastructure (Automated or manual) used in organization • Artificial Intelligence in HR Practices lowers cost • Artificial Intelligence in HR practices saves time • AI in HR Practices makes business more efficient & effective					
○ ***Positive Attitude towards Change – Part 3*** • Artificial Intelligence in HR Practices gives me more control over my daily work lives. • Products and services that use Artificial Intelligence in HR are much more convenient to use. • I would like AI programs in HR Practices that allow me to tailor things to fit my own needs. • Artificial Intelligence in HR Practices makes me more efficient in my occupation. • I find using Artificial Intelligence in HR Practices to be mentally encouraging. • Learning about Artificial Intelligence can be as rewarding as the technology itself. • I feel confident that Artificial Intelligence tools in HR practices will follow through with what I instructed them to do.					
○ ***Creativity – Part 4*** • I am always open to learning about new and different technologies. • I can usually figure out new high-tech products and services without help from others • I can keep up with the latest technological developments in areas of my interest. • I enjoy the challenge of figuring out high-tech gadgets. • I find, I have fewer problems than other people in making technology work for me.					
○ ***Self-Efficacy – Part 5*** • I expect to succeed after Artificial Intelligence in HR Practices is implemented.					

• I have the skills that are required to work with AI enabled HR Practices. • When my organization implement Artificial Intelligence in HR Practices, I feel I can handle it with ease. • The organization will provide me with the training necessary to successfully implement AI in HR Practices.					
• **Perceived User-friendliness (Ease of use)**					
○ ***Complexity – Part 6*** • Whenever something gets automated, I need to check carefully that the Artificial Intelligence Tool or Software is not making mistakes. • For me, the human touch is very important when doing business with a company. • When I call a business, I prefer to talk to a person rather than Artificial Intelligence tool. • If I provide information to Artificial Intelligence, I can never be sure it really gets to the right place. • No one has explained to me why Artificial Intelligence must be implemented in our organization. • I don't understand how Artificial Intelligence will make things better than the way it is now. • According to me, my organization does not have a problem that will be addressed by Artificial Intelligence • I am concerned with the risks associated with this change that Artificial Intelligence in HR Practices will bring					
○ ***Resistance to change – Part 7*** • Artificial Intelligence is too complicated to be useful and are not designed for use by ordinary people/less techno-savvy people • It is helpful to have Artificial Intelligence product or service explained to me by a knowledgeable person. • There should be caution in replacing important people-tasks with technology because Artificial Intelligence can breakdown or get disconnected. • Artificial Intelligence tools always seems to fail at the worst possible time. • Artificial Intelligence may have health or safety risks that are not discovered until after people have used them. • Artificial Intelligence makes it too easy for governments and companies to spy on people. • This change will disrupt many of the personal relationships I have developed. • This change makes me question my future employment with current organization.					

Organization Readiness – Section 2					
• **Top Management Support – Part 8** • Top management considers AI adoption into HR Practices as important to the organization in digital transformation. • Top management effectively communicates its support for the use of AI in HR Practices • Top management is likely to invest funds in Artificial Intelligence related technologies in HR Practices. • Top management has established goals and standards to monitor the AI usage in the firms HR Practices • Top management encourages the employees to use AI in HR Practices					
• **Social Characteristics – Part 9** • People who are important to me think that I should use AI in HR Practices • People who influence my behaviour think that I should use AI in HR Practices • Most people surrounding me use AI tools in HR Practices • I get help from colleagues while using AI in HR Practices					
• **Performance Expectancy – Part 10** • Using AI in HR Practices would improve my performance • Using AI in HR Practices would save my time • I would use AI in HR Practices at any time and place • I would find AI in HR Practices useful					
• **Effort Expectancy -Part 11** • Learning to use AI in HR Practices is easy for me • Becoming skilful at using AI in HR Practices is easy for me • Interaction with AI system is easy for me					
• ***Environment Readiness – Section 3***					
• **Social Influence (Competitive Pressure) – Part 12** • It is a strategic requirement to utilize AI in HR Practices to compete in the market. • Our firm will be affected by competitive disadvantages if AI in HR Practices will not be adopted. • Our organization believe we will lose our market share if we do not adopt AI in HR Practices.					

• **External Support (Support from service Provider) - Part 13** • A specific person is available for assistance with difficulties when using AI enabled HR Practices • You have technological support to use AI based system in HR Practices • All the tools and peripherals required to use AI in HR practices are available in organization • The service provider would provide the training as and when required for AI in HR Practices					
• **Facilitating Conditions – Part 14** • Your organization have the resources necessary to use AI Systems in HR Practices • AI based system in HR Practices is compatible with HR Practices of our Organization • I feel that I can make informed decisions about which tools/resources to use within AI enabled HR system • I feel that you can fully take advantage of AI enabled HR practices thanks to the resources within the system					
• ***Behavioural Intention – Section 4 (Part 15)***					
• I would like to use Artificial Intelligence based HR Application • Assuming I had access to the AI based HR system, I intend to use it. • Given that I had access to the AI based HR system, I predict that I would use it. • I plan to use the AI based HR system in the future.					
Perceived AI Acceptance – Section 5					
User Acceptance					
○ *Compatibility – Part 16* • AI in HR Practices is consistent with current values and believes of organization • AI in HR Practices is compatible with managerial and operational needs • AI enabled HR system is compatible with existing systems • AI adoption is influence by previous adoption experience of other technologies					
○ *Uncertainty/Risk – Part 17* • I believe AI in HR Practices will keep my information confidential					

• I believe your transactions are secured using AI enabled HR system • I believe my privacy would not be divulged by AI enabled HR system					
• ***Perceived AI Implementation – Section 6***					
• I think the current technological infrastructure of our organization can support AI in HR systems • I believe that our organization is ready to adopt AI in HR practices • I think that the stakeholders involved in decision making process are ready to implement AI in HR Practices • The organization has a clear and well-defined strategy for implementing the AI in HR practices • The AI in HR practices implementation plan aligned with the overall organizational goals and objectives. • I believe that our organization has accessed and is ready to manage the risks associated with implementation of AI in HR practices • I suppose that training programs are in place to support the employees in adopting AI in HR practices • The technical support will be available during and after the implementation of AI systems in HR practices • The organization will be using well-defined criteria to evaluate the success of AI implementation in HR Practices • The implementation of AI in HR practices will increase the effectiveness of HR function • Implementation of AI in HR practices will enhance my professional development • AI in HR practices will be successful only if the system will be maintained regularly by technical staff					
• ***Organizational Effectiveness – Section 7***					
• The objectives of the organization for acceptance and implementation of AI in HR Practices are realistic and worthwhile • The superiors of the organization are ahead of time in planning and scheduling work related to AI in HR Practices • The communication I receive from top management regarding AI in HR Practices are well intentioned and well thought off • I usually want my immediate supervisor to tell you what to do regarding adoption of AI in HR Practices • When I have a problem related to my work, I like to solve it myself, without anybody is help? • I like to act according to my own judgement, regarding my job?					

• People in our organization do their duties irrespective of the fact that the management do not bother to reward for their sincerity on job? • People in our organization do their duties irrespective of the fact that the management will not care to punish them for their lapses in job? • I usually show up for work a little early, to get things ready • I often try on my own to find better or faster way of doing something on my job? • I often try to express my ideas on the job, either or after checking with my boss? • I am willing to put a great deal of effort beyond that normally expected to help this organization be successful. • I would accept almost any type of job assignment to keep working with current organization • I feel that I have a chance of advancement on this job • There are chances of my future growth in current organization • I find my values & organizations values very similar • I feel sense of pride in working for this organization					

Annexture B – Content Validity

By Industry Expert – Mr. Jay Hulani (Assistant Manager – Cluster HR (Gujarat Region), Samsung India Electronics Pvt. Ltd.

Comment :- The model is relevant to the organisations & questions are relatable with the industry norms. The Fraternity would be able to understand the questions properly.

SAMSUNG INDIA ELECTRONICS PVT. LTD.

SAMSUNG INDIA ELECTRONICS PVT. LTD.

(Jay Hulani)

SAMSUNG

Jay Hulani
Assistant Manager, Cluster HR

Samsung India Electronics Pvt. Ltd.
Office No 404-408, Shapath-V Building,
Opp - Karnavati Club, S G Road,
Ahmedabad - 380015
+91.97.3775.8745
jay.hulani@samsung.com

By Academic Expert Dr. Vishal Dahiya (Professor & Director iMCA - Sardar Vallabhbhai Global University)

Vishal Dahiya <director-i-mca@cpi.edu.in> Sat, Apr 6, 11:16 AM
to me

Dear Ms. Meet,

I have gone through your questionnaire , I found you have considered all the variables and parameters of your research topic.
It is an exhaustive analysis done by you.
I wish all the very best for your research publication and defence.

Regards,

Annexture C – List of Publications

1. UGC Care paper titled "EMPLOYEE PERCEPTION TOWARDS ACCEPTANCE OF HR ANALYTICS" by Meet Bhatt & Dr. Priyanka Shah (Meet Bhatt & Dr. Priyanka Shah, 2024b)
    - which is published in UGC care Journal (Annals of the Bhandarkar Oriental Research Institute ISSN: 0378-1143)
    - Meet Bhatt & Dr. Priyanka Shah. (2024). EMPLOYEE PERCEPTION TOWARDS ACCEPTANCE OF HR ANALYTICS. *Annals of the Bhandarkar Oriental Research Institute*, *2024*(1), 115–123.

2. Peer-Reviewed Paper Publication Titled "EMPOWERING EMPLOYEES: EMBRACING ARTIFICIAL INTELLIGENCE (AI) IN HR PRACTICES IN RETAIL SECTOR" (Meet Bhatt & Dr. Priyanka Shah, 2025b)
    - Which is published in International Journal of Business Analytics and Intelligence for Volume 13 Issue April
    - Meet Bhatt & Dr. Priyanka Shah. (2025). Empowering Employees : Embracing Artificial Intelligence (AI) in HR Practices in Retail Sector. *International Journal of Business Analytics and Intelligence*, *13*(1), 23–31. http://publishingindia.com/ijbai/

3. Scopus Emerald Publishing - Chapter Publication "ACCEPTANCE OF ARTIFICIAL INTELLIGENCE IN HUMAN RESOURCE PRACTICES BY EMPLOYEES"
    - Published in The Adoption and Effect of Artificial Intelligence on Human Resources Management, Part B, 13–30 Copyright © 2023
    - Meet Bhatt and Dr. Priyanka Shah Published under exclusive license by Emerald Publishing Limited doi:10.1108/978-1-80455-662-720230002
    - Bhatt, M., & Shah, P. (2023). Acceptance of Artificial intelligence in human resource practices by employees. In *The Adoption and Effect of Artificial Intelligence on Human Resources Management, Part B* (pp. 13-30). Emerald Publishing Limited.