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How Unified Factors Impact AI Usage Intention in the Workplace: A Study from Employee Perspective

Asima Asif, Muneeb Hussain, You Jun

School of Economics and Management Sciences, Chongqing University of Posts and Telecommunications, Chongqing, China

Abstract: The rapid advancement of Artificial Intelligence (AI) presents significant opportunities for enhancing workplace productivity and efficiency. As AI technologies continue to evolve, understanding the factors that influence employees' intention to adopt AI becomes increasingly crucial. This study investigates the psychological mechanisms underlying AI usage intention among employees, with a specific focus on three key predictors: Innovation Preference (IP), Social Influence (SI), and Performance Expectancy (PE). Additionally, Attitude toward AI is examined as a mediating variable, while Anxiety and Firm Reputation are explored as moderators that may affect these relationships. To examine these relationships, the study employed a structured, valid, and reliable questionnaire to gather data from employees in Pakistan. A total of 610 valid responses were collected and analyzed using hierarchical regression and moderation-mediation analysis. The results demonstrate that IP, SI, and PE significantly predict Attitude toward AI, which in turn has a strong impact on the Intention to use AI. The mediating role of Attitude was confirmed across all three predictors (IP, SI, and PE), indicating that a favorable attitude is a key psychological pathway through which these factors influence AI adoption intentions. The study's findings highlight the importance of fostering positive employee attitudes toward AI to promote its adoption in organizational settings. Furthermore, the moderation analysis reveals that Anxiety significantly moderates the relationship between Social Influence and Attitude, while Firm Reputation moderates the link between Attitude and Intention to use AI. These results emphasize the need for organizations to consider both psychological and contextual factors—such as emotional responses and perceived organizational credibility—when implementing AI technologies. Overall, the study contributes valuable insights into the social and psychological dynamics that shape technology adoption decisions in the workplace.

Keywords: AI Usage Intention; Unified Factors; AI in Workplace; Employee's AI Use; UTAUT Theory.

1. Introduction

1.1. Background

With the rapid development in Artificial Intelligence (AI), its use in the workplace has the potential to dramatically increase productivity and efficiency marking a pivotal shift in organizational strategies and operations in response to the digital age [12]. AI technologies have evolved at an unprecedented pace, providing new solutions that have the potential to transform the way in which employees perform their work. However, as AI continues to proliferate, understanding how employees perceive, accept, and intend to use these technologies within their workplaces is important. Employee's intention to use AI is shaped by personal preferences, social influences, and perceived benefits, underscoring the importance of gaining insights from the employees' perspective. AI's ability to provide a new way to revolutionize the workplace through the automation of routine work, the provision of data-driven insights, and the encouragement of more effective workflows is tremendous. The effective use of AI in the workplace, however, has a strong dependence on the intention of employees to use it.

Organizations, candidates, and employees view AI in different ways. For organizations, AI is a way to streamline their work, cut down costs, and gain a competitive advantage. Candidates see AI as a tool that automates the process of getting into the right job role and connecting them with the right job opportunities. Employees see AI as a way to augment their work performance, cut down on mundane work, and increase job satisfaction. In spite of the tremendous scholarly interest that AI has generated, it has a perceptible gap in understanding employees' intentions to use AI technologies. Previous research has directed its focus on the technological capabilities as well as organizational benefits of AI and has given less importance to the psychological factors that govern individuals' acceptance and use of AI in the workplace. Filling this gap is essential to devising strategies for the stimulation of the adoption of AI by employees and thereby increasing the effectiveness of AI implementations in organizational environments.

The key problem that this research aims to tackle is the lack of knowledge about what is driving employees' intention to use artificial intelligence (AI) in the workplace. More specifically, the research examines the effect of performance expectancy, social influence, and innovation preference on the intention to use AI among employees, with attitude as mediating variables, and anxiety and firm reputation as a moderating variable. The research attempts to fill up this gap by delivering an understanding of the psychological processes through which AI usage intention is generated from an employee perspective.

Knowledge about the working of AI usage intention from a psychological perspective assumes great significance for organizations that wish to adopt AI technologies successfully. The research would not only help in identifying new situational variables that are influencing AI adoption, but also contribute to determining the full picture of the determinants of intention to use AI among employees. The research is important from the perspective that it is the first of its kind that aims at delving into AI usage intention among employees in Pakistan and, thus, would offer a different kind of dimension about AI adoption taking place in a developing country setup. Moreover, the research would facilitate

comparison of AI usage intentions among employees in Pakistan and China that would generate further insights into the cultural and contextual discrepancies across AI adoption.

1.2. Problem Statement

Despite the rapid advancement and potential benefits of AI technologies, there remains a significant gap in understanding the factors that influence employees' intention to use AI in the workplace. Current literature often focuses on technological aspects or managerial perspectives, neglecting the psychological and social dimensions from the employees' viewpoint. This gap in knowledge poses a barrier to the effective implementation and acceptance of AI technologies. To bridge this gap, this study aims to explore the unified factors that impact AI usage intention from an employee perspective.

1.3. Research Questions

This study aims to address the following research questions:

Q1: How do unified factors impact AI usage intention among employees?

Q2: How does attitude moderates the relationship between unified factors and AI usage intention?

Q3: How does anxiety moderate the relationship between unified factors, and attitude?

Q4: How does firm reputation moderate the relationship between attitude and AI usage intention?

1.4. Research Significance

This study has several potential contributions:

Understanding Psychological Mechanics: This study aims to uncover the psychological mechanisms underlying AI usage intentions among employees, providing deeper insights into their attitudes.

Identifying New Situational Variables: The research identify new variables that influence AI usage intention, contributing to the broader literature on technology acceptance.

First AI Usage Intention Study in Pakistan: This study is the first to investigate AI usage intention among employees in Pakistan, offering valuable country-specific insights and contributing to the global discourse on AI usage intention.

2. Theory and Literature Review

The research is grounded theoretically on the Unified Theory of Acceptance and Use of Technology (UTAUT). This theory is a combination of different theories [5]. The UTAUT model, definitively articulated by [39], argues four key constructs that play a part in user acceptance as well as usage behavior: performance expectancy, effort expectancy, social influence, and facilitating conditions. The current research works on the first half of the theory, i.e. performance expectancy, social influence, and innovation preference (instead of effort expectancy), and their effect on AI usage intention. Intention to use AI is the main focus of this study from employee's perspective. Performance expectancy refers to the degree of which an individual believes that using AI will lead him or her to achieve gains in job performance which strongly influences AI usage intention [2]. Performance expectancy is expected to have a positive effect on AI usage intention. Employees who see AI as a tool that is helpful in boosting their job performance are more likely to be willing to use it. Social influence captures the degree to which an individual believes that important others think that he or she should use AI. Social influence is expected to have a positive effect on AI usage intention. When employees believe that their peers, supervisors, or even the organizational culture are behind the use of AI, they are more likely to adopt the technology. Given Pakistan's collectivist society, where group norms and relationships hold sway, social influence plays a pivotal role in shaping AI usage intention and acceptance [10].

Innovation preference, which replaces effort expectancy, captures an individual's predisposition to using new technologies and innovations. Innovation preference is hypothesized to have a positive effect on AI usage intention. Employees who are inclined to move in the direction of the adoption of new technologies are more likely to be willing to use AI. For example, in industries such as construction and oil and gas, the adoption of AI is influenced by its perceived functional value and reliability [12]. Similarly, trust in AI tools, like chatbots, can stimulate innovative applications in daily business operations. Understanding how AI can be innovatively used is crucial for organizations to enhance work practices and operational efficiency [23]. Attitude [17] is used as mediating variables in this study. Attitude is how employees personally feel about AI, whether they like or dislike it. It focuses on their individual feelings and opinions about using AI at work, without being influenced by their preference for new ideas, what others think, or how useful they believe AI will be for their job performance. [14], including feelings of excitement, anxiety, or fear. Positive affective states, may assist in the greater likelihood of AI usage intention, whereas negative affective states are likely to act as barriers.

Firm reputation is hypothesized to play a moderating role between the mediators (attitude) and the usage intention of AI. A strong firm reputation may contribute to the trust and confidence of employees in AI-based technologies and thus extend the positive effect of attitude on the usage intention of AI. A positive firm reputation can reinforce employees' positive attitudes towards AI adoption, thereby enhancing overall AI usage intention within the workplace. Many of the researches show that AI has influenced almost all aspects of business activities [19]. However most of the employees do not intend to use AI in the workplace because they believe companies cannot fulfill the ethical obligations needed for meaningful work [1] specially employees in Pakistan.

2.1. Innovation Preference

Innovation preference refers to the degree to which an individual enjoys using new and innovative technologies. In the context of AI adoption, this concept captures how willing employees are to embrace AI tools within their work environment. Existing literature highlights innovation preference as a critical driver of technology adoption behavior [27]. Employees who exhibit a strong preference for innovation tend to be early adopters, motivated by the potential benefits AI can provide, such as streamlining tasks, automating routine processes, and improving decision-making. This aligns closely with their intrinsic desire for efficiency and productivity enhancement. Research by [24] emphasizes that individuals with a higher innovation preference are more adaptable to technological changes, viewing AI as an opportunity for continuous learning and professional development rather than as a threat to job security.

This positive orientation toward AI supports the formation of favorable attitudes and a stronger intention to use AI in

their roles. Despite the recognized importance of innovation preference in general technology adoption, few studies have specifically examined its role in AI adoption from the employees' perspective, particularly in workplace contexts. This gap is significant because employees are the primary users who operationalize AI technologies. By focusing on employees' innovation preference, this study contributes to the theoretical understanding of AI adoption by linking an individual's inclination towards innovation with their attitudes and intention to use AI. Integrating this construct within the Unified Theory of Acceptance and Use of Technology (UTAUT) framework enhances the explanatory power of the model, addressing emotional and cognitive dimensions specific to AI. Thus, the inclusion of innovation preference enriches the theoretical framework and provides a nuanced insight into the human factors that facilitate AI adoption in organizations.

2.2. Social Influence

Social influence refers to the extent to which an individual's decisions to use technology are affected by others around them. In the context of AI adoption, social influence captures how much employees are swayed by colleagues, supervisors, or external factors—such as media and societal trends—in their choice to use AI technologies at work. This construct is especially significant in the Pakistani workplace, where cultural norms and social dynamics heavily shape technology acceptance behaviors [7]. Employees tend to rely on social cues and the behavior of influential figures within their professional networks when deciding whether to embrace new technologies like AI.

Previous research highlights that the attitudes and behaviors of peers and leaders within organizations play a vital role in encouraging or discouraging AI adoption [15]. Employees who perceive their social environment as supportive and positive toward AI are more likely to develop favorable attitudes and stronger intentions to use AI tools. This is partly driven by the human tendency to conform to social norms and expectations to maintain group cohesion. Conversely, skepticism or resistance from key individuals within the workplace can create barriers to AI acceptance and usage.

Moreover, informal communication channels—such as word-of-mouth and social interactions—serve as important sources of information and reassurance, helping employees form opinions about AI based on their peers' experiences. These social processes amplify the influence of social norms on employees' attitudes and intentions toward AI adoption. Despite the acknowledged importance of social influence in technology acceptance, few studies have explored its role specifically in the context of AI usage intentions from the employee perspective, especially within collectivist cultures like Pakistan.

This study addresses that gap by integrating social influence into the UTAUT framework to better explain how social factors interact with individual attitudes to shape AI adoption. By focusing on employees' social environment and cultural context, the research extends theoretical understanding of technology acceptance and highlights the critical role social influence plays in shaping AI usage intentions in the workplace.

2.3. Performance Expectancy

Performance expectancy refers to the degree to which an individual believes that using a technology will improve their job performance. In the context of AI adoption, this concept captures employees' perceptions of how AI tools can enhance their productivity, efficiency, and overall work quality. Performance expectancy is widely recognized as a fundamental factor shaping employees' attitudes and intentions toward adopting new technologies [18]. When employees believe that AI can simplify tasks, reduce errors, and support more informed decision-making, they are more motivated to integrate AI into their daily workflows.

Research has demonstrated that employees are particularly receptive to AI technologies that provide tangible benefits, such as AI-driven analytics tools that enable faster and more accurate data analysis, helping users identify patterns and trends that may otherwise remain hidden. Such technologies empower employees by enhancing their capabilities rather than threatening job security, which helps to reduce resistance to AI adoption. This perception of AI as an enabler rather than a replacement is crucial for fostering a positive attitude toward its use.

Additionally, organizational efforts to communicate the practical advantages of AI adoption—such as increased productivity, improved accuracy, and better decision support—play a vital role in shaping employees' performance expectancy. When these benefits are clearly articulated, employees develop stronger intentions to use AI, reinforcing the importance of performance expectancy as a key predictor in technology acceptance models [4].

Despite the extensive literature on performance expectancy in general technology adoption, relatively few studies have focused specifically on AI adoption from the employees' perspective. This study addresses that gap by incorporating performance expectancy within the UTAUT framework to better explain how employees' beliefs about AI's impact on their job performance influence their attitudes and intentions. This theoretical integration advances understanding of the cognitive factors driving AI adoption and underscores the importance of highlighting AI's practical value to promote its use in organizational settings.

2.4. Attitude

Attitude refers to employees' overall evaluation of AI in the workplace, capturing their feelings of favorability or unfavorability toward using AI technologies. It reflects an emotional and cognitive response shaped by perceptions of AI's relevance, usefulness, and impact on their work. As a psychological construct, attitude plays a crucial role in shaping employees' intentions to adopt and use AI, acting as a mediator that links external influences—such as innovation preference, social influence, and performance expectancy—to behavioral outcomes [17]. This mediating role of attitude is well established in foundational technology acceptance theories like the Theory of Planned Behavior [45] and the Technology Acceptance Model [33], where it consistently predicts behavioral intention.

In the context of AI adoption, a positive attitude toward AI enhances the likelihood of its use, while negative feelings, such as fear or skepticism, can hinder adoption. Employees who view AI as beneficial and relevant to their work are more inclined to integrate it into their daily tasks. Conversely, negative attitudes may arise from concerns about job security, complexity, or lack of understanding, which can act as barriers to AI acceptance. Existing literature highlights the importance of fostering positive attitudes through

organizational efforts such as effective communication, training programs, and addressing employee concerns directly [14].

Despite the broad recognition of attitude's importance in technology acceptance, there remains limited research focusing on attitude as a mediating factor specifically in AI adoption from the employee perspective. This study fills that gap by emphasizing attitude's mediating role within the UTAUT framework to better understand how employees' perceptions and beliefs translate into AI usage intentions. By doing so, it advances theoretical knowledge on how affective and cognitive evaluations influence AI adoption behaviors in the workplace, highlighting attitude as a key lever for organizations seeking to encourage AI use.

2.5. Anxiety

Anxiety is widely recognized as a significant emotional factor influencing employees' behavior toward adopting new technologies, including artificial intelligence (AI) in the workplace. Existing research consistently highlights anxiety as a negative emotional response that can create barriers to technology acceptance by causing feelings of uncertainty, fear, and resistance [21]. Specifically, anxiety related to AI often emerges from the fear of the unknown, concerns about potential job displacement, and the perceived complexity of AI systems [20]. These fears may result in employees feeling overwhelmed and reluctant to engage with AI, despite recognizing its potential benefits. This emotional barrier is critical because it can weaken the positive impact of key drivers such as innovation preference, social influence, and performance expectancy on employees' intention to use AI [3]. For example, even employees who prefer innovation or trust social cues to adopt AI may hesitate if anxiety is high, reducing the overall likelihood of AI usage.

This study builds on this understanding by hypothesizing that anxiety moderates the relationships between innovation preference, social influence, performance expectancy, and AI usage behavior. By doing so, it extends existing technology adoption models, such as the Technology Acceptance Model and Unified Theory of Acceptance and Use of Technology, which often overlook emotional responses like anxiety. The theoretical significance lies in recognizing anxiety not just as a direct predictor but as a contextual factor that shapes how other beliefs influence behavior. Furthermore, literature emphasizes that organizations can actively reduce anxiety through interventions like training, transparent communication, and creating a supportive environment that aligns AI adoption with career security and growth [9]. Incorporating anxiety as a moderating variable in this study highlights the importance of addressing employees' emotional responses to maximize AI acceptance, thereby offering practical insights for organizations aiming to implement AI technologies effectively. This focus on anxiety enriches the theoretical framework by linking cognitive, social, and emotional dimensions of technology adoption in the workplace, which is particularly relevant in the emerging context of AI use among employees.

2.6. Reputation

Firm reputation plays a crucial role in shaping employees' trust and confidence in adopting AI technologies in the workplace. A strong and positive reputation signals to employees that the organization is reliable, ethical, and committed to innovation, which can extend and strengthen the positive effects of employees' cognitive and emotional responses on their intention to use AI [13]. Even when employees may have mixed or negative attitudes toward AI itself, their positive attitude toward the firm can encourage continued engagement and loyalty, influencing their behavior in subtle but important ways. Existing research shows that AI is transforming nearly every aspect of business activities, but despite its potential, many employees remain reluctant to use AI at work due to concerns that organizations may fail to meet ethical standards or provide meaningful and responsible work environments [1]. This gap highlights the importance of firm reputation as a key factor in fostering positive attitudes toward AI.

Organizations known for transparency, ethical practices, and innovation tend to cultivate more favorable employee attitudes toward AI adoption, which in turn increases their usage intention [16]. On the other hand, negative perceptions about AI's reliability or doubts about organizational motives can damage employee trust, weakening the relationship between attitude and AI usage intention. Therefore, firm reputation acts as a critical moderator in the technology adoption process, influencing how employees' attitudes translate into their actual intention to use AI in the workplace. The theoretical significance of including firm reputation in this study lies in its ability to bridge organizational-level factors with individual technology acceptance, enriching traditional models that often focus narrowly on personal attitudes or technological attributes. By considering reputation, this research provides a more holistic understanding of AI adoption that accounts for the broader organizational context in which employees operate.

2.7. AI Usage Intention

AI usage intention refers to the degree to which an employee plans or intends to use AI technologies in their job tasks. This construct is central to understanding what drives employees to adopt AI in the workplace. In organizational AI adoption research, AI usage intention acts as a key mediator that connects employees' attitudes and perceptions with their actual behavior of integrating AI into daily work routines [6]. Existing literature shows that employees' intention to use AI is influenced by various factors, including how useful and easy to use they perceive AI to be [8]. When employees see AI as helpful in simplifying their work, improving productivity, and aiding decision-making, they are more motivated to use it. On the other hand, if they view AI as complicated, unreliable, or not fitting well with their tasks, their intention to adopt AI decreases, leading to resistance or reluctance.

The usability and ease of use of AI systems also play a significant role in shaping usage intention. AI tools that are user-friendly, intuitive, and well-integrated with employees' existing workflows encourage higher intention to use. In contrast, poorly designed or complex AI systems may discourage employees from adopting them. Furthermore, employees' attitudes towards AI, which are influenced by factors such as innovation preference, social influence, and performance expectancy, are critical determinants of their AI usage intention [11]. Positive attitudes towards AI correspond with greater willingness to explore and use AI technologies in everyday work, while negative attitudes contribute to resistance or rejection. Overall, AI usage intention reflects a complex combination of individual perceptions, attitudes, and behaviors, all shaped by personal, organizational, and

contextual influences [22]. Understanding these relationships is theoretically significant because it helps organizations identify which factors to target to increase employee willingness to use AI, thereby supporting successful AI integration and maximizing its potential benefits in the workplace [25].

3. Theoretical Framework

This research employs the Unified Theory of Acceptance and Use of Technology (UTAUT) as its theoretical foundation. UTAUT explains user intentions and subsequent technology usage behavior. The proposed model integrates UTAUT with additional constructs relevant to AI adoption.

3.1. Hypothesis Development

Artificial Intelligence (AI) technologies are transforming workplaces across industries by automating tasks, enhancing decision-making, and improving efficiency. Despite this rapid growth, there remains a significant gap in research regarding employees' intentions to use AI tools at work. Most existing studies on technology adoption focus broadly on organizational or managerial perspectives, or on general technology use, without specifically examining the employees' viewpoint concerning AI adoption in the workplace. This is an important omission because employees are the actual users who decide whether and how AI tools are incorporated into daily work processes. Understanding the factors that influence employees' intention to adopt AI is therefore critical for successful implementation and maximizing AI's benefits.

To address this gap, this study constructs a research model grounded in the well-established Unified Theory of Acceptance and Use of Technology (UTAUT), which explains user intentions and technology use behavior based on factors like performance expectancy and social influence [40]. UTAUT has been widely applied to study various technologies, but AI poses unique cognitive, emotional, and organizational challenges that UTAUT alone cannot fully capture. Hence, this study extends UTAUT by including additional constructs relevant to AI, such as innovation preference, anxiety, and firm reputation, to provide a more comprehensive explanation of AI adoption from the employee perspective.

Innovation Preference reflects an employee's tendency to embrace and try out new technologies. Prior research has shown that individuals with a high preference for innovation are more likely to adopt new tools because they are motivated by curiosity and the desire to improve their work practices [2]. For example, studies in industries like construction and oil and gas highlight that innovation preference drives the use of AI to improve operational reliability and efficiency [12]. However, no prior study has directly linked innovation preference to employees' intention to use AI in the workplace, especially in the context of developing countries like Pakistan. Therefore, this research hypothesizes:

H1: Innovation preference significantly influences AI usage intention.

Social Influence is another core UTAUT construct that has been demonstrated to affect technology adoption decisions, particularly in collectivist cultures where social norms and peer opinions carry great weight [40]. In Pakistan, where interpersonal relationships strongly impact workplace behavior, social influence plays a key role in shaping employees' attitudes and intentions toward AI adoption [10]. Despite this, most previous AI adoption studies have not explicitly examined social influence from the employee viewpoint. This study fills that gap by proposing:

H2: Social influence significantly influences AI usage intention.

Performance Expectancy — the belief that AI will improve job performance — has consistently been shown to be one of the strongest predictors of technology acceptance across numerous studies [2], [40]. Employees who perceive AI as a tool that can enhance productivity, automate repetitive tasks, and improve decision-making are more likely to intend to use it. Yet, existing AI research has rarely focused on employees' performance expectancy specifically. This study integrates this factor into the model to assess its effect on AI adoption intentions:

H3: Performance expectancy significantly influences AI usage intention.

Attitude towards AI represents employees' positive or negative feelings about using AI tools. While UTAUT does not explicitly include attitude as a core construct, many technology adoption studies highlight its importance as a mediator between external factors (e.g., innovation preference, social influence, performance expectancy) and behavioral intention [17]. Attitude captures the emotional and cognitive response to AI, which can either facilitate or hinder adoption. Fear, anxiety, or distrust can lead to negative attitudes, while enthusiasm and perceived benefits promote positive attitudes [14]. This study therefore considers attitude as a key mediator to explain how employees' beliefs and social environment translate into AI usage intentions:

H4a: Attitude mediates the relationship between innovation preference and AI usage intention.

H4b: Attitude mediates the relationship between social influence and AI usage intention.

H4c: Attitude mediates the relationship between performance expectancy and AI usage intention.

Anxiety towards AI is an emotional response that reflects employees' fear, uncertainty, or discomfort with using AI tools. While UTAUT acknowledges facilitating conditions and effort expectancy, it does not adequately address emotional barriers like anxiety, which have been shown in other studies to negatively impact technology adoption [2]. Anxiety can weaken or distort the effects of innovation preference and performance expectancy on attitude, as even motivated and performance-focused employees might hesitate to use AI if they feel anxious. Additionally, anxiety may strengthen the effect of social influence because anxious employees tend to seek reassurance and guidance from peers or supervisors [17]. Prior research has mostly overlooked anxiety's moderating role in AI adoption, especially in workplace settings. This study thus hypothesizes:

H5a: Anxiety moderates the relationship between innovation preference and attitude.

H5b: Anxiety moderates the relationship between social influence and attitude.

H5c: Anxiety moderates the relationship between performance expectancy and attitude.

Firm Reputation represents employees' perceptions of their organization's trustworthiness, ethical standards, and support for innovation. Research suggests that when employees trust their organization and believe it values ethical conduct, they feel more confident adopting new technologies, including AI [19]. This is especially relevant in contexts like Pakistan where concerns about organizational ethics and reliability can

hinder technology acceptance [1]. Despite this, firm reputation has rarely been examined as a moderator in AI adoption models. This study contributes theoretically by integrating firm reputation as a factor that strengthens the link between positive attitude and AI usage intention:

H6a: Firm reputation moderates the relationship between attitude and AI usage intention.

3.2. Conceptual Model

The conceptual model Figure 3.1 consists of three independent variables: Innovation Preference, Social Influence, and Performance Expectancy, which influence the dependent variable, AI Usage Intention. Attitude serves as a mediating variable, linking the independent variables to the intention to use AI. Furthermore, Anxiety acts as a moderating variable between the independent variables and Attitude, potentially altering how the independent variables influence employees' attitudes towards AI. Additionally, Firm Reputation is hypothesized to moderate the relationship between Attitude and AI Usage Intention, potentially enhancing or weakening the impact of employees' attitudes on their intention to use AI. This model aims to provide a comprehensive understanding of the factors influencing AI adoption in the workplace, incorporating cognitive, emotional, and organizational factors to explain AI usage intention.

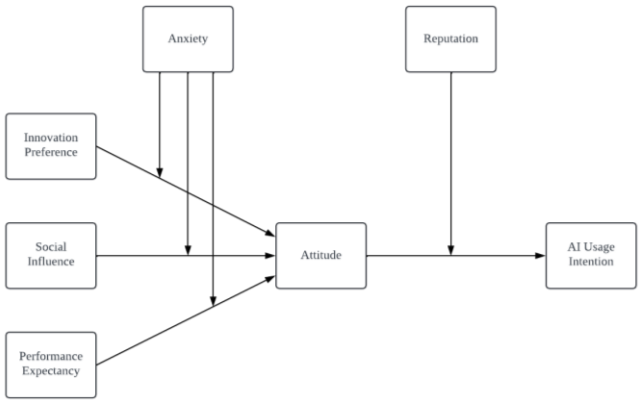

Figure 3.1. Conceptual Framework

4. Methodology

4.1. Measurement Instrument

To test our hypotheses, we developed a questionnaire by adapting scales previously employed in the specialized literature. Innovation Preference was assessed using four items adapted from [41]. Social Influence was measured with three items from [42]. Performance Expectancy was evaluated using three items based on [5]. Attitude was measured using three items from [5]. Anxiety was assessed using three items from [43]. Firm Reputation was measured with three items from [37]. AI Usage Intention was measured with three items from [44]. A five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree) was used to measure all variables in this study. Table 4.1 shows all the scales.

Table 4.1. Measurement Scales

Constructs	Items	Reference
Innovation Preference	1) I enjoy experimenting with new AI technologies in both my professional tasks and workflows. 2) If I hear about a new AI technology that could enhance my job, I actively look for opportunities to try it out. 3) Among my colleagues, I am usually the first to explore and adopt new AI technologies in the workplace. 4) In general, I am confident and willing to try out new AI technologies that could improve my work performance.	Tian [41]
Social Influence	1) People who influence me at work, such as managers or colleagues, think that I should adopt AI and related technologies. 2) People whose professional opinions I respect encourage me to adopt AI and related technologies in my job. 3) In general, the people around me have positive views about adopting AI and related technologies to improve workplace performance and efficiency.	James [42]
Performance Expectancy	1) I believe that AI technologies will significantly enhance my efficiency in performing work-related tasks. 2) I believe using AI tools will increases my ability to successfully complete important tasks in my job. 3) Incorporating AI technologies into my work will increases my overall productivity and effectiveness.	Dwivedi [5]
Attitude	1) I like the idea of using AI tools and technologies. 2) Using the AI tools and technologies is a good idea. 3) Using the AI tools and technologies is a wise idea.	Dwivedi [5]
Anxiety	1) I would feel uneasy if I were required to perform job tasks involving heavy reliance on AI technologies. 2) I am concerned that the increasing use of AI in the workplace could negatively impact job opportunities for employees. 3) I feel that over-reliance on AI technologies in the workplace might lead to unforeseen negative consequences.	Nomura [43]
Intention	1) I intend to use AI technologies in my work in the future. 2) Assuming that I had access to AI technologies, I predict that I would use them in my job. 3) I plan to use AI technologies to support and enhance my work tasks.	Das [44]
Firm Reputation	1) My company has a reputation as being an excellent employer. 2) My company is known as a great place to work. 3) My company has a reputation for being a high-quality employer.	Highhouse [37]

4.2. The Sampling

The sample was collected from Pakistan using google questionnaire. Questionnaire was screened strictly and those participants were strictly eliminated who failed to pass the screening questions, whose answers were regular and whose filling time was either too short or too long. 610 valid responses were collected in total. Prior power analysis was done to determine the sample size. G*Power was used with the following settings: alpha: 0.05; effect size: 0.15; and power: 0.95. The sample size needed for this study calculated by G power is 146 and the sample size of this study thus met the requirement. Table 4.2 presents the demographic characteristics of the participants.

4.2.1. Gender Distribution

The sample consists of 610 respondents, with a gender distribution showing that the majority of participants are male (56.9%, n = 347) while female respondents make up 43.1% (n = 263) of the sample (M = 1.43, SD = 0.496). This indicates a slight male predominance, although the gender distribution remains relatively balanced overall.

4.2.2. Age Distribution

The majority of participants are in the 20-30 years age group (42.5%, n = 259), followed by those aged 31-40 years (40.5%, n = 247). Smaller proportions of respondents fall into the under 20 years (6.1%, n = 37) and above 50 years (1.6%, n = 10) categories (M = 2.58, SD = 0.807). This shows a predominant participation from younger adults, which is consistent with trends in technology adoption, where younger populations tend to be more engaged with emerging innovations such as artificial intelligence (AI).

4.2.3. Educational Background

The majority of respondents are Bachelor's degree holder (34.9%, n = 213), followed by those with a Master's degree (29%, n = 177). A smaller percentage of participants possess a Diploma (15.7%, n = 96) or PhD (3.3%, n = 20) (M = 2.86, SD = 1.115). The data shows a significant representation of individuals with higher educational qualifications, particularly at the Bachelor's and Master's levels. Higher

educational attainment is often associated with greater professional experience and access to better-paying jobs, which could influence the participants' familiarity with or intention to engage with technologies like AI.

4.2.4. Salary Distribution

The salary distribution reveals that the majority of participants earn between 40,001-60,000 (32.5%, n = 198), followed by those earning in the range of 20,000-40,000 (16.9%, n = 103) and 60,001-80,000 (18%, n = 110). A smaller proportion of respondents report earning more than 100,000 (9%, n = 55) (M = 3.52, SD = 1.354). These results indicate a broad spectrum of income levels, with the most respondents earning within the mid-range salary bracket. Furthermore, higher levels of education are likely linked with higher income levels, suggesting that individuals with advanced degrees or qualifications are more likely to occupy higher-paying roles.

4.2.5. Job Experience

When examining job experience, the largest proportion of respondents (31.3%, n = 191) have between 3-4 years of work experience, followed by those with 1-2 years (26.9%, n = 164). Smaller proportions report having 5-6 years (17.5%, n = 107), 7-8 years (13.9%, n = 85), or 8-10 years or more (10.3%, n = 63) of experience (M = 2.50, SD = 1.300). This suggests that the majority of participants are relatively early in their careers, with a significant proportion having 1-4 years of experience. This trend is consistent with the assumption that younger individuals, who tend to have less job experience, are more engaged with technological advancements like AI.

Table 4.2. Demographics of Participants

Item	Category	Frequency	Percentage Rates (%)
Gender	Male	347	56.9
	Female	263	43.1
Age	Under 20 years old	37	6.1
	20-30 years old	259	42.5
	31-40 years old	247	40.5
	41-50 years old	57	9.3
	Above 50 years old	10	1.6
Education	High School and Below	104	17.0
	Diploma	96	15.7
	Bachelor	213	34.9
	Master	177	29.0
	PhD	20	3.3
Salary	Less than 20000	35	5.7
	20000-40000	103	16.9
	40001-60000	198	32.5
	60001-80000	110	18.0
	80001-100000	109	17.9
	More than 100000	55	9.0
Job Experience	1-2 years or less	164	26.9
	3-4 years	191	31.3
	5-6 years	107	17.5
	7-8 years	85	13.9
	8-10 years or more	63	10.3

5. Results

5.1. Reliability and Validity

SPSS and Smart PLS was used to test data reliability. The reliability and validity analysis of the constructs reveals strong internal consistency and robust measurement properties demonstrated by the Cronbach's alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) values. The Cronbach's alpha values for all constructs range from 0.838 to 0.896, exceeding the accepted threshold of 0.7. This indicates excellent internal consistency, signifying that the items within each construct are consistently measuring the same underlying concept. High Cronbach's alpha values suggest that the measurement scales are reliable and provide consistent results across different samples. These results indicate that the scales used to measure each construct are reliable, ensuring the validity of the findings. The Composite Reliability (CR) values for all constructs fall between 0.863 and 0.917, further supporting the internal consistency of the constructs. CR is a more robust indicator of reliability in the context of structural equation modeling, as it considers the error variance of the individual items. Values exceeding the threshold of 0.7 suggest strong internal consistency and reliability, confirming that the constructs measured in this study are stable and dependable. The Average Variance Extracted (AVE) values for the constructs range from 0.678 to 0.788, all of which are above the recommended threshold of 0.5, indicating good convergent validity. AVE is an indicator of the amount of variance captured by the items within a construct. Higher AVE values signify that the construct is well represented by its indicators and that the items share significant common variance. These results shows that the constructs measured are valid, as the items are sufficiently capturing the intended latent constructs. The factor loadings for the items across all constructs are strong, ranging from 0.805 to 0.896, and all exceed the minimum threshold of 0.7. Standardized factor loadings reflect the strength of the relationship between the observed variables (items) and the latent constructs they represent. Higher factor loadings indicate a strong connection between the items and their respective constructs, further confirming that the items are valid indicators of the latent constructs they measure. Table 5.1 shows reliability and validity.

Table 5.1. Reliability and Validity

Constructs	Items	Standard Factor Loading	Cronbach's a	CR	AVE
Innovation Preference	IP1	0.862	0.884	0.912	0.721
	IP2	0.835			
	IP3	0.843			
	IP4	0.858			
Social Influence	SI1	0.870	0.870	0.900	0.750
	SI2	0.872			
	SI3	0.856			
Performance Expectancy	PE1	0.886	0.840	0.883	0.715
	PE2	0.825			
	PE3	0.826			
Attitude	AT1	0.835	0.880	0.897	0.744
	AT2	0.884			
	AT3	0.869			
Anxiety	A1	0.862	0.838	0.882	0.678
	A2	0.856			
	A3	0.817			
Intention	I1	0.839	0.896	0.863	0.714
	I2	0.827			
	I3	0.805			
Firm Reputation	FR1	0.898	0.895	0.917	0.788
	FR2	0.879			
	FR3	0.887			

The Innovation Preference construct has factor loadings ranging from 0.835 to 0.862 for its items (IP1 = 0.862, IP2 = 0.835, IP3 = 0.843, IP4 = 0.858). These values reflect a strong relationship between the items and the construct, and the corresponding t-values were highly significant, further validating the robustness of the measurement model. The Cronbach's alpha for Innovation Preference is 0.884, the Composite Reliability is 0.912, and the Average Variance Extracted is 0.721, all of which suggest high reliability and convergent validity for this construct.

The Social Influence construct has factor loadings ranging from 0.856 to 0.872 (SI1 = 0.870, SI2 = 0.872, SI3 = 0.856), indicating that the items are strong and consistent indicators of the latent construct. The corresponding Cronbach's alpha for Social Influence is 0.870, the Composite Reliability is 0.900, and the AVE is 0.750, all of which reflect high internal consistency and convergent validity.

For Performance Expectancy, the factor loadings ranges from 0.825 to 0.886 (PE1 = 0.886, PE2 = 0.825, PE3 = 0.826). The Cronbach's alpha for Performance Expectancy is 0.840, the Composite Reliability is 0.883, and the Average Variance Extracted is 0.715, suggesting strong internal consistency and convergent validity.

For Attitude, the factor loadings for the items (AT1 = 0.835, AT2 = 0.884, AT3 = 0.869) are all above the 0.7 threshold, indicating a strong relationship between the items and the construct. The Cronbach's alpha for Attitude is 0.880, the Composite Reliability is 0.897, and the Average Variance Extracted is 0.744, suggesting excellent reliability and good convergent validity.

For Anxiety, the factor loadings are slightly lower compared to other constructs, ranging from 0.817 to 0.862 (A1 = 0.862, A2 = 0.856, A3 = 0.817). Despite this, the Cronbach's alpha is 0.838, the Composite Reliability is 0.882, and the Average Variance Extracted is 0.678, indicating acceptable reliability and convergent validity for this construct.

The Intention construct has factor loadings ranging from 0.805 to 0.839 (I1 = 0.839, I2 = 0.827, I3 = 0.805), with Cronbach's alpha at 0.896, Composite Reliability at 0.863, and Average Variance Extracted at 0.714, which suggests strong internal consistency and convergent validity for this construct. Firm Reputation construct has the highest factor loadings, ranging from 0.879 to 0.898 (FR1 = 0.898, FR2 = 0.879, FR3 = 0.887), with Cronbach's alpha of 0.895, Composite Reliability of 0.917, and Average Variance Extracted of 0.788. These values indicate excellent reliability and good convergent validity for Firm Reputation.

The results of the reliability and validity analyses shows that the constructs are both reliable and valid. The Cronbach's alpha, Composite Reliability, and Average Variance Extracted values all exceed the recommended thresholds, confirming that the constructs are robust and consistent. The factor loadings and t-values further validate the strong relationships between the items and their respective constructs.

Table 5.2. Mean, SD and Correlation

Constructs	Mean	SD	1	2	3	4	5	6	7
1. Innovation Preference	2.962	1.146	1						
2. Social Influence	2.932	1.191	0.305**	1					
3. Performance Expectancy	3.180	1.163	0.178**	0.105**	1				
4. Attitude	2.918	1.184	0.402**	0.285**	0.179**	1			
5. Anxiety	2.985	1.072	-0.177**	-0.148**	-0.206**	-0.136**	1		
6. Intention	3.032	1.211	0.382**	0.360**	0.434**	0.315**	-0.422**	1	
7. Firm Reputation	2.961	1.222	0.290**	0.153**	0.171**	0.273**	-0.299**	-0.165**	1

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The correlations among the constructs are displayed in Table 5.2. The Innovation Preference construct shows significant positive correlations with Social Influence ($r = 0.305$, $p < 0.01$), Attitude ($r = 0.402$, $p < 0.01$), Intention ($r = 0.382$, $p < 0.01$), and Firm Reputation ($r = 0.290$, $p < 0.01$). A negative correlation is observed with Anxiety ($r = -0.177$, $p < 0.01$), indicating that higher innovation preference is associated with lower anxiety levels. Social Influence is positively correlated with Innovation Preference ($r = 0.305$, $p < 0.01$), Attitude ($r = 0.285$, $p < 0.01$), Intention ($r = 0.360$, $p < 0.01$), and Firm Reputation ($r = 0.153$, $p < 0.01$). A negative correlation is observed with Anxiety ($r = -0.148$, $p < 0.01$), suggesting that social influence has a stronger positive impact on attitudes and intentions, while also negatively correlating with anxiety.

The Performance Expectancy (PE) construct shows moderate positive correlations with Innovation Preference ($r = 0.178$, $p < 0.01$), Attitude ($r = 0.179$, $p < 0.01$), Intention ($r = 0.434$, $p < 0.01$), and Firm Reputation ($r = 0.171$, $p < 0.01$). It exhibits a negative correlation with Anxiety ($r = -0.206$, $p < 0.01$), indicating that higher performance expectancy is linked to more favorable attitudes and intentions, as well as lower anxiety levels. Attitude is positively correlated with Innovation Preference ($r = 0.402$, $p < 0.01$), Social Influence ($r = 0.285$, $p < 0.01$), Performance Expectancy ($r = 0.179$, $p < 0.01$), Intention ($r = 0.315$, $p < 0.01$), and Firm Reputation ($r = 0.273$, $p < 0.01$). A negative relationship is found with Anxiety ($r = -0.136$, $p < 0.01$), highlighting the importance of attitude in fostering stronger intentions and a positive perception of the firm. The Intention construct shows strong positive correlations with Innovation Preference ($r = 0.382$, $p < 0.01$), Social Influence ($r = 0.360$, $p < 0.01$), Performance Expectancy ($r = 0.434$, $p < 0.01$), and Attitude ($r = 0.315$, $p < 0.01$). A negative correlation is also observed with Anxiety ($r = -0.422$, $p < 0.01$), suggesting that higher intentions to act are linked to lower anxiety levels. Anxiety has negative correlations with all other constructs, notably Innovation Preference ($r = -0.177$, $p < 0.01$), Performance Expectancy ($r = -0.206$, $p < 0.01$), Attitude ($r = -0.136$, $p < 0.01$), Intention ($r = -0.422$, $p < 0.01$), and Firm Reputation ($r = -0.165$, $p < 0.01$), indicating that higher anxiety levels are associated with lower preferences, performance expectations, attitudes, intentions, and perceptions of firm reputation. Firm Reputation is positively correlated with Innovation Preference $r = 0.290$, $p < 0.01$), Social Influence ($r = 0.153$, $p < 0.01$), Performance Expectancy ($r = 0.171$, $p < 0.01$), Attitude ($r = 0.273$, $p < 0.01$), and Intention ($r = 0.299$, $p < 0.01$). A negative correlation is observed with Anxiety ($r = -$

0.165, $p < 0.01$), suggesting that a higher perception of firm reputation is linked to more positive responses across the other constructs and lower anxiety levels. All correlations are statistically significant at the 0.01 level (2-tailed), highlighting the robustness and reliability of these relationships.

5.2. Multicollinearity Check

The multicollinearity of the constructs was assessed by examining the Tolerance and Variance Inflation Factor (VIF) values. Tolerance values greater than 0.1 and VIF values less than 10 generally indicate that multicollinearity is not a concern. The Innovation Preference construct shows a Tolerance value of 0.759 and a VIF of 1.318, indicating no significant multicollinearity with other constructs. For Social Influence, the Tolerance value is 0.868 and the VIF is 1.153, suggesting that it also does not suffer from multicollinearity. The Performance Expectancy construct has a Tolerance value of 0.918 and a VIF of 1.090, both of which are well within the acceptable range, indicating no multicollinearity issues.

The Attitude construct has a Tolerance value of 0.779 and a VIF of 1.284, further supporting the absence of multicollinearity. The Anxiety construct shows a Tolerance value of 0.920 and a VIF of 1.086, suggesting that it is not affected by multicollinearity. Finally, Firm Reputation exhibits a Tolerance value of 0.868 and a VIF of 1.152, also indicating no multicollinearity concerns. The Tolerance and VIF values in Table 5.3 for all constructs are well within acceptable thresholds, indicating that multicollinearity is not a significant issue in this dataset.

Table 5.3. Multicollinearity Check

Constructs	Tolerance	VIF
Innovation Preference	0.759	1.318
Social Influence	0.868	1.153
Performance Expectancy	0.918	1.090
Attitude	0.779	1.284
Anxiety	0.920	1.086
Firm Reputation	0.868	1.152

5.3. Testing Direct Effects

The regression analysis reveals several key insights into the factors influencing employees' intention to use AI. The model, which includes eight independent variables—Job Experience, Social Influence, Performance Expectancy, Gender, Innovation Preference, Qualification, Salary, and Age—explains about 36.7% of the variance in employees' intention to use AI, as indicated by the R^2 value of 0.367. This suggests that while the predictors explain a significant portion of the variance, other unaccounted factors may also contribute to AI adoption intentions. The Adjusted R^2 value of 0.359, which accounts for the number of predictors in the model, further supports the model's fit. In terms of overall significance, the ANOVA test yields an F-statistic of 43.568 and a p-value of 0.000, which confirms the model is statistically significant and that the relationship between the predictors and the dependent variable (AI usage intention) is not due to chance.

The regression results in Table 5.4 highlight the significant predictors of AI usage intention. The analysis of the direct effects provides a comprehensive understanding of how various factors influence an individual's intention (IN) to use or adopt a particular system. The findings reveal that Performance Expectancy (PE) exerts the strongest positive influence on intention, with a unstandardized coefficient (B) of 0.364 and a highly significant p-value ($p < 0.001$). This indicates that individuals who believe that the system will improve their job performance or productivity are much more likely to form an intention to use it. The strong t-value (10.396) further reinforces the robustness of this effect. Similarly, Social Influence (SI) demonstrates a significant and positive relationship with intention ($B = 0.244$, $p < 0.001$), suggesting that individuals who perceive encouragement, support, or expectations from others (such as peers, supervisors, or social networks) are more inclined to intend to use the system. This aligns with theories emphasizing the power of social norms and peer pressure in shaping technology adoption behaviors.

Another important factor, Innovation Preference (IP), also shows a significant and positive effect on intention ($B = 0.275$, $p < 0.001$). This finding implies that individuals who are more open to trying new ideas, technologies, or innovations are more likely to form a strong intention to use the system. The positive relationship indicates that fostering a culture of innovation can enhance adoption intentions among users. On the other hand, Age exhibits a negative and significant effect on intention ($B = -0.198$, $p = 0.042$). This suggests that as individuals age, their intention to adopt or use the system slightly decreases. While the effect is not as strong as other variables, it highlights that younger individuals tend to have higher adoption intentions, possibly due to greater familiarity with technology, less resistance to change, or higher perceived adaptability. Conversely, several demographic factors—Gender, Salary, Qualification, and Job Experience—do not significantly predict intention. Gender shows a small, positive but non-significant effect ($B = 0.110$, $p = 0.206$), indicating that being male or female does not substantially influence adoption intentions in this sample. Similarly, Salary ($B = 0.064$, $p = 0.129$) and Job Experience ($B = 0.059$, $p = 0.238$) also have non-significant effects, suggesting that an individual's income level or years of experience do not meaningfully shape their intention to use the system. Furthermore, Qualification has a small, negative but non-significant effect ($B = -0.048$, $p = 0.291$), indicating that educational background does not play a significant role in forming intention in this context.

Overall, the model explains approximately 36.7% of the variance in intention ($R^2 = 0.367$), which is a moderate level of explanatory power for a behavioral model. The F-statistic (43.568, $p < 0.001$) indicates that the overall model is statistically significant, meaning that the combination of predictors provides a meaningful explanation for variations in intention. In summary, the findings highlight that fostering perceptions of usefulness (performance expectancy), leveraging social influence, and encouraging openness to innovation are the key factors in driving intention to adopt a system, while demographic characteristics such as gender, salary, qualification, and job experience play a much smaller or negligible role.

Table 5.4. Direct Effects Testing

Direct Path	Effect	DV	Beta	SE	t-value	95% Confidence Interval (CI)		R^2	Adjusted R^2	F
						Lower	Upper			
Constant			0.778	0.254	3.063	0.279	1.277			
IP			0.275***	0.037	7.402	0.202	0.348			
SI			0.244***	0.035	6.907	0.174	0.313			
PE		IN	0.364***	0.035	10.396	0.296	0.433			
Age			-0.198	0.097	-2.036	-0.388	-0.007	0.367	0.359	43.568
Gender			0.110	0.087	1.267	-0.061	0.281			
Salary			0.064	0.042	1.520	-0.019	0.147			
Qualification			-0.048	0.045	-1.056	-0.136	0.041			
Job Experience			-0.069	0.059	-1.180	-0.184	0.046			

Note: * p < 0.05, ** p < 0.01, *** p < 0.001

5.4. Testing Mediating Effects

The mediation analysis reveals significant mediating effects for all three paths, demonstrating that Attitude acts as a mediator between the independent variables (Innovation Preference, Social Influence, and Performance Expectancy) and Intention.

5.4.1. Attitude Mediation Between Innovation Preference and Intention

The mediating role of Attitude (AT) in the relationship between Innovation Preference (IP) and Intention (IN) was examined using hierarchical regression and bootstrapped mediation analysis shown in Table 5.5. In the first stage, regression results demonstrated that IP had a statistically significant and positive effect on Attitude (β = 0.4325, SE = 0.0383, t = 11.290, 95% CI [0.3572, 0.5077], p < .001). This suggests that individuals with higher levels of innovation preference tend to form more favorable attitudes. The model including IP and the control variables (age, gender, salary, education, and job experience) explained approximately 18.63% of the variance in Attitude (R^2 = 0.1863), and the model was statistically significant (F = 23.003).

In the second stage, the dependent variable Intention (IN) was regressed on both the independent variable IP and the mediator AT, along with the same control variables. The results revealed that IP remained a significant predictor of Intention (β = 0.3524, SE = 0.0422, t = 8.344, 95% CI [0.2695, 0.4354], p < .001), and Attitude also significantly predicted Intention (β = 0.1817, SE = 0.0408, t = 4.454, 95% CI [0.1016, 0.2618], p < .001). The inclusion of Attitude in the model led to a reduction in the direct effect of IP on Intention, which is indicative of a partial mediation effect. This model accounted for 22.16% of the variance in Intention (R^2 = 0.2216), and the overall model fit was statistically significant (F = 24.477).

Table 5.5. Mediating Role of AT between IP and IN

DV	IV	Beta	SE	t-value	95% Confidence Interval (CI)		R^2	F
					Lower	Upper		
AT	Constant	2.1423***	0.2475	8.657	1.6563	2.6283	0.1863	23.003
	IP	0.4325***	0.0383	11.290	0.3572	0.5077		
	Age	-0.2663**	0.1061	-2.510	-0.4747	-0.0580		
	Gender	-0.2654**	0.0960	-2.763	-0.4540	-0.0768		
	Salary	0.0202	0.0463	0.437	-0.0706	0.1110		
	Education	0.0868	0.0494	1.758	-0.0102	0.1837		
	Job Exp	0.0971	0.0645	1.506	-0.0296	0.2238		
IN	Constant	1.9134	0.2628	7.279	1.3971	2.4296	0.2216	24.477
	IP	0.3524***	0.0422	8.344	0.2695	0.4354		
	AT	0.1817***	0.0408	4.454	0.1016	0.2618		
	Age	-0.2767**	0.1068	-2.590	-0.4865	-0.0669		
	Gender	0.0751	0.0968	0.775	-0.1151	0.2652		
	Salary	0.0936*	0.0463	2.020	0.0026	0.1846		
	Education	-0.0015	0.0496	-0.030	-0.0989	0.0959		
	Job Exp	-0.0697	0.0647	-1.077	-0.1969	0.0574		

Note: * p < 0.05, ** p < 0.01, *** p < 0.001

To further validate the mediation, a bootstrapping analysis with 5,000 resamples was performed to estimate the indirect effect of IP on IN through Attitude shown in Table 5.6. The indirect effect was found to be statistically significant (indirect effect = 0.0786, SE = 0.0207, 95% CI [0.0392, 0.1205], p < .001), as the confidence interval did not include zero. This provides robust support for the mediating role of Attitude. The findings suggest that individuals who have a stronger preference for innovation are more likely to develop a positive attitude, which subsequently enhances their intention. Therefore, Attitude acts as a crucial psychological mechanism that partially explains how innovation preference translates into behavioral intentions.

Table 5.6. Indirect Effect of IP on IN through AT

Path	Indirect Effect	SE	95% Confidence Interval (CI)
IP → AT → IN	0.0786	0.0207	0.0392, 0.1205

5.4.2. Attitude Mediation Between Social Influence and Intention

The study further investigated the mediating effect of Attitude (AT) in the relationship between Social Influence (SI)

and Intention (IN) shown in Table 5.7. In the first regression model, SI significantly predicted Attitude (β = 0.3684, SE = 0.0371, t = 9.938, 95% CI [0.2955, 0.4412], p < .001), indicating that greater perceived social influence is associated with more positive attitudes. This model, which also included the control variables (age, gender, salary, education, and job experience), accounted for 18.79% of the variance in Attitude (R^2 = 0.1879) and was statistically significant (F = 23.200).

In the second model, which regressed Intention on both SI and AT (while controlling for the same demographic factors), both predictors were found to be significant. Social Influence continued to significantly predict Intention (β = 0.2787, SE = 0.0421, t = 6.623, 95% CI [0.1961, 0.3612], p < .001), while Attitude also significantly contributed to Intention (β = 0.1813, SE = 0.0411, t = 4.409, 95% CI [0.1009, 0.2616], p < .001). Notably, the coefficient for SI decreased when Attitude was included in the model, suggesting partial mediation. This model explained 20.35% of the variance in Intention (R^2 = 0.2035), and the overall model was statistically significant (F = 21.842).

Table 5.7. Mediating Role of AT between SI and IN

DV	IV	Beta	SE	t-value	95% Confidence Interval (CI)		R^2	F
					Lower	Upper		
AT	Constant	2.2852***	0.2322	9.841	1.8291	2.7414	0.1879	23.200
	SI	0.3684***	0.0371	9.938	0.2955	0.4412		
	Age	-0.2720**	0.1054	-2.580	-0.4800	-0.0641		
	Gender	-0.2428*	0.0954	-2.545	-0.4307	-0.0549		
	Salary	0.0063	0.0458	0.137	-0.0841	0.0968		
	Education	0.0977*	0.0490	2.034	0.0031	0.1964		
	Job Exp	0.1083	0.0639	1.694	-0.0171	0.2337		
IN	Constant	1.9915***	0.2603	7.650	1.4796	2.5033	0.2035	21.842
	SI	0.2787***	0.0421	6.623	0.1961	0.3612		
	AT	0.1813***	0.0411	4.409	0.1009	0.2616		
	Age	-0.2855**	0.1062	-2.688	-0.4938	-0.0772		
	Gender	0.0584	0.0962	0.607	-0.1310	0.2478		
	Salary	0.0970*	0.0460	2.108	0.0060	0.1880		
	Education	-0.0081	0.0492	-0.165	-0.1043	0.0880		
	Job Exp	-0.0786	0.0643	-1.222	-0.2050	0.0479		

Note: * p < 0.05, ** p < 0.01, *** p < 0.001

To confirm the mediation effect, a bootstrapping procedure with 5,000 resamples was used to test the indirect effect of SI on IN via AT shown in Table 5.8. The bootstrapped indirect effect was statistically significant (indirect effect = 0.0668, SE = 0.0156, 95% CI [0.0390, 0.1001]), as the confidence interval did not include zero. These results provide strong evidence for the mediating role of Attitude in the relationship between Social Influence and Intention. In essence, the findings suggest that individuals who perceive higher levels of social influence are more likely to develop positive attitudes, which in turn increase their intention, thereby supporting the hypothesis of partial mediation.

Table 5.8. Indirect Effect of SI on IN through AT

Path	Indirect Effect	SE	95% Confidence Interval (CI)
SI → AT → IN	0.0668	0.0156	0.0390, 0.1001

5.4.3. Attitude Mediation Between Performance Expectancy and Intention

The mediation path from Performance Expectancy to Intention to Use AI through Attitude is shown in Table 5.9. The mediation analysis examined whether Attitude (AT) mediates the relationship between Performance Expectancy (PE) and Intention (IN). In the first regression model, PE significantly predicted Attitude (β = 0.2528, SE = 0.0407, t = 6.213, 95% CI [0.1728, 0.3327], p < .001), indicating that individuals who perceive greater usefulness or benefits from the system tend to have more favorable attitudes toward its use.

The model, which controlled for demographic variables (age, gender, salary, education, and job experience), accounted for 13.86% of the variance in Attitude (R^2 = 0.1386) and was statistically significant (F = 15.510). In the second regression model, Intention was regressed on both PE and Attitude while controlling for the same covariates.

Both PE (β = 0.2073, SE = 0.0440, t = 4.710, 95% CI [0.1209, 0.2936], p < .001) and Attitude (β = 0.1816, SE = 0.0415, t = 4.373, 95% CI [0.0998, 0.2634], p < .001) remained significant predictors of Intention. The inclusion of Attitude in the model slightly reduced the direct effect of PE on Intention, indicating a partial mediation. This model explained 17.19% of the variance in Intention (R^2 = 0.1719) and was statistically significant (F = 17.973).

Table 5.9. Mediating Role of AT Between PE and IN

DV	IV	Beta	SE	t-value	95% Confidence Interval (CI)		R^2	F
					Lower	Upper		
AT	Constant	2.2888***	0.2306	9.926	1.8361	2.7415	0.1386	15.510
	PE	0.2528***	0.0407	6.213	0.1728	0.3327		
	Age	-0.2389*	0.1064	-2.245	-0.4481	-0.0298		
	Gender	-0.2701**	0.0966	-2.795	-0.4603	-0.0798		
	Salary	0.0302	0.0463	0.652	-0.0605	0.1209		
	Education	0.0885	0.0495	1.788	-0.0077	0.1848		
	Job Exp	0.1013	0.0674	1.566	-0.0253	0.2280		
IN	Constant	1.9370	0.2638	7.345	1.4177	2.4564	0.1719	17.973
	PE	0.2073	0.0440	4.710	0.1209	0.2936		
	AT	0.1816	0.0415	4.373	0.0998	0.2634		
	Age	-0.2502	0.1067	-2.346	-04610	-0.0394		
	Gender	0.0177	0.0968	0.183	-0.1726	0.2081		
	Salary	0.0874	0.0463	1.889	-0.0040	0.1789		
	Education	0.0022	0.0493	0.045	-0.0944	0.0988		
	Job Exp	-0.0584	0.0646	-0.903	-0.1850	0.0682		

Note: * p < 0.05, ** p < 0.01, *** p < 0.001

To formally test the mediating effect, a bootstrapping procedure with 5,000 samples was used. The results confirmed a statistically significant indirect effect of PE on Intention via Attitude shown in Table 5.10 (indirect effect = 0.0459, SE = 0.0123, 95% CI [0.0236, 0.0718]), as the confidence interval did not include zero. These findings provide robust evidence that Attitude partially mediates the relationship between Performance Expectancy and Intention. In summary, individuals who perceive higher usefulness of the system develop more positive attitudes, which in tum enhance their behavioral intention to use it.

Table 5.10. Indirect Effect of PE on IN through AT

Path	Indirect Effect	SE	95% Confidence Interval (CI)
PE → AT → IN	0.0459	0.0123	0.0236, 0.0718

5.5. Testing Moderating Effects

The moderation analysis explores the interaction effects between the independent variables (Innovation Preference, Social Influence, and Performance Expectancy) with Anxiety on Attitude, and the interaction between Attitude and Firm Reputation on Intention and is shown by Table 5.11 and 5.12. A hierarchical multiple regression was conducted to examine the influence of demographic variables (age, gender, salary, qualification, job experience), main predictors (IP, SI, PE), the moderator (AN), and their interactions on the dependent variable (AT).

The moderation analysis results examine how Anxiety (AN) moderates the relationship between Innovation Preference (IP), Social Influence (SI), and Performance Expectancy (PE) on Intention (IN), while controlling for demographic variables: Age, Gender, Salary, Qualification, and Job Experience. Starting with the control variables across the models, Age consistently shows a significant negative effect on Intention across all models (e.g., Model 4: B = -0.220, $p < 0.001$), indicating that younger individuals are more likely to have higher Intention. Gender also shows a significant negative relationship with Intention (e.g., Model 4: B = -0.268, $p < 0.001$), suggesting that one gender group (likely females if coded 0/1) reports higher Intention. Other control variables, including Salary, Qualification, and Job Experience, are not significant predictors in any model, indicating minimal influence on Intention.

Moving to the predictors and interaction effects, Model 1 serves as the baseline with only control variables, showing a low explained variance ($R^2 = 0.014$). When the main predictors are added in Model 2, the model's explanatory power significantly increases ($R^2 = 0.217$, Adjusted $R^2 = 0.218$, Sig. F Change = 0.000***). Specifically, IP (B = 0.362, $p < 0.001$), SI (B = 0.157, $p < 0.001$), and PE (B = 0.090, $p < 0.001$) are all significant positive predictors of Intention, indicating that higher innovation preference, stronger social influence, and higher performance expectancy lead to greater intention. In Model 3, Anxiety (AN) is added as a predictor and has a small negative, non-significant effect (B = -0.041, p = n.s.), suggesting no direct effect on Intention. However, IP (B = 0.357, $p < 0.001$), SI (B = 0.153, $p < 0.001$), and PE (B = 0.084, $p < 0.01$) remain significant predictors, indicating their robust direct effects even when accounting for anxiety.

Model 4 includes the interaction (moderation) terms to test for moderation by Anxiety. Here, the interaction of IP*AN is not significant (B = 0.036, p = n.s.), indicating that Anxiety does not moderate the relationship between Innovation Preference and Intention. Similarly, the interaction term for PE*AN is not significant (B = -0.003, p = n.s.), suggesting no moderation effect of Anxiety on the Performance Expectancy–Intention relationship. However, the interaction term for SI*AN is significant (B = 0.185, $p < 0.001$), indicating that Anxiety does moderate the relationship between Social Influence and Intention. Specifically, the positive effect of Social Influence on Intention is stronger for individuals with higher levels of Anxiety. The overall model fit improves across steps, with R^2 increasing from 0.014 (Model 1) to 0.258 (Model 4). The Adjusted R^2 in Model 4 is 0.253, indicating that approximately 25% of the variance in Intention is explained by the final model. The F value for Model 4 is 14.709, and the Sig. F Change remains significant ($p < 0.001$), confirming the statistical significance of adding the interaction terms.

Table 5.11. Moderation of Anxiety

Predictors	Model 1	Model2	Model 3	Model 4
Constant	3.334***	3.361***	3.348***	3.505***
Age	-0.199	-0.195	-0.197	-0.220*
Gender	-0.214*	-0.236**	-0.239**	-0.268**
Salary	-0.008	-0.002	-0.002	-0.014
Qualification	0.059	0.072	0.074	0.086
Job Experience	0.105	0.080	0.087	0.081
IP	-	0.362***	0.357***	0.349***
SI	-	0.157***	0.153***	0.170***
PE	-	0.090*	0.084*	0.063
AN	-	-	-0.041	-0.060
IP*AN	-	-	-	-0.054
SI*AN	-	-	-	0.185***
PE*AN	-	-	-	0.045
R	0.119	0.465	0.467	0.508
R^2	0.014	0.217	0.218	0.258
Adjusted R^2	0.006	0.206	0.206	0.243
F Value	1.746	51.743	0.942	10.709
Sig. F Change	0.122	0.000***	0.332	0.000***

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

For Firm Reputation as a moderator, In the first model, only control variables were included—Age, Gender, Salary, Qualification, and Job Experience—to account for their baseline effects. Among these, Age showed a statistically significant negative effect, meaning that as individuals get older, their scores on the dependent variable tend to decrease slightly. The other control variables, including Gender, Salary, Qualification, and Job Experience, did not show significant effects at this stage. The explanatory power of this initial model was quite low, accounting for just 3.3% of the variance in the dependent variable.

In Model 2, the main predictor, AT, was introduced into the regression. The inclusion of AT had a substantial impact, with AT showing a strong and highly significant positive effect on the dependent variable. This indicates that individuals with higher attitudes tend to score higher on the outcome measure, confirming the importance of AT as a predictor. The effect of Age remained significant and negative, although slightly weaker. The addition of AT also markedly increased the explained variance, more than tripling it to 13.2%, demonstrating that AT is a key factor influencing the dependent variable. Other control variables continued to show no significant effects.

Model 3 extended the analysis by adding the proposed moderator, FR, as an additional predictor. FR also showed a significant positive effect, meaning that higher FR is associated with higher scores on the dependent variable, independent of AT. This suggests that FR itself is an important contributor to the outcome. Interestingly, the positive effect of AT was somewhat reduced in this model, likely because some of the variance explained by AT overlaps with FR. In addition to the main predictors, Salary became a significant positive predictor in this step, indicating that individuals with higher salaries tend to have higher outcome scores. The explanatory power of the model improved further to 17.6%, suggesting that including FR and Salary enhances the understanding of what drives the dependent variable.

Finally, Model 4 introduced the interaction term between AT and FR to formally test the moderation hypothesis—whether the effect of AT on the outcome changes depending on the level of FR. The interaction term was statistically significant and negative, which means that FR moderates the relationship between AT and the dependent variable in a way that weakens the positive impact of AT when FR is high. Put simply, while AT generally has a positive effect on the outcome, this effect diminishes as FR increases. Both AT and FR individually continue to have significant positive effects on the dependent variable, indicating their independent contributions. Salary also remains a significant positive predictor, while Age continues to exert a small negative effect. The overall explained variance of this final model is 18.3%, representing the highest level of variance accounted for among the models tested and confirming that including the interaction term provides a more complete explanation of the data.

In summary, the analysis reveals that Age negatively predicts the outcome, whereas AT and FR both positively predict it. The moderation analysis shows a more complex relationship where FR reduces the strength of the positive association between AT and the outcome. This suggests that interventions or interpretations considering the effect of AT on the dependent variable should take into account the level of FR, as the benefit of a positive attitude may be less pronounced when FR is high. This nuanced finding highlights the importance of examining interactions between predictors to fully understand their effects on outcomes.

Table 5.12. Moderation of Firm Reputation

Predictors	Model 1	Model2	Model 3	Model 4
Constant	3.490***	3.356***	3.391***	3.399***
Age	-0.172*	-0.129*	-0.158*	-0.153*
Gender	0.032	0.060	0.027	0.031
Salary	0.077	0.080	0.111*	0.113*
Qualification	-0.012	-0.030	-0.019	-0.025
Job Experience	-0.047	-0.084	-0.057	-0.058
AT	-	0.316***	0.251***	0.258***
FR	-	-	0.226***	0.219***
AT*FR	-	-	-	-0.082*
R	0.181	0.363	0.420	0.428
R^2	0.033	0.132	0.176	0.183
Adjusted R^2	0.025	0.123	0.167	0.172
F Value	1.197	1.135	0.106	1.103
Sig. F Change	4.095	68.551	32.865	4.798

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.6. Hypothesis Results

The analysis reveals significant relationships among key factors influencing individuals' intentions to adopt AI. Hypotheses H1, H2, and H3 were supported, indicating that innovation preference, social influence, and performance expectancy each have a significant effect on AI usage intention. This suggests that individuals who value innovation, are influenced by social pressures, or expect AI to enhance their performance are more likely to develop an intention to use AI technologies. Additionally, the mediation hypotheses H4a, H4b, and H4c were supported, demonstrating that attitude plays a mediating role in the relationships between innovation preference, social influence, and performance expectancy, and AI usage intention.

Individuals with a positive attitude toward AI are more likely to translate these factors into stronger intentions to adopt AI. Regarding the moderation effects of anxiety,

hypotheses H5a, H5b, and H5c explored whether anxiety moderates the relationships between innovation preference, social influence, and performance expectancy, respectively, on attitude. The results show that H5a and H5c were not supported, indicating that anxiety does not moderate the relationship between innovation preference and attitude, nor between performance expectancy and attitude.

This may be because individuals who prefer innovation are more open to new technologies and less influenced by anxiety, while beliefs about AI's performance benefits remain a strong, rational factor unaffected by anxiety.

In contrast, H5b was supported, revealing that anxiety moderates the relationship between social influence and attitude. Specifically, individuals experiencing anxiety are more likely to be influenced by social factors in shaping their attitude toward AI. This finding highlights that anxiety amplifies the effect of social influence, as anxious individuals may seek guidance or reassurance from others when considering AI adoption. Finally, hypothesis H6 was supported, confirming that firm reputation moderates the relationship between attitude and AI usage intention. This suggests that a strong and positive firm reputation enhances the influence of a user's positive attitude on their intention to use AI. Overall, these results demonstrate that while anxiety plays a significant moderating role in the social influence-attitude link, it does not significantly impact the relationships involving innovation preference or performance expectancy. The varying influence of anxiety underscores the complex interplay between cognitive, emotional, and social factors in shaping technology adoption behavior. Table 5.13 shows the hypothesis results.

Table 5.13. Hypothesis Results

Hypothesis	Result
H1: Innovation preference significantly influences the AI usage intention.	Supported
H2: Social influence significantly influences the AI usage intention.	Supported
H3: Performance expectancy significantly influences AI usage intention.	Supported
H4a: Attitude mediates the relationship between the Innovation Preference and AI usage intention.	Supported
H4b: Attitude mediates the relationship between the Social influence and AI usage intention.	Supported
H4c: Attitude mediates the relationship between the Performance expectancy and AI usage intention.	Supported
H5a: Anxiety moderates the relationship between the Innovation Preference and Attitude.	Not Supported
H5b: Anxiety moderates the relationship between the Social influence and Attitude.	Supported
H5c: Anxiety moderates the relationship between the Performance expectancy and Attitude.	Not Supported
H6a: Firm Reputation moderates the relationship between Attitude and AI usage intention.	Supported

6. Conclusion

6.1. Discussion & Conclusion

The findings of this study highlight the complex psychological factors that influence employees' intention to use Artificial Intelligence (AI) in the workplace. Performance expectancy, social influence, and innovation preference were all found to have significant positive effects on employees' intention to use AI, reinforcing previous research in technology adoption. Specifically, performance expectancy emerged as a powerful predictor, suggesting that employees are more likely to embrace AI when they perceive it as a tool that will enhance their job performance and efficiency. This aligns with the Technology Acceptance Model (TAM), which underscores the importance of perceived usefulness in technology adoption [39].

Social influence also played a critical role in shaping employees' attitudes toward AI. Employees who perceive that influential figures in their workplace support the use of AI are more likely to adopt the technology themselves. This finding supports social-cognitive theory, which suggests that individuals are influenced by the behaviors and opinions of others around them [28]. The positive relationship between innovation preference and AI usage intention further emphasizes the importance of individual openness to new technologies. Employees who are more willing to embrace technological changes are naturally more inclined to accept AI in their work environment, supporting the idea that early adopters play a crucial role in the diffusion of innovations. Another significant finding was the mediating role of attitudes between the influencing factors (performance expectancy, social influence, and innovation preference) and AI usage intention. This suggests that while the perception of AI's usefulness and social endorsement are critical, employees' attitudes toward AI ultimately determine whether they will adopt the technology. This highlights the need for organizations to foster a positive attitude toward AI through targeted communication, training, and support mechanisms [35].

The study also explored the moderating roles of anxiety and firm reputation, revealing nuanced insights. Anxiety was found to moderate only the relationship between social influence and attitude. Specifically, employees experiencing higher levels of anxiety were more likely to be influenced by social factors, suggesting that anxious individuals may rely on others' opinions for reassurance when forming their views about AI. In contrast, anxiety did not moderate the relationships between innovation preference or performance expectancy and attitude. This could be because individuals with a strong preference for innovation tend to approach new technologies with excitement and openness, reducing the impact of anxiety. For instance, an employee who enjoys experimenting with new tools may continue to have a positive attitude toward AI despite feeling anxious about uncertainties. Similarly, the perceived usefulness of AI—its expected ability to improve performance—likely remains a rational, goal-driven factor that is less susceptible to emotional barriers like anxiety. For example, an employee may recognize that AI will streamline tasks or provide valuable insights, and this rational benefit may outweigh any emotional hesitation they feel. Additionally, firm reputation was found to positively

moderate the relationship between attitude and AI usage intention. Employees who perceived their organization as reputable and trustworthy [37] were more likely to translate a positive attitude toward AI into actual intention to use it. This underscores the significant role of organizational culture and leadership in shaping employees' willingness to embrace AI technologies. For instance, if an organization is known for ethical practices, data protection, and employee well-being, individuals may feel more confident in adopting AI solutions endorsed by such a firm.

Demographic factors (such as age, gender, qualification, salary, and job experience) were controlled for in the analysis, ensuring that the observed relationships reflect the unique effects of the study variables without confounding influences. Overall, these findings suggest that while anxiety may not universally dampen enthusiasm for AI, it does make employees more sensitive to the opinions of others, highlighting the need for supportive social environments when introducing AI in the workplace. Furthermore, a strong firm reputation can strengthen the link between positive attitudes and behavioral intentions, emphasizing the importance of organizational trust and leadership in technology adoption processes.

6.2. Theoretical Implications

This research offers significant theoretical insights into the adoption of Artificial Intelligence (AI) by applying the Unified Theory of Acceptance and Use of Technology (UTAUT) as the foundation. The study demonstrates that the core constructs of UTAUT—performance expectancy, effort expectancy, social influence, and facilitating conditions—are critical to understanding AI adoption in a developing country context, specifically Pakistan. By adding psychological variables such as anxiety and attitude, the research expands the UTAUT model, highlighting how emotional and cognitive factors influence AI adoption. A notable theoretical contribution is the identification of the mediating role of attitude in AI adoption. The research shows that not only does attitude toward AI influence an individual's intention to adopt AI, but it also serves as a key mediator between UTAUT constructs and the adoption process. This indicates that the perception of AI, influenced by anxiety or social influences, plays a pivotal role in how employees view and accept AI technologies. Additionally, the study reveals the significant impact of psychological factors like anxiety, which has not been adequately explored within the UTAUT framework, thereby offering a more nuanced understanding of AI adoption.

Furthermore, the research highlights the moderating role of firm reputation and anxiety in AI adoption. These external factors significantly affect how employees perceive and respond to AI technologies. This finding suggests that future studies should explore how such contextual factors interact with UTAUT constructs in different cultural and organizational settings. The study also advocates for an expanded UTAUT model, incorporating emotional and organizational factors, to provide a more comprehensive understanding of technology adoption, particularly in developing countries like Pakistan.

6.3. Practical Implications

This research presents practical insights for organizations in Pakistan, and similar developing countries, aiming to adopt AI technologies. One of the most critical factors influencing AI adoption is performance expectancy. Organizations should emphasize how AI can enhance job performance and increase productivity. This can be achieved through showcasing AI's practical benefits, conducting pilot projects, and sharing success stories that demonstrate AI's value in a way that resonates with employees.

Social influence is another powerful factor in AI adoption. In Pakistan, where organizational structures often follow hierarchical norms, leadership support is essential for AI acceptance. Senior management must be the first to advocate for AI, demonstrating its benefits and addressing concerns about job displacement. Peer influence also plays a role, so organizations can encourage early adopters or AI advocates to influence their colleagues, building broader acceptance.

Anxiety, identified as a significant barrier to AI adoption, needs to be addressed through comprehensive training and support programs. Many employees may view AI with skepticism, fearing job loss or the complexity of the technology. To alleviate these concerns, organizations should focus on providing clear, accessible training and ensuring ongoing support for employees. Furthermore, open communication about how AI will be integrated into work processes can help employees feel more secure and willing to adopt the technology.

The reputation of the organization also significantly impacts AI adoption. Organizations with a positive reputation for trust, transparency, and ethical practices are more likely to experience higher acceptance rates for AI technologies. In Pakistan, where organizational trust and loyalty are crucial, companies should prioritize building and maintaining a strong reputation. This includes clear communication about how AI adoption will benefit both the organization and its employees.

The study shows that demographic factors, such as age, education, and prior technological experience, influence AI adoption. Younger, more educated employees were found to be more receptive to AI. Organizations should consider these demographic differences and tailor their AI adoption strategies accordingly. For instance, additional support and training might be needed for older employees or those with less technical experience.

6.4. Limitations and Future Research

The primary limitation of this study is that data was collected exclusively from employees in Pakistan. This geographic and cultural limitation may affect the generalizability of the findings to other countries or regions, particularly those with different technological landscapes or cultural attitudes toward AI. Additionally, the research only focused on employees, which means that the perspectives of other stakeholders, such as managers, IT specialists, or customers, were not included. This limits the scope of the research in understanding the broader organizational dynamics influencing AI adoption. Future studies should aim to include a more diverse range of respondents, including organizational leadership, technology experts, and end-users, to provide a more holistic view of AI adoption. Future research can build on this study by exploring additional factors that may influence AI adoption. One such area is the impact of personality traits on AI usage intention. Personality traits, such as openness to experience or technological self-efficacy, may play a significant role in shaping how individuals perceive and use AI. Investigating these personality-related factors could provide deeper insights into the variability in AI adoption among employees.

Furthermore, expanding the research to include other regions or countries with different technological landscapes and cultural contexts would provide a more comprehensive understanding of the global factors influencing AI adoption. Future research could examine the long-term impact of AI adoption on employee performance and organizational outcomes. This would involve a longitudinal study to assess how employees' attitudes and behaviors toward AI evolve over time, particularly as AI technologies become more integrated into organizational practices. Investigating the influence of AI on job satisfaction, productivity, and overall employee engagement would be valuable for organizations considering AI implementation. This research contributes valuable theoretical and practical insights into AI adoption, highlighting the importance of psychological, emotional, and organizational factors. While the findings are based on a study in Pakistan, they offer actionable guidance for organizations in similar contexts. Future research could explore additional factors like personality traits and the long-term effects of AI adoption, further enriching the understanding of AI integration in organizational setting.

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