QUALITATIVE RESEARCH JOURNAL FOR SOCIAL STUDIES

ISSN Online: 3006-4686, ISSN Print: 3006-4678
Volume No: 03 Issue No: 01 (2026)

FROM CURIOSITY TO COMMITMENT: HOW EXPLORATION, AI TRUST, AND INTENTION TO USE AI FUEL EMPLOYEE'S AI ADOPTION

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Abstract
This research examines direct effects of three psychological behavioural factors; exploration behaviour, intention to use artificial intelligence (AI) and trust in AI, on employee adoption of AI tools. Although these variables have been previously studied as moderators or consequences of AI adoption, their direct impact on actual adoption is under-explored in emerging markets. An exploratory survey was conducted with 410 full time employees in multiple industries in Pakistan with hands on experience of using AI. Exploration, intention to use AI, AI trust and AI adoption were measured using validated Likert scales. The direct hypotheses were tested using structural equation modelling (SEM). Exploration significantly and positively influenced intention to use AI ($\beta = 0.422$, $p < 0.001$) and AI trust ($\beta = 0.357$, $p < 0.001$). Both intention to use AI ($\beta = 0.463$, $p < 0.001$) and AI trust ($\beta = 0.389$, $p < 0.001$) strongly predicted AI adoption. Exploration positively influenced AI adoption directly ($\beta = 0.244$, $p < 0.001$). The best predictor of AI adoption was intention to use AI, followed by AI trust.To increase intention to use AI, organisations should foster experimentation, ensure that AI is transparent and trustworthy, and communicate the benefits of using AI to individuals and groups. The creation of a safe space for exploration and programs that build trust are important strategies to enhance adoption. This research represents the novel study to simultaneously test the direct effects of exploration, intention to use AI and AI trust on AI adoption all in one model, and the first in the context of Pakistani organisations.

Keywords: Exploration; AI trust; intention to use AI; AI adoption; direct effects; Pakistan

INTRODUCTION

Artificial intelligence (AI) is increasingly changing the nature of work, processes and jobs in organisations. AI is being embraced in Pakistan in industries like banking, telecommunications, manufacturing and IT to enhance operational efficiency and productivity (Dwivedi et al., 2021; Kong et al., 2024). However, having cutting-edge algorithms in place is no guarantee of success. Organisations often face issues of low adoption, under-use or active resistance to the use of AI in the workplace (Glikson & Woolley, 2020; Makarius et al., 2023). So, what drives the direct behavioural acceptance of AI is a critical question for both researchers and practitioners.

Existing models of technology acceptance such as the Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) have emphasised cognitive beliefs such as perceived usefulness and perceived ease of use. Although these models offer a good starting point, they fail to account for important behavioural and emotional processes that are relevant for AI - a technology that is autonomous, opaque, and self-learning (Shin, 2021; Rijswijk, 2022). Specifically, three constructs have been consistently identified in recent research as potentially important direct drivers of AI acceptance; exploration, intention to use AI, and trust in AI.

Exploration is the curiosity driven, active experimentation with AI tools such as experimenting with new functions, exploring the boundaries of the system, and finding new uses for the system (March, 1991; Wilden et al., 2018). Exploration by employees helps them develop

ISSN Online: 3006-4686, ISSN Print: 3006-4678
Volume No: 03 Issue No: 01 (2026)

familiarity with AI, minimise uncertainty, and construct models of AI behaviour (Zhang et al., 2023). Intention to use AI is the conscious willingness and planned effort to engage with AI systems; it's the closest psychological predictor of behaviour according to TAM and the Theory of Planned Behaviour (Ajzen, 1991; Dabbous et al., 2022). Trust in AI is the user's belief that the system is trustworthy, transparent, fair, and can perform the intended tasks without harm (Glikson & Woolley, 2020; Lankton et al., 2022). Trust is particularly important for AI due to the unpredictable nature of its autonomous decisions.

While these three factors have been examined separately, few researchers have tested their direct effects on AI acceptance in a single model. Furthermore, existing evidence is largely from Western or technologically advanced economies, with limited research on exploration, intention, and trust, in developing countries like Pakistan, where digital literacy, technology infrastructure, and regulations are still developing (Al Emran & Granic, 2023; Wamba et al., 2023). To fill this void, this paper examines five direct effects from a thesis model. The research uses data from 410 employees from different industries, and employs structural equation modelling (SEM) to test the relative significance of these direct hypotheses. This research provides a clear prescription for managers: to promote adoption of AI, stimulate exploration, AI trust, and intention to use AI.

LITERATURE REVIEW

Exploration as a Behavioural Driver in Technology Adoption

Exploration is a concept originating from organisational learning theory, which describes the search for new knowledge and experimentation with new alternatives, and the willingness to enter unknown territory (March, 1991). In the context of AI, exploration is the active efforts of employees to experiment with AI features, understand how the system works under various scenarios, and identify new ways to integrate AI into their tasks (Kong et al., 2024; Wilden et al., 2018). Exploration is especially important for AI since AI technologies are often not intuitive; it is difficult for users to understand how it works without exploring it. Exploration helps employees learn about the inner workings of AI systems, increases their self-efficacy, and alleviates technophobia (Jasperson et al, 2005; Zhang et al, 2023).

Previous research demonstrated that exploration is a strong predictor of future attitudes and behaviours towards new technology (Rosenbusch et al., 2019; Sun et al., 2022). However, existing studies have mostly considered exploration as a mediator, rather than a direct driver, of intention, trust and adoption. For instance, Kong et al. (2024) discovered that exploration mediated the link between autonomy supportive AI and innovation, but did not explore the direct impact of exploration on adoption. Our paper places exploration as a key behavioural predictor that not only affects cognitive states (intention and trust) but also the final behaviour (adoption).

Intention to Use AI as a Proximal Predictor

Intention is a key term in technology acceptance. Intention has been consistently found as a main proximal predictor of behaviour in TAM and TPB (Ajzen, 1991; Davis, 1989). Behavioural intention reflects a person's conscious plan, motivation and effort to engage in a certain action. In the context of AI, employees' intention to use AI captures their willingness to adopt AI tools in their work (Dabbous et al., 2022; Venkatesh et al., 2021).

Although intention is a popular construct, its direct relationship with adoption, particularly in a workplace where the use of AI may be required or monitored, needs to be continually tested. Also, not as much research has focused on the factors preceding intention (such as exploration). This research examines the direct influence of exploration on intention and direct influence of

ISSN Online: 3006-4686, ISSN Print: 3006-4678
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intention on adoption (Khan & Ullah, 2025). Recent meta analyses verify that intention is indeed a strong predictor for this type of technology as well as AI (Dwivedi et al., 2023; Mariani & Borghi, 2022).

AI Trust as a Cognitive-Emotional Bridge

AI trust is defined as the user's belief that the system is reliable, transparent, fair, and able to perform the tasks required without harmful consequences (Glikson & Woolley, 2020; Mayer et al., 1995). AI systems can make independent decisions, learn, and exhibit unpredictable behavior, unlike conventional software. This unpredictability highlights the importance of trust as a psychological construct (Shin, 2021; Rijswijk, 2022).

Studies have shown that trust reduces the perceived risk and enhances the willingness to outsource to AI (Lankton et al., 2022; Rahman et al., 2023). Trust may be fostered through reliability, explainability (XAI) and value congruence (Nagy & Zhang, 2023). In this paper, we explore whether exploration (trial and error) directly increases trust, and whether trust directly increases adoption. Some researchers have suggested that trust may be more critical than intention for autonomous systems because employees may adopt AI as long as they are confident, even if they don't have a conscious intention to do so (Glikson & Woolley, 2020; Shin, 2021; Khan & Ullah, 2025).

AI Adoption as the Ultimate Behavioural Outcome

AI adoption is operationalised as the extent to which employees have integrated AI tools into their regular work routines, can adjust to updates, and feel confident using AI for job-related tasks (Chatterjee & Bhattacharjee, 2020). Adoption is distinct from intention because it reflects actual behaviour rather than a plan (Khan & Ullah, 2025). Measure the adoption is crucial and researchers should go beyond attitudinal research and prove actual technology acceptance from real world scenarios (Ransbotham et al., 2023; Venkatesh et al., 2021).

Despite the importance of adoption, many studies stop at intention or usage intentions. This paper directly measures adoption as the dependent variable, contributing to the scarce literature on post-acceptance behaviour in AI contexts.

Hypothesis Development

Building on the literature review, the following five direct hypotheses are proposed:

H1: Exploration has a positive impact on Intention to Use AI.

Rationale: When employees actively experiment with AI tools they learn how the tools work and this increases their conscious motivation to use AI (Kong et al., 2024; Zhang et al., 2023).

H2: Exploration has a positive impact on AI Trust.

Rationale: Interacting with the system provides employees with the opportunity to perceive reliability and predictability, which are central to trust (Glikson & Woolley, 2020; Lankton et al., 2022).

H3: Intention to Use AI has a positive impact on AI Adoption.

Rationale: TPB and TAM consider behavioural intention as the most likely predictor of future behaviour (Ajzen, 1991; Davis, 1989; Dabbous et al., 2022).

H4: AI Trust has a positive impact on AI Adoption.

Rationale: If employees perceive that an AI system is trustworthy (reliable, fair, transparent), they will be more likely to use it at work (Glikson & Woolley, 2020; Shin, 2021).

H5: Exploration has a positive impact on AI Adoption.

Rationale: Exploration can allow employees to directly adopt AI, instead of first forming intention and then trust, particularly if they perceive the immediate usefulness of AI (Wilden et al., 2018; Kong et al., 2024).

These hypotheses are depicted in the research model (Figure 1).

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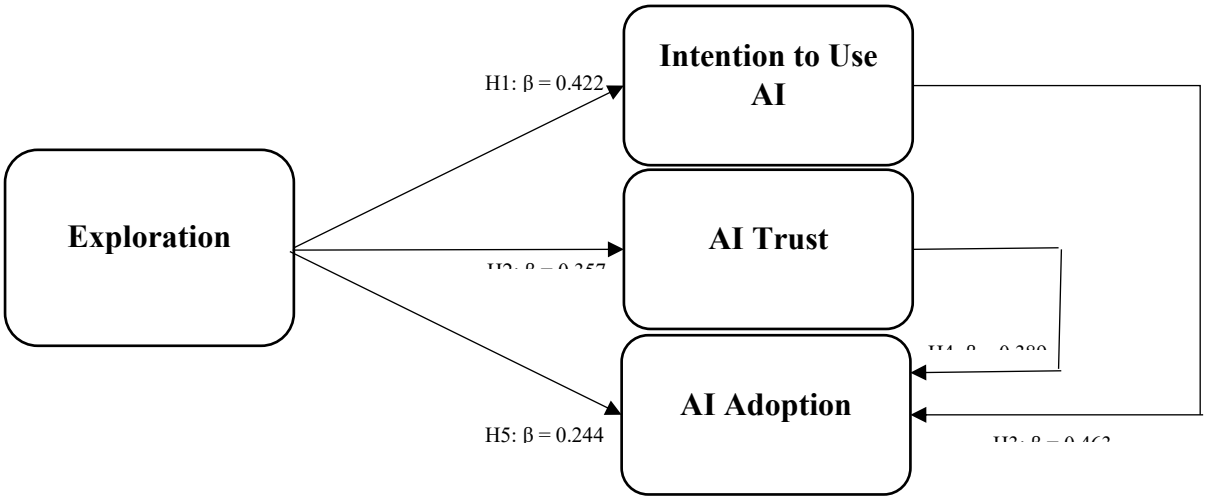

Figure 1 - Research Model

Hypotheses	Path	Standardised Coefficient (β)	Significance
H1	Exploration → Intention to Use AI	0.422	$p < 0.001$
H2	Exploration → AI Trust	0.357	$p < 0.001$
H3	Intention to Use AI → AI Adoption	0.463	$p < 0.001$
H4	AI Trust → AI Adoption	0.389	$p < 0.001$
H5	Exploration → AI Adoption	0.244	$p < 0.001$

METHODOLOGY

Research Design and Sample

This study has a quantitative, cross sectional survey design with a positivist paradigm. The sample comprised of full time employees in Pakistan who had used AI tools at their work. A purposive sampling technique was adopted. A total of 410 responses were used after cleaning the data. The respondents were mostly young (82% 20-29 years of age), women (66.6%) and had a bachelor's degree or higher (70.5%). The majority of participants had 1-3 years of experience (56.1%), suggesting early career professionals.

Measurement Instruments

All constructs were measured using previously validated Likert scales (1 = strongly disagree to 5 = strongly agree):

Exploration (EXPL): 10 items from Kong et al. (2024). Sample item: *"I have developed new competencies for myself through AI."*

Intention to Use AI (IUAI): 4 items from Dabbous et al. (2022). Sample item: *"I intend to learn about using AI."*

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AI Trust (AIT): 11 items from Kong et al. (2024). Sample item: *"I have confidence in the use of AI technology."*
AI Adoption (AIA): 5 items from Chatterjee & Bhattacharjee (2020). Sample item: *"I can easily integrate new AI technologies into my existing work routines."*

Data Analysis

Descriptive statistics and reliability analysis were performed using SPSS and structural equation modelling (SEM) using AMOS. The analysis was conducted in two steps: *(1)* the measurement model was tested for validity and *(2)* the structure model was estimated to test the five direct hypotheses (H1, H2, H3, H4, H5). Maximum likelihood estimation with bootstrapping (10,000 samples) was applied to get standard errors and confidence intervals.

RESULTS

Measurement Model

The measurement model demonstrated acceptable psychometric properties. Cronbach's alpha values were: Exploration (0.836), Intention to use AI (0.812), AI Trust (0.876), AI Adoption (0.856). All constructs' composite reliability (CR) was above 0.88. Average variance extracted (AVE) scores ranged from 0.583 – 0.663, establishing convergent validity. The Fornell-Larcker criterion and HTMT ratios (all < 0.85) demonstrated discriminant validity. The five-factor model fit the data well: $\chi^2/df = 2.66$, CFI = 0.929, TLI = 0.892, RMSEA = 0.064.

Descriptive Statistics and Correlations

Table 1: presents means, standard deviations, and correlations among the key constructs.

Table 1: Descriptive Statistics and Correlations

Variable	Mean	SD	1	2	3	4
1. Exploration (EXPL)	4.24	0.79	(0.775)			
2. Intention to Use AI (IUAI)	4.14	0.79	0.811**	(0.764)		
3. AI Trust (AIT)	3.35	0.86	0.159**	0.103*	(0.814)	
4. AI Adoption (AIA)	3.39	0.93	0.268**	0.183**	0.445**	(0.786)

*Notes: **p < 0.01; *p < 0.05. Diagonal values (parentheses) are square roots of AVE.*

Exploration was significantly correlated to intention to use AI (r = 0.811) and moderately to AI adoption (r = 0.268). AI Trust was moderately correlated with AI adoption (r = 0.445). Exploration was significant but less strongly correlated with AI trust (r = 0.159).

Direct Effects (Hypotheses Testing)

Table 2: summarize the path coefficients for the five hypotheses.

Table 2: Direct Effects Results

Hypothesis	Path	β (Standardised)	S.E.	t-value	p-value	Decision
H1	Exploration → Intention to Use AI	0.422	0.046	9.117	< 0.001	Supported
H2	Exploration → AI Trust	0.357	0.048	7.504	< 0.001	Supported
H3	Intention to Use AI → AI Adoption	0.463	0.043	10.801	< 0.001	Supported
H4	AI Trust → AI Adoption	0.389	0.043	8.992	< 0.001	Supported

ISSN Online: 3006-4686, ISSN Print: 3006-4678
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H5	Exploration → AI Adoption	0.244	0.041	5.983	< 0.001	Supported

The five hypotheses were significantly supporting at $p < 0.001$. Intention to use AI (IUAI) and AI trust (AIT) were the strongest direct predictors of AI adoption ($\beta = 0.463$ and $\beta = 0.389$, respectively). Exploration (EXPL) also had a large influence on intention to use AI ($\beta = 0.422$) and AI trust ($\beta = 0.357$). Exploration also had a statistically significant direct effect on AI adoption, albeit at a lesser degree ($\beta = 0.244$).

DISCUSSION AND CONCLUSION

Interpretation of Findings

The findings empirically support the direct effects of exploration, intention to use AI and AI trust on AI adoption among Pakistani employees.

Exploration as a powerful antecedent (H1, H2, H5): Exploration had a strong effect on intention to use AI ($\beta = 0.422$) and AI trust ($\beta = 0.357$), but also directly affected AI adoption ($\beta = 0.244$). This supports the idea that employees who explore AI tools; experimenting, experimenting, experimenting; and learn from their failures and successes, form an intention to use AI tools, as well as trust in the technology. The direct path from exploration to AI adoption means that some employees may adopt AI purely through experience, rather than having to form an intention or trust to use AI. This is especially important for Pakistan where there may not be extensive training programs; a cheap strategy towards adoption may be to promote self-directed exploration (Zhang et al., 2023; Sun et al., 2022).

Intention to Use AI as the strongest predictor of AI adoption (H3, $\beta = 0.463$): This is in line with TAM and TPB, and confirms that intention is a direct, psychological predictor of behaviour (Ajzen, 1991; Davis, 1989). In Pakistan, those who are more inclined to incorporate AI in their work because they plan to use it (they perceive AI as relevant to their work and have positive expectations) are more likely to use AI at work. Therefore, managers should focus on communication and motivating strategies to strengthen intention.

AI Trust as a critical direct driver (H4, $\beta = 0.389$): Trust is second only to intention in predicting adoption. This is particularly important for AI, given that employees might fear the use of unexplainable algorithms, misuse of data or even job loss. In Pakistan, where the regulatory framework and environment for AI is still at its growing stage, trust based on transparency, reliability and ethics is important (Glikson & Woolley, 2020; Shin, 2021). The fact trust directly predicts use (skipping intention) shows that while an employee may not be fully committed to use, trust may lead to use AI.

Theoretical Implications

Our study is in line with international research; Kong et al. (2024) found exploration enhanced innovation related outcomes in hospitality. Dabbous et al. (2022) identified a strong connection between intention and adoption of AI in marketing and service organisations. Glikson and Woolley (2020) found trust important in human-AI interaction. However, it is the first to examine the five direct effects in the integrated model in an emerging economy. The effect sizes are comparable to Western studies, suggesting that the psychological factors are universal, but the level of trust and AI adoption may be lower in Pakistan due to infrastructure and regulatory problems (Al Emran & Granic, 2023; Wamba et al., 2023; Khan & Ullah, 2025).

Practical Implications for Organisations

Our research provides managers and policymakers with a practical guide.

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Encourage exploration through low-risk experimentation: Businesses should provide safe spaces for workforce to experiment with AI features without the risk of failure or adverse consequences to the business. This can be done through AI playgrounds, hackathons or "test drives". Exploration is very cost effective, as it boosts intention, trust and adoption.

Boost intention through clear communication and incentives: The strongest predictor of AI adoption is intention to use AI, so managers should communicate to their employees the personal and team advantages of using AI. Employees should be told stories of how AI users have benefited, and rewarded and promoted for using it. Training should focus on promotions from using AI.

Trust building through transparency and reliability: AI Trust is second to intention to use AI. Businesses should have explainable AI (XAI) dashboards. Regular bias tests, data privacy policies and successful error reduction strategies will foster trust. Managers should discuss AI errors and imperfections to manage expectations and trust.

Use exploration as a direct switch to AI adoption: Even without intention and trust, exploration can result in AI adoption. This is especially important for sceptical or fearful staff. Peer led exploration teams or "AI champions" who show how to use AI can accelerate AI adoption.

Integrate these insights into change management: AI adoption should not be seen as just a technology roll-out. Change management programs should be explicitly geared towards opportunities for exploration, trust building messages and intention building actions. Training should start with exploration, followed by trust building and adoption.

Conclusion

This study explored the direct effects of exploration on intention to use AI, AI trust and AI adoption, and the direct effects of intention to use AI and AI trust on AI adoption, with a sample of 410 employees from Pakistan. Hypotheses H1, H2, H3, H4 and H5 were confirmed. Exploration was a strong predictor of behaviour, with intention to use AI and AI trust being the two strongest direct predictors of AI adoption. The research adds to the body of knowledge by showing that while exploration is indeed a direct predictor of AI adoption, and that intention to use AI and AI trust are indeed the strongest direct predictors of AI adoption. Practically, the study recommends providing safe exploration opportunities, promoting the benefits of AI to boost intention to use AI, and enhancing AI trust through transparency and reliability. These measures will help boost AI adoption, and enable organisations to derive maximum value from their technology investments.

Academic researchers should explore the effects of moderators and mediators (e.g., management support, job insecurity, technology literacy), take a longitudinal approach, and test the model across industries and cultures.

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