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Role of innovative behaviour as a missing linchpin in artificial intelligence adoption to enhancing job security and job performance

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Abstract

Building upon the sociotechnical system theory, the present study contributes by examining the relationship between artificial intelligence (AI) adoption, employees' innovative behaviour on employee performance and job security (JS). The primary data is collected from 340 employees from firms located in the industrial hub of a developing economy using a simple random technique, and data is analysed using Smart-PLS 3 from the manufacturing sector. The study evidences that employees' adoption and utilization of AI technologies positively influence their innovative behaviour, job performance (JP), and security. Moreover, the study finds a mediating role of innovative behaviour to connect the dots. Organizations can prioritize using AI-driven training programmes so employees can use AI tools efficiently. Study findings also encourage employees to engage in innovative work behaviours like investigating novel concepts and experimenting with AI technologies to improve JP. This study invalidates that AI will replace employees at the workplace, as we can safely conclude that AI adoption enhances JP and JS.

KEYWORDS

artificial intelligence, innovative behaviour, job performance, job security, sociotechnical system theory

1 | INTRODUCTION

The likelihood that employees will keep their employment and continue earning a living is known as job security (Bazzoli & Probst, 2023). Artificial Intelligence (AI) might boost or hurt JS (Yu et al., 2023). AI has the potential to both positively and negatively impact JS. AI may automate monotonous jobs, improve efficiency, and allow workers to focus on more complicated and creative work, creating new job prospects and security. Productivity and job satisfaction may increase. While on the other hand, AI could also disrupt some jobs and sectors. AI technology may automate various chores and jobs, reducing the need for human workers. Automation can displace workers and reduce JS (Eshiett & Eshiett 2024; Probst et al., 2021).

AI is changing the workplace, affecting innovation, task efficiency, and employee performance. Empirical evidence suggests that AI adoption (AIA) improves JS and performance, especially among younger workers who embrace new technologies (Bazzoli & Probst, 2023). Job insecurity is emerging among older workforce segments that may be less likely to adopt new technology (Probst et al., 2020, 2021). Despite these insights, academic discourse still lacks understanding of how innovative behaviour, job performance (JP), and JS interact and change in response to AIA across employee demographics (Yu et al., 2023).

AI's impact on JS is complex and can vary depending on industry, job type, and organizational implementation. AI can automate routine tasks that require human labour, displacing workers in manufacturing, data entry, and customer service (Eshiett & Eshiett, 2024; Probst et al., 2021). This automation can cost jobs if workers are not trained for AI-enhanced roles. Advances in machine learning and robotics are allowing machines to perform complex tasks, including decision-making that previously required human insight (Lawal, 2024). AI can also drive innovation and create new industries, creating new roles that require specialized skills and training and opening up career paths. Businesses and governments must take proactive steps to make AI more job-secure (Eshiett & Eshiett, 2024; Lawal, 2024). These include reskilling the workforce through education and training, designing AI technologies that complement human skills, and establishing ethical AI development and deployment policies (Eshiett & Eshiett, 2024; Yu et al., 2023).

AI is being recognized for its potential to boost innovation and performance in proactive and skilled workers. This recognition has prompted research into how AI disrupts traditional work paradigms (Desouza et al., 2020). The sociotechnical system theory, which integrates technology, human interaction, language, and environmental context, can be used to study how AI affects workplace outcomes. This theory illuminates the complex interdependencies between the workplace's technological and social systems (Ehn, 1988). The current research uses this theoretical framework to examine how AI affects JS and performance, informing workplace AI integration strategies.

Although there has been a lot of research on how AI is used in workplaces, there is still a lack of understanding about the specific ways in which adopting AI affects JP and security (Eshiett & Eshiett, 2024; Prentice et al., 2023). The current body of research has primarily concentrated on the immediate effects of AI implementation, such as increased efficiency and the automation of repetitive tasks. However, there is a lack of empirical studies that investigate the intermediary role of innovative work behaviour (IWB) in this particular context (Islam et al., 2024). The ability of employees to generate, promote, and implement new ideas, known as IWB, is crucial for fully utilising AI technologies to improve JP and security (Lawal, 2024). Though the sociotechnical system theory has been extensively studied in science, innovation, and technology, its application in business and human resource management has gotten little attention (Prentice et al., 2020; Wilkens, 2020).

This study aims to address this deficiency by examining the intricate mechanisms through which the adoption of AI promotes IWB, subsequently influencing JP and JS. The current body of knowledge frequently neglects this intermediate process, potentially leading to an incomplete understanding of the intricate dynamics of AI's influence on employee outcomes. The present research is based on sociotechnical system theory, which suggests that organizational outcomes are determined by the interaction between an organization's social and technical subsystems (Wilkens, 2020). This framework offers a strong perspective for examining the effects of technological integrations on human actors within the organizational environment. The variables chosen for this study—AIA, employees' innovative behaviour, JP, and security—are carefully selected to align with the fundamental principles of this theory. The theory aims to clarify and optimize the interactions between human and technological factors. Organizations that embrace technology must analyse how AIA, innovative behaviour, JP, and security change daily work practices, employee engagement, and JS perceptions for operational and strategic decision-making.

The primary objective is to investigate how employees' adoption and utilization of AI technologies influence their JP and security, specifically focusing on the mediating role of IWB. By delving into the mechanisms through which AIA impacts JP and security, mainly through IWB, this study aims to offer valuable insights for organizations seeking to leverage AI technologies while enhancing employee performance effectively.

2 | THEORETICAL FOUNDATION AND HYPOTHESIS DEVELOPMENT

2.1 | Socio-technical system theory

Trist and Bamforth first presented the idea of the socio-technical system in the 1950s to increase work system performance by addressing the technological challenges and uncertainties employees face (Trist & Bamforth, 1951). To provide meaningful work for employees, Davis and Cherns (1975) promoted "Quality of Work life" in several businesses throughout the 1970s. The relationship between workers and technologies in the workplace has evolved dramatically in recent years due to the rise of digitalization and AI, making the sociotechnical system more important than ever (Pasmore et al., 2019; Yu et al., 2023). In the age of intelligent robots, people would have to decide whether to become their masters or their slaves, according to Sirianni and Zuboff (1989). Therefore, creating work systems that can handle both scenarios is necessary. The sociotechnical system believes enterprises can achieve joint optimization by fusing human objectives with technological advancement.

Organizations face difficulties bringing their social systems into line with the rate of technology innovation as they adopt AI to improve outcomes. They struggle to engage the workforce, develop efficient work procedures, and strengthen organizational capacities (Pasmore et al., 2019). They also struggle to attract high-calibre people. The idea prioritizes developing a good fit between the social and technological subsystems to maximize intended individual and organizational outcomes through AIA and implementation. The current study, from the standpoint of a sociotechnical system, focuses on the efficient use of AI in organizations that call for a combined strategy that considers both social and technological advancements (Yu et al., 2023). The technical subsystem, which considers technology-related aspects, and the personnel subsystem, which concentrates on social and people-related factors, are included in this approach (Høyland et al., 2019; Yu et al., 2023).

2.2 | AI

AI includes a computer's capacity to learn from experience and carry out difficult tasks comparable to human talents, such as making logical decisions (Pomerol, 1997; Zirar, 2023). The idea that machines can carry out complex, human-like tasks using algorithms and data in various contexts, including the workplace and society, is a recurring theme in definitions of AI. AI mimics human cognitive processes such as perception, learning, reasoning, and decision-making (Zirar, 2023).

One of the central issues for workers concerning AI in the workplace is the potential loss of employment (Braganza et al., 2021). Many workers are at risk of job displacement due to the implementation of AI applications (Zirar, 2023). Consequently, the work performed by AI may no longer require the involvement of human workers, leaving them uneasy about how AI applications help or affect them (Holford, 2019; Wright & Schultz, 2018).

A potential strategy to address this concern is enabling workers to recognize how technological advancements stimulate innovative behaviour (Braganza et al., 2021). However, the reality often contrasts with this notion (Gligor et al., 2021; Zirar, 2023). In this technological landscape, the inner workings of AI systems typically remain unknown to workers (Gligor et al., 2021), leaving it up to workers to upskill and reskill themselves to engage in innovative behaviour and coexist with AI systems (Zirar, 2023).

Scholarly research on innovative behaviour encompasses the process of generating and implementing new and original ideas, including idea conception, development, and completion (Baer, 2012; Scott & Bruce, 1994; Somech & Drach-Zahavy, 2013). This behaviour is evident in creating and implementing novel goods, services, or work methods (Baer, 2012; Perry-Smith & Mannucci, 2017).

AI technologies aim to enhance and support individuals' creativity in problem-solving, serving as a creative tool in their own right (Anantrasirichai & Bull, 2022). In management literature, IWB is more commonly observed in reactive activities, such as devising workarounds to address limitations. Idea generation, elaboration, promotion, and implementation are integral to developing workarounds (Perry-Smith & Mannucci, 2017). Within this perspective, IWB serves as a means to compensate for AI limitations. Innovative behaviour is manifested through identifying issues and the generation, initiation, and implementation of new and original ideas, rather than a dramatic shift in an individual's perspective (Perry-Smith & Mannucci, 2017).

2.3 | Job performance

According to Deng et al. (2023), performance refers to a group's collective organizational actions in which members, directly and indirectly, help the organization achieve its objectives. So, rather than being an activity, work performance results from behaviours connected to the job (Ajzen, 2011; Aung et al., 2023). Performance on the job is ultimately a result of these behaviours. Task and contextual performances are two variables that can be used to classify the critical characteristics of JP. According to Cheng et al. (2007), these are the main domains used to assess how well construction workers perform. Task performance refers to the actions necessary to run and maintain an organization's essential technology operations. Contrarily, contextual performance measures how well a system's wider organizational, social, and psychological contexts support its technological core functions (Aung et al., 2023). Employee underperformance has a negative impact on project results and reduces the profitability of construction companies (Cheng et al., 2007). The decline in profitability is attributed chiefly to the unfavourable actions taken by low-performing workers, such as increasing absenteeism, frequent tardiness, high turnover, and resistance to supervision. According to Deng et al. (2023), performance refers to a group's collective organizational actions in which members, directly and indirectly, help the organization achieve its objectives. So, rather than being an activity, work performance results from behaviours connected to the job (Ajzen, 2011; Aung et al., 2023). Performance on the job is ultimately a result of these behaviours. Task and contextual performances are two variables that can be used to classify the critical characteristics of JP. According to Cheng et al. (2007), these are the main domains used to assess how well construction workers perform. Task performance refers to the actions necessary to run and maintain an organization's essential technology operations. Contrarily, contextual performance measures how well a system's wider organizational, social, and psychological contexts support its technological core functions (Aung et al., 2023). Employee underperformance has a negative impact on project results and reduces the profitability of construction companies (Cheng et al., 2007). The decline in profitability is attributed chiefly to the unfavourable actions taken by low-performing workers, such as increasing absenteeism, frequent tardiness, high turnover, resistance to supervision, and a lack of willingness to work with coworkers (Aung et al., 2023). Therefore, the success of construction organizations must understand the aspects that affect JP.

2.4 | Job security

JS is typically defined as a legal employment contract that assures employees of continued employment (Greenhalgh & Rosenblatt, 1984). JS is defined as the perceived stability and continuity of one's job as one understands it (Probst, 2003). While asserting that JS is essentially a global concept, this definition acknowledges that an individual's perception of JS can be influenced by both the continuation of their job and the stability of desired job features (Probst, 2003). Job insecurity is not limited to situations where an individual believes their job's future is unstable and reacts negatively. Instead, it proposes that job insecurity exists when an individual perceives their job's future as unstable or at risk. Therefore, the construct solely encompasses job stability and continuity (Hur, 2022; Probst, 2003). By focusing on perceptions of JS, researchers can investigate the factors regarding individuals' perception of job insecurity and their evaluative and emotional responses. JS is an individual's cognitive evaluation of their job's future regarding perceived stability and continuity and evaluates satisfaction with JS. This perception of greater JS among employees can lead to more positive work attitudes due to their higher expectations of employment continuity (Hur, 2022).

2.5 | AI adoption and innovative work behaviour

Due to the adoption of AI technologies, employees may use cutting-edge tools and skills to analyse data, automate activities, and discover new insights (Anantrasirichai & Bull, 2022; Yu et al., 2023). These AI-driven skills increase IWB by encouraging employees' curiosity, creativity, and problem-solving mindset (Zirar, 2023). Furthermore, AI systems can assist decision-making by offering data-driven insights and predictive analytics. Employees with access to such AI-enabled decision support systems may be better equipped to make informed decisions that promote innovation, which may lead to more inventive work behaviour (Saether, 2019). Automating tedious and repetitive work is another common AIA practice that frees up employees' time and cognitive resources. This improved capacity enables workers to concentrate on more valuable, imaginative, and inventive tasks, fostering an organizational culture of IWB (Zirar, 2023).

Sociotechnical system theory recognizes the importance of social interactions and dynamics within organizations. Adopting AI technologies can influence the social environment by promoting collaboration, knowledge sharing, and learning (Yu et al., 2023; Zirar, 2023). AIA can create opportunities for cross-functional teams, interdisciplinary collaboration, and diverse perspectives, fostering IWB among employees. Employees who feel supported and empowered by AI technologies are likelier to engage in innovative thinking and take risks to develop novel solutions (Holford, 2019; Wang, 2019). Hence, based on these arguments:

H1. Adopting AI positively influences IWB.

2.6 | Adoption of AI and job performance

AI can automate repetitive jobs, streamline workflows, and improve operational effectiveness. The time and effort needed for employees' jobs are reduced when they can use AI tools to execute tasks more quickly (Wang, 2019; Yu et al., 2023). Employee productivity might grow due to this enhanced efficiency because it allows them to complete more work in less time. Additionally, AI systems can offer predictive analytics, decision-support tools, and data-driven insights (Zirar, 2023). Employee performance can be improved by utilizing these AI capabilities to help them make more informed and precise decisions. Employees may use AI tools to analyse complex data, spot patterns, and suggest the best next steps, improving outcomes (Aung et al., 2023; Yu et al., 2023).

Based on sociotechnical system theory, the study emphasizes the crucial interplay between technological and social aspects. AIA requires employees to interact with AI systems, leveraging their capabilities while integrating their expertise, knowledge, and creativity (Matsunaga, 2022). A positive interaction between humans and AI can improve JP by capitalizing on the strengths of both components (Ajzen, 2011). Employees may perform better on the job and achieve higher customer satisfaction when they have access to AI-powered solutions that help them better cater products or services to specific client needs (Matsunaga, 2022). Hence, based on these arguments:

H2. AIA positively influences JP.

2.7 | Adoption of AI and job security

AIA introduces advanced technologies that can automate tasks, optimize processes, and enhance operational efficiency. These technological advancements can contribute to JS by improving productivity and creating new opportunities within the organization. AI-powered systems can help employees develop new skills, adapt to changing job requirements, and remain relevant in an evolving technological landscape (Bhargava et al., 2021; Vasunandan & Annamalai, 2023).

With support from the tenets embedded in the sociotechnical system theory, the current study emphasizes the importance of social interactions and organizational support. The successful adoption of AI requires effective collaboration, communication, and integration between employees and AI technologies. Building supportive social systems around AIA can enhance JS by promoting employee engagement, providing training and upskilling opportunities, and fostering a positive work environment (Bhargava et al., 2021; Yu et al., 2023). Davenport and Ronanki (2018) claimed that AIA often necessitates employees to acquire new skills and adapt to technological changes. Organizations that invest in employee training and development programs in the context of AIA can enhance JS by equipping employees with the necessary skills to work alongside AI technologies. Employees with relevant AI skills are more likely to be valued and have increased JS (Bhargava et al., 2021).

Bhargava et al. (2021) suggested that technology and humans will complement each other as future systems will leverage human and machine intelligence. Technology and humans will only be able to work effectively with the support of each other (Davenport & Ronanki, 2018). AIA can lead to redesigning job roles and reallocating tasks between employees and AI systems. When implemented strategically, AI technologies can automate routine and repetitive tasks, allowing employees to focus on more complex and value-added work. This job redesign can contribute to JS by ensuring employees are engaged in meaningful and intellectually challenging tasks (Davenport & Ronanki, 2018). Hence, based on these arguments:

H3. AIA positively influences JS.

2.8 | IWB and JP

Sociotechnical system theory recognizes the significance of social interactions and dynamics in organizations. Integrating IWB within this framework involves fostering a culture of collaboration, knowledge sharing, and learning (Høyland et al., 2019; Yu et al., 2023). Organizations can facilitate employee exchange of ideas, experimentation, and creativity by encouraging open communication, diverse perspectives, and supportive relationships. These positive social dynamics contribute to higher levels of IWB and enhance JP (Kirkpatrick, 2017; Prentice et al., 2020).

Integrating IWB within a sociotechnical system promotes knowledge creation and exchange. Employees who engage in innovative practices generate new knowledge, insights, and expertise (Yu et al., 2023). This knowledge creation and exchange contribute to organizational learning, continuous improvement, and enhanced JP. Integrating IWB within a sociotechnical system fosters adaptability and agility in response to dynamic environments and changing market conditions (Kirkpatrick, 2017). Innovative employees are more likely to embrace change, explain new possibilities, and adapt their approaches to meet evolving challenges. This adaptability and agility positively impact JP by enabling employees to stay ahead of the curve, identify opportunities, and effectively respond to organizational needs (Mariani et al., 2023; Musiolik et al., 2020). Hence, based on these arguments:

H4. IWB positively influences JP.

2.9 | IWB and JS

Based on sociotechnical system theory, integrating IWB promotes adaptability to changing circumstances and market dynamics. Employees who exhibit IWB are more likely to embrace new technologies, investigate new ideas, and adapt their skills to meet evolving job requirements (Butali & Njoroge, 2016; Chen et al., 2022; Yu et al., 2023). This adaptability enhances JS by making employees more resilient to changes and increasing organizational value (Chen et al., 2022). Organizations that foster a culture of innovation provide employees with the necessary resources, encouragement, and autonomy to examine new ideas and take calculated risks (Bysted, 2013). This supportive environment increases employee engagement, job satisfaction, and commitment, ultimately enhancing JS. Hence, based on these arguments:

H5. IWB positively influences JS.

2.10 | Innovative workplace behaviour as a mediator

The role of IWB in influencing the connection between the adoption of AI and JP is of utmost significance (Bhargava et al., 2021). Employees who demonstrate a proclivity for IWB are instrumental in facilitating the successful implementation and utilization of AI technologies within organizations (Anantrasirichai & Bull, 2022; Yu et al., 2023). Their eagerness to investigate and experiment with AI tools empowers them to uncover fresh applications and optimize the utilization of AI systems, resulting in improved JP outcomes (Aung et al., 2023; Yu et al., 2023). By cultivating a mindset inclined towards creativity and problem-solving, employees engage in critical thinking and generate innovative ideas to harness AI technologies, ultimately positively impacting JP. The continuous learning and improvement associated with IWB also contribute to long-term enhancements in JP (Matsunaga, 2022; Yu et al., 2023). However, it is crucial to acknowledge that the influence of IWB on the relationship between AI and JP may vary across individuals and organizational contexts, highlighting the need for further comprehensive empirical research in this area (Aung et al., 2023).

IWB influences the relationship between AIA and JP through various other mechanisms (Ajzen, 2011). It fosters knowledge creation and sharing within organizations, enabling employees to actively pursue and generate new knowledge related to AI technologies (Kirkpatrick, 2017; Prentice et al., 2020). This knowledge exchange facilitates the effective utilization of AI systems, yielding improved JP outcomes. Moreover, IWB enhances employees' adaptive capacity by nurturing a mindset that embraces change and encourages modifying work processes and roles to align with AI integration (Saether, 2019; Zirar, 2023). Employees displaying high levels of IWB are more adaptable, open to change, and proactive in acquiring the skills necessary to work alongside AI technologies, ultimately leading to enhanced JP (Prentice et al., 2020). Organizations encourage employees to experiment, learn from failures, and continuously refine AI-related processes and practices (Wang, 2019; Yu et al., 2023). This continuous learning and adaptation bolster the organization's ability to capitalize on the benefits of AI, positively impacting JP at both individual and organizational levels (Anantrasirichai & Bull, 2022). Hence, based on these arguments:

H6. IWB mediates the relationship between AIA and JP.

The role of IWB in shaping the connection between AI and JS is substantial. Employees who display IWB demonstrate adaptability to technological advancements, perceiving AI as an opportunity rather than a threat (Butali & Njoroge, 2016; Chen et al., 2022; Yu et al., 2023). Their proactive approach involves acquiring relevant skills that align with the evolving requirements of the AI-driven workplace, thereby enhancing their employability and JS (Bysted, 2013). Additionally, IWB fosters a problem-solving mindset and emphasizes value creation, empowering employees to utilize AI in solving intricate problems and contributing to organizational success (Chen et al., 2022). Moreover, organizations that cultivate a culture of IWB are more likely to exhibit organizational agility by proactively embracing AI disruptions and mitigating potential JS risks (Bysted, 2013; Chen et al., 2022). While the positive influence of IWB on JS in the context of AIA is evident, it is crucial to acknowledge the significance of additional factors such as organizational support and proactive management practices. Further comprehensive research is warranted to fully comprehend the precise mechanisms through which IWB shapes JS in the era of AI (Yu et al., 2023). Hence, based on these arguments:

H7. IWB mediates the relationship between AIA and JS.

The research framework of this study is depicted in Figure 1, which indicates the relationship between AI, IWB, JP, and job satisfaction. The model proposed a direct relationship between AI and IWB, JP and JS, and between IWB and JP and JS. In addition, this study hypothesized the mediating role of IWB in the relationship between AI and JP and JS.

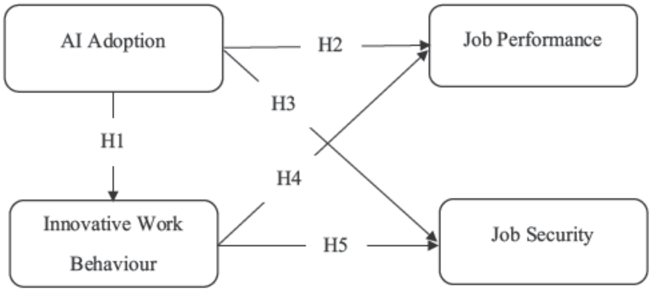

FIGURE 1 Research conceptual model.

3 | RESEARCH METHODOLOGY

3.1 | Data collection and sample

This cross-sectional study focuses on the adoption of AI technology in manufacturing organizations in Tehran, Iran. The industry is known for its significant role in AI technology, leading to increased productivity, product quality, and worker safety. The study selected a sample of full-time employees who were part of organizations implementing AI technology. The screening process included providing a definition of AI, presenting examples of AI applications, and asking if respondents were aware of similar technologies in their workplace.

Data was collected through questionnaires administered by the lead author, with random sampling ensuring equal representation across manufacturing subsectors. The initial survey found that AI technology is being adopted in two large-scale manufacturing sectors, auto and textiles, mostly dominated by family firms. A list of about 520 firms was identified, and a sample size of 340 was determined.

The researchers used simple random sampling to collect data, distributing 400 surveys with the manufacturing sector contributing 18.7% to GDP. Of these, 340 surveys were considered fully usable, resulting in an 85% response rate. The sample consisted of employees from diverse backgrounds and management levels, ranging from upper to lower management. The sample size of 340 respondents was determined based on Hair et al.'s rule of thumb, which suggests having a minimum of 10 respondents per item for data analysis. Respondents' characteristics are presented in Table 1.

The study mentioned selecting organizations in industries with a high innovation rate. So, for clarity and justification, these were the organizations in the manufacturing industry themselves that had a high innovation rate. Additionally, the explanation regarding why organizations or industries with a high innovation rate were chosen is because AIA was possible in such firms in any developing economy like Iran. The same was observed in our pilot study.

TABLE 1 Demographic profile of respondents.

	N	%
Gender		
Male	190	55.8
Female	150	44.2
Age		
Less/equal to 30 years	42	12.3
31–35 years	103	30.3
36–40 years	100	29.4
41–45 years	81	23.8
46 years and above	14	4.2
Length of service		
Less than 5	65	19.2
6–10 years	156	45.8
More than 10 years	119	35
Designation		
First-line manager	134	39.4
Middle manager	172	50.6
Top manager	34	10

3.2 | Measures

All measurement items were adapted from the literature and were assessed using a seven-point Likert-type scale ranging from 1 strongly disagree to 7 strongly agree. To assess AIA, seven items were employed (Saleem et al., 2023). The measurement of innovative behaviour referred to six items from Scott and Bruce (1994). JP measurement involved five items (Groen et al., 2017). The measurement of JS adopted three items from Oldham et al. (1986). To provide the most appropriate measurement items for respondents in Iran, we revised the wording of some items. The items are listed in Table 3.

4 | DATA ANALYSIS AND RESULTS

SEM, or structural equation modelling, is a multivariate technique that combines multiple regression and factor analysis. PLS-SEM is considered an effective method for examining the relationships between constructs and generating results that accurately reflect the complexities of real-life situations, as suggested by Moguluwa et al. (2021).

Data should be normal for statistical analysis (Hair et al., 2017). On the contrary, PLS-SEM is the non-parametric statistical software where normal data for analysis is not essential. Although the assumption to use PLS-SEM is non-normal data, it is necessary to check the normality of data at the univariate level because data should not be extremely non-normal (Hair et al., 2017).

We checked the normality assumption at the univariate level by checking its skewness and kurtosis values. Skewness should be less than 2, and kurtosis should be less than 7 (Curran et al., 1996). Absolute values of skewness and kurtosis of our research variables are in the acceptable range, as shown in Table 2. Multivariate skewness and kurtosis were checked, as suggested by Mardia (1970). Test results revealed that our research data was multivariate normal ($p < 0.001$). For nonnormal data, the best technique to be used is PLS-SEM.

4.1 | Common method bias

During our study, we simultaneously measured both dependent and independent variables, which could have caused common method bias to impact the data. Common method bias refers to variations caused by the instruments rather than the respondents' actual behaviour (Podsakoff et al., 2003). We followed the guidelines of Podsakoff et al. (2003) to mitigate common method bias through various measures. Firstly, we deliberately surveyed the constructs in a different order than the model's sequence and emphasized the confidentiality of respondents' answers, reducing the likelihood of systematic bias. Additionally, each survey page focused solely on items about the same construct, enhancing data quality by aiding respondents' comprehension of the items. Lastly, statistically, we conducted Harmen's one-factor test (Aguirre-Urreta & Hu, 2019), which revealed that a single factor only accounted for 30% of the variances. As a result, we can conclude that common method bias did not significantly affect our study.

4.1.1 | Measurement model assessment

During the evaluation of the measurement model, three key criteria were emphasized: discriminant validity, convergent validity, and internal consistency. As depicted in Table 3, all constructs exhibited good reliability, as revealed by their Cronbach's alphas and CR values exceeding the threshold of 0.70 (Hair et al., 2019). Additionally, all factor loading values surpassed 0.5, and no items within any construct exhibited excessive residual variance shared with other constructs. Moreover, the AVE values for all constructs exceeded the threshold of 0.5 (Hair et al., 2019), indicating satisfactory convergent validity.

To assess discriminant validity between variables, the Fornell–Larcker criterion and HTMT ratio were employed. As demonstrated in Table 4, the square roots of the AVE for each variable in the overall model were higher than the correlation coefficients between the variable and other variables. This supports the conclusion that the variables exhibited good discriminant validity (Fornell & Larcker, 1981). Furthermore, the HTMT values, as shown in Table 5, were all below 0.85, further confirming the presence of good discriminant validity in line with the criteria established by Henseler et al. (2015).

4.1.2 | Structural model assessment

This study evaluated the model fit and predictive ability using two indicators: coefficient of determination (R^2) and predictive relevance (Q^2). The R^2 values for each endogenous variable in the model were deemed acceptable (0.713–0.864), indicating that the model possessed satisfactory predictive accuracy. Furthermore, the Q^2 values, calculated using the blindfolding method, for each endogenous variable were greater than 0, signifying good predictive ability (Hair et al., 2019). The findings are presented in Table 6.

TABLE 2 Descriptive statistics.

			Skewness		Kurtosis					
Variables	Mean	SD	Statistics	S.E.	Statistics	S.E.	AIA	IWB	JP	JS
AIA	3.78	1.34	−0.44	0.23	−2.41	0.42	1.000			
IWB	4.1	1.81	−0.31	0.23	−2.13	0.42	0.780**	1.000		
JP	4.78	1.38	−0.87	0.23	−1.72	0.42	0.530**	0.656**	1.000	
JS	2.23	1.13	0.54	0.23	−1.87	0.42	−0.423**	0.142	−0.123*	1.000

Note: Artificial intelligence (AIA), innovative work behavior (IWB), job performance (JP), and job security (JS).
*$p < 0.05$, and **$p < 0.01$.

TABLE 3 Results of measurement model.

Latent and observed variables	Factor loading
AI adoption (AIA) → CR:0.930; Cronbach's α: 0/912; AVE:0.657	
AI adoption is more cost-effective than other technologies. (AIA1)	0.811
AI adoption saves cost and time related to other terminologies. (AIA2)	0.877
AI adoption saves time, effort, and cost required for relative advantages. (AIA3)	0.843
AI adoption assists human resource managers in their selection of the right candidate. (AIA4)	0.800
AI adoption facilitates enhanced quality decisions for recruitment and selection. (AIA5)	0.772
AI adoption increases the effectiveness of technology-related actions. (AIA6)	0.780
AI adoption provides control and better speed for decisions related to security and confidentiality. (AIA7)	0.784
Innovative work behaviour (IWB) → CR:0.934; Cronbach's α: 0/916; AVE:0.704	
"Innovation is a process involving both the generation and implementation of ideas. As such, it requires a wide variety of specific behaviors on the part of individuals. While some people might be expected to exhibit all the behaviors involved in innovation, others may exhibit only one or a few types of behaviour. Please rate each of your subordinates on the extent to which he or she:"	
Searches out new technologies, processes, techniques, and/or product ideas. (IWB1)	0.861
Generates creative ideas. (IWB2)	0.932
Promotes and champions ideas to others. (IWB3)	0.885
Investigates and secures funds needed to implement new ideas. (IWB4)	0.783
Develops adequate plans and schedules for the implementation of new ideas. (IWB5)	0.783
Is innovative. (IWB6)	0.777
Job performance (JP) → CR:0.929; Cronbach's α: 0/904; AVE:0.724	
He/she always performs all essential duties. (JP1)	0.766
He/she always fulfills all responsibilities required by his/her job. (JP2)	0.843
He/she always meets all formal performance requirements of the job. (JP3)	0.876
He/she always completes all duties specified in his/her job description. (JP4)	0.889
He/she never neglects aspects of the job that he/she is obligated to perform. (JP5)	0.873
Job security (JS) → CR:0.954; Cronbach's α: 0/946; AVE:0.673	
I'll be able to keep my present job as long as I wish. (JS1)	0.829
My organization will not cut back on the number of hours I work each week. (JS2)	0.788
If this organization were facing economic problems, my job would be the first to go. (JS3)	0.839
I am confident that I will be able to work for this organization as long as I wish. (JS4)	0.814
My job will be there as long as I want it. (JS5)	0.822
If my job were eliminated, I would be offered another job in the organization. (JS6)	0.801
Regardless of economic conditions, I will have a job in this organization. (JS7)	0.770
I am secure in my job. (JS8)	0.866
The organization would transfer me to another job if I were laid off from my present job. (JS9)	0.820
My job is not a secure one®. (JS10)	0.848

Note: CR = composite reliability; AVE = average extracted values; ® indicates items that were reverse coded.

The bootstrapping algorithm in Smart PLS 3.0 software was employed to select a resampling sample of 5000 to analyse the path testing results of the model. The results of hypothesis testing can be found in Table 7.

The results of our study revealed that AIA positively influenced IWB. The relationship was significant, having values (β 0.845, t 20.471, $p < 0.000$). Hence, H1 is supported. Moreover, the study showed that AI positively influenced JP with values (β 0.128, t 2.162, $p < 0.031$), which supported H2. Furthermore, the study revealed that H3 is supported. AIA positively influenced JS with values (β 0.423, t 6.433, $p < 0.000$). In

TABLE 4 Fornell–Larcker criterion.

	AIA	IWB	JP	JS
AIA	***0.810***			
IWB	0.745	***0.839***		
JP	0.709	0.714	***0.851***	
JS	0.783	0.702	0.776	***0.820***

Abbreviations: AIA, artificial intelligence adoption; IWB, innovative work behavior; JP, job performance; JS, job security.

TABLE 5 Heterotrait—Monotrait ratio of correlations (HTMT).

	AIA	IWB	JP	JS
AIA				
IWB	0.613			
JP	0.783	0.677		
JS	0.544	0.450	0.773	

Abbreviations: AIA, artificial intelligence adoption; IWB, innovative work behaviour; JP, job performance; JS, job security.

TABLE 6 Model fit.

Constructs	R^2	Q^2
Innovative work behaviour	0.713	0.462
Job performance	0.840	0.556
Job security	0.864	0.534

TABLE 7 Results of the direct and indirect effect hypotheses.

Path relationship	β	SE	T	Results
H1 (AIA ... IWB)	0.845	0.022	20.471	Accept
H2 (AIA ... JP)	0.128	0.053	2.433	Accept
H3 (AIA ... JS)	0.423	0.065	6.481	Accept
H4 (IWB ... JP)	0.806	0.045	18.061	Accept
H5 (IWB ... JS)	0.423	0.064	8.439	Accept

Abbreviations: AIA, artificial intelligence adoption; IWB, innovative work behaviour; JP, job performance; JS, job security.

addition, the study revealed that IWB has a positive association with JP and JS with values (β 0.806, t 16.641, $p < 0.000$) and (β 0.545, t 8.482, $p < 0.000$) respectively. Therefore, H4 and H5 are supported. The final model path diagram is illustrated in Figure 2.

4.1.3 | Mediation testing

In the analysis of mediating effects, we employed the bootstrapping technique with 5000 resamples to assess the statistical significance of the indirect effects. This non-parametric resampling method provides an estimation of the standard errors for the path coefficients, enabling the evaluation of indirect effects in the presence of mediation. Hypotheses 6 and 7 predicted that the relationships between AIA with JP and AIA with JS are mediated by IWB. To test these hypotheses, we conducted a serial mediation analysis using bootstrapping. When the 95% confidence interval does not contain zero, it indicates that the indirect effect is significant (Preacher & Hayes, 2004). As Table 8 shows, the bootstrapping results showed that the indirect effects of AIA and JP and AIA and JS was positively significant with values (β 0.681, t 16.296, $p < 0.000$) and (β 0.460, t 8.091, $p < 0.000$) respectively. Thus, H6 and H7 are supported.

5 | DISCUSSION

This study enhanced our comprehension of the interactions among employees' innovative behaviour, technology adoption, JP, and JS. Furthermore, by expanding the existing literature on sociotechnical system theory within business management, this article contributes to understanding the relationship between AI and innovative behaviour. It examines the mediating role of IWB in the relationship between AIA, JP, and JS.

This study confirmed the relationship between AI and IWB. This finding is consistent with other research showing that implementing AI technologies allows employees to utilize advanced tools and abilities to analyse data, automate tasks, and uncover new insights (Anantrasirichai & Bull, 2022; Yu et al., 2023). Similarly, AIA positively influences JP. Our results are consistent with the findings of similar studies (see, e.g. Matsunaga, 2022; Ajzen, 2011). The reason is that improved efficiency can increase employee productivity by accomplishing more work within a shorter timeframe. Moreover, AI systems provide predictive analytics, decision-support tools, and data-driven insights (Zirar, 2023), further enhancing productivity. By leveraging AI capabilities, employees can enhance their performance through the assistance of informed and accurate decision-making (Yu et al., 2023). The study suggests that AIA often necessitates employees to acquire new skills and adapt to technological changes. Organizations that invest in employee training and development programs in the context of AIA can enhance JS by equipping

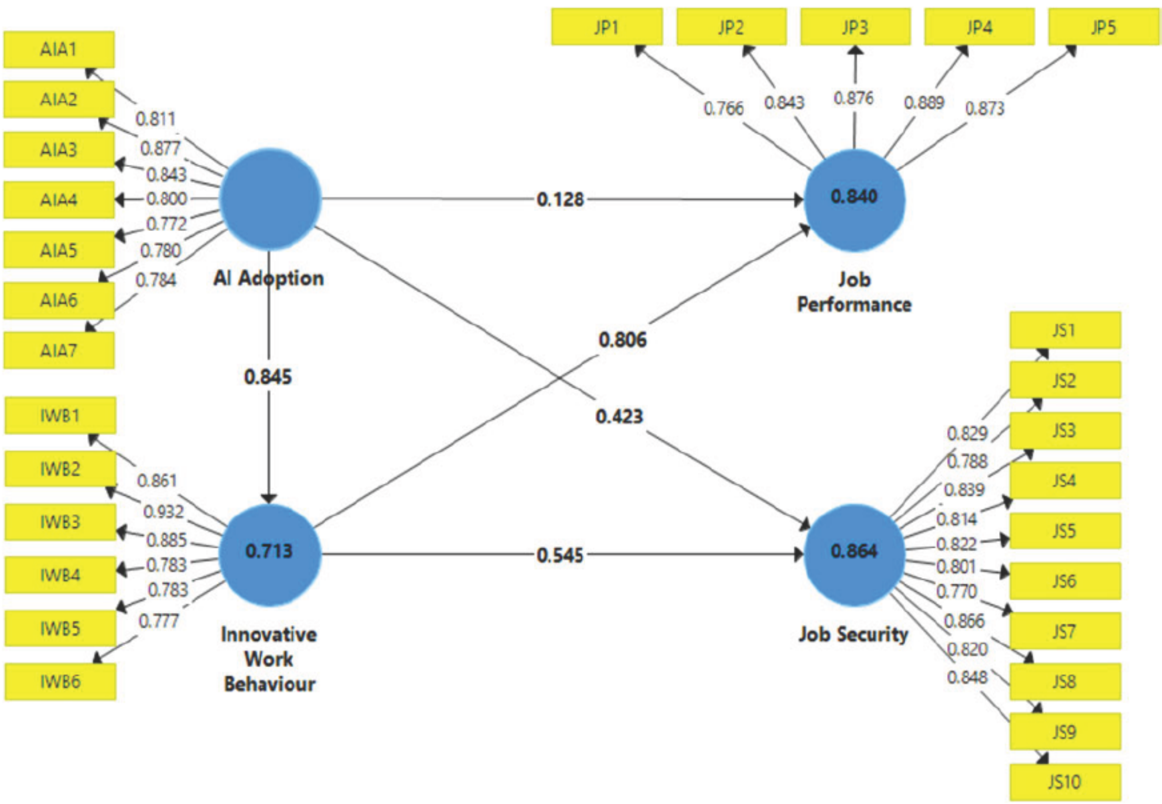

FIGURE 2 Results of path analysis. [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 8 Results of the indirect effect.

Path relationship	*β*	*t*	LLCI	ULCI	*P*	Results
(H6) AIA → IWB → JP	0.681	16.713	0.588	0.750	0.000	Completed mediation
(H7) AIA → IWB → JS	0.460	8.91	0.331	0.542	0.000	Completed mediation

Abbreviations: AIA, artificial intelligence adoption; IWB, innovative work behaviour; JP, job performance; JS, job security; LLCI, lower-limit confidence interval; ULCI, upper-limit confidence interval.

employees with the necessary skills to work alongside AI technologies (Bhargava et al., 2021; Davenport & Ronanki, 2018). The study's findings also suggested that employees who actively participate in innovative practices are responsible for generating fresh knowledge, insights, and expertise (Yu et al., 2023). This knowledge creation and exchange process plays a significant role in organizational learning, facilitating continuous improvement and boosting JP (Kirkpatrick, 2017). The study finds that employees who demonstrate IWB are inclined to embrace emerging technologies, explain novel concepts, and adjust their skills to meet evolving job demands (Butali & Njoroge, 2016; Yu et al., 2023). This adaptability strengthens JS and enhances employees' resilience in the face of changes, thereby increasing their value within the organization (Chen et al., 2022).

One of our study's crucial contributions was explaining and testing the mediating relationships. The study suggests that employees with a propensity for IWB play a crucial role in facilitating the effective implementation and utilization of AI technologies in organizations (Anantrasirichai & Bull, 2022; Yu et al., 2023). Their willingness to investigate and experiment with AI tools empowers them to discover new applications and maximize the use of AI systems, ultimately leading to enhanced JP outcomes (Aung et al., 2023; Yu et al., 2023). Finally, we postulated that IWB positively mediates the relationship between AI and JS. Employees who exhibit IWB showcase their ability to adapt to technological advancements and view AI as a chance for growth rather than a source of concern (Butali & Njoroge, 2016; Yu et al., 2023). Their proactive mindset involves actively acquiring relevant skills that align with the evolving demands of the AI-driven workplace, thus augmenting their employability and JS (Bysted, 2013). Hence, the study evidences that employees' adoption and utilization of AI technologies positively influence their innovative behaviour, JP and security. Similarly provides evidence that IWB has a significant and positive relationship with JP and security. Moreover, the study finds a significant mediating role of IWB in the relationship between JP and security.

The indirect relationship where IWB mediates the impact of AIA on JP and JS is crucial for several reasons. It not only bridges the gap between technology and human elements in the workplace but also provides a clear pathway for organizations to leverage AI effectively. By focusing on innovation, organizations can enhance employee performance, ensure JS, and foster a culture that is adaptable to technological advancements. This holistic approach is essential for thriving in an increasingly AI-driven world.

6 | THEORETICAL CONTRIBUTIONS

Building upon the sociotechnical system theory principles, this study contributes to the existing body of literature by examining the relationship between AIA, employees' innovative behaviour, JP, and JS. The study investigates AIA's direct and significant impact on employees' innovative behaviour, JP, and JS. By investigating these factors, the current research aims to deepen our understanding of the interplay between employee innovative behaviour, technology adoption, JP, and JS. Moreover, extending the sociotechnical system theory within business management adds value to understanding AI and innovative behaviour in the workplace, stimulating further research to bridge knowledge gaps in this field. The current study aims to offer insightful advice to businesses using AI technologies to boost worker productivity and JS.

6.1 | Practical contributions

The results of this study have significant organizational implications. First, organizations should prioritize encouraging the use of AI technology and offering thorough training programmes to give staff members the skills they need to use AI tools efficiently. This might increase job stability and result in better work performance. Second, encouraging employees to engage in IWBs like investigating novel concepts and experimenting with AI technologies can improve JP. Additionally, using AI to automate repetitive operations frees staff time to focus on more important work, thus increasing productivity. Lastly, recognizing the mediating role of IWB underscores the significance of creating an environment that supports and encourages innovation, empowering employees to contribute innovative ideas and approaches, thereby enhancing JP and security. By considering these practical implications, organizations can effectively embrace AI technologies, drive JP, and promote JS in the rapidly evolving technological landscape.

6.2 | Limitations and future research

This study focuses on manufacturing organizations in Tehran, Iran, and its findings may not be generalizable to other industries. The cross-sectional nature of the study may lead to method bias. Future research should consider time-lagged or longitudinal studies to understand the long-term effects of AIA on JP and JS. Cross-cultural studies can help examine the impact of cultural elements on workers' views towards AI and IWB. Understanding the contextual dynamics of AIA, IWB, JP, and JS can be improved by considering organizational factors like leadership styles and change management strategies. This method provides insights into the mechanisms by which leadership and change management techniques affect the overall impact of AI on JP and JS.

7 | CONCLUSION

The research's conclusions have essential ramifications for businesses looking to use AI technologies wisely and benefit their workers. The current study has shown that implementing AI technology can significantly impact how well employees do their jobs. Employers may improve employee performance by embracing AI and utilizing its potential to help employees make more informed and precise decisions. Additionally, automating repetitive operations with AI frees workers to focus on more complex and value-added work, improving their ability to execute their jobs. Employees with a favourable view of AI are more adaptable to change and can better match their skill sets to the changing demands of AI-driven workplaces, which promotes job stability.

ETHICS DECLARATIONS

All procedures performed in studies involving human participants were by ethical standards and with the Helsinki Declaration and its later amendments or comparable ethical standards.

INFORMED CONSENT

Informed consent was obtained from all individual participants included in the study.

DATA AVAILABILITY STATEMENTS

The datasets generated during and/or analysed during the current study are available from the corresponding author upon reasonable request.

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