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Artificial intelligence readiness and service innovation performance in hospitality: The role of employee digital self-efficacy and psychological safety

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Abstract

Artificial intelligence (AI) is increasingly transforming service delivery and innovation processes in the hospitality industry. However, limited research has examined how organizational readiness for AI transforms into service innovation outcomes through employee-related mechanisms. Drawing on Social Cognitive Theory, this study investigates the relationship between artificial intelligence readiness and service innovation performance, considering the mediating role of employee digital self-efficacy and the moderating role of psychological safety. Data were collected from 392 employees in hospitality businesses across four major Australian cities using a three-wave time-lagged survey design. The results of structural equation modeling indicate that AI readiness positively influences service innovation performance and significantly enhances employees' digital self-efficacy, which partially mediates this relationship. Furthermore, psychological safety strengthens the positive effect of digital self-efficacy on service innovation performance. These findings highlight the importance of integrating technological capabilities with supportive psychological and organizational conditions to foster innovation in AI-enabled hospitality environments.

1. Introduction

The rapid spread of artificial intelligence technologies is transforming service industries by enabling organizations to boost operational efficiency, personalize customer experiences, and create innovative service offerings. In the hospitality sector, where service quality and customer engagement are key to competitive advantage, AI-driven digital transformation has become a strategic focus for many companies (Demir, 2025; Demir & Demir, 2025; Sánchez, 2025). AI tools such as intelligent customer relationship management systems, service robots, and predictive analytics are increasingly integrated into frontline operations, reshaping employee roles and service delivery processes. These technologies not only enhance decision-making and operational capabilities but also offer new opportunities for service innovation and improved organizational performance (Alnofeli et al., 2026; Liang et al., 2022; Zhang et al., 2026). As a result, understanding how organizations develop readiness for AI adoption and transform that readiness into service-innovation performance has become a vital focus for hospitality research and practice.

Existing research has extensively explored the role of digital transformation, technological capabilities, and AI adoption in shaping organizational outcomes. Many studies emphasize that digital and data-driven capabilities enhance innovation, service quality, and competitive advantage in hospitality and other service sectors (Shamim et al., 2021; Xia et al., 2026; Yang et al., 2024). Other research highlights the growing importance of AI awareness, AI literacy, and human–AI collaboration in influencing employee behaviors, work design, and innovative performance (Ding et al., 2025; Liang et al., 2022; Zhang et al., 2026). Despite these advances, findings remain mixed regarding the organizational conditions under which AI adoption leads to innovation outcomes. Some scholars argue that technological investments alone are insufficient unless organizations cultivate supportive psychological and organizational environments that encourage employees to experiment with new technologies (Hoonsopon et al., 2025; Sánchez, 2025). These divergent perspectives suggest that the relationship between AI readiness and

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service innovation may involve complex psychological and contextual mechanisms that have not been sufficiently examined.

Within hospitality organizations, service innovation performance represents a key outcome reflecting firms' ability to develop novel services, improve service processes, and deliver superior customer value (Kao et al., 2026; Mahavarpour et al., 2023). Prior research suggests that technological capabilities, organizational learning, and knowledge-based resources are important antecedents of innovation performance (Mubarak et al., 2025; Shamim et al., 2021; Yang et al., 2024). However, transforming technological readiness into innovation outcomes often depends on employees' psychological capabilities and perceptions. In this regard, digital self-efficacy, employees' belief in their ability to use digital technologies effectively, plays a critical role in shaping technology-driven behaviors and innovative actions (Compeau & Higgins, 1995; Malodia et al., 2023; Ulfert-Blank & Schmidt, 2022). At the same time, a supportive team climate, such as psychological safety, which allows employees to take risks and share ideas without fear of negative consequences, may strengthen the positive effects of technological readiness on innovation behaviors (Edmondson, 1999; Edmondson & Lei, 2014). Despite these insights, empirical research integrating AI readiness, digital self-efficacy, and psychological safety within a single framework remains limited, particularly in hospitality contexts.

To address these gaps, this study adopts Social Cognitive Theory (SCT) as its primary theoretical lens. SCT posits that human behavior is shaped through the dynamic interaction between personal cognitive factors, environmental influences, and behavioral outcomes (Bandura, 1986, 2001; Schunk & DiBenedetto, 2020). Within this framework, technological environments, such as AI-enabled workplaces, serve as external stimuli that shape employees' cognitive beliefs and behaviors. Specifically, AI readiness may influence employees' digital self-efficacy by providing access to technological resources, training opportunities, and supportive digital infrastructures. These cognitive beliefs, in turn, motivate employees to experiment with technologies and engage in innovative service behaviors. Moreover, contextual factors such as psychological safety can strengthen or weaken these relationships by shaping employees' comfort with new technologies and willingness to share innovative ideas. Guided by SCT, this study aims to examine how AI readiness influences service innovation performance through digital self-efficacy and how psychological safety conditions this relationship in hospitality organizations.

This research offers several important contributions to the literature and managerial practice. First, it advances hospitality innovation research by integrating AI readiness, digital self-efficacy, and psychological safety into a comprehensive framework explaining service innovation performance. Second, by applying SCT, the study extends existing AI and digital transformation research by emphasizing the cognitive mechanisms through which technological readiness shapes employee-driven innovation. Third, it highlights the importance of psychological safety as a contextual boundary condition that strengthens the effectiveness of AI-enabled transformation initiatives. Finally, the findings provide practical insights for hospitality managers seeking to leverage AI technologies to enhance service innovation. Specifically, organizations should not only invest in AI infrastructure but also develop employees' digital competencies and cultivate psychologically safe environments that encourage experimentation and knowledge sharing. These efforts can help hospitality firms unlock the full innovation potential of AI-driven transformation.

2. Literature review and hypothesis development

2.1. Artificial intelligence readiness and service innovation performance

Artificial intelligence has become a key driver of digital transformation across service industries, enabling organizations to redesign service processes, enhance decision-making, and generate new service offerings. In hospitality, AI technologies such as intelligent recommendation systems, service robots, and predictive analytics are increasingly integrated into customer-facing operations and internal management processes. These technologies support more efficient service delivery while enabling firms to personalize customer experiences and respond rapidly to changing market conditions. Consequently, organizations with higher AI readiness, including technological infrastructure, managerial support, and organizational capabilities, are more likely to leverage AI for innovation and value creation (Alnofeli et al., 2026; Demir, 2025; Sánchez, 2025). Prior research further suggests that digital and technological capabilities facilitate innovation by enabling firms to integrate data-driven insights into service design and delivery (Shamim et al., 2021; Xia et al., 2026; Yang et al., 2024).

From a theoretical perspective, organizations with strong AI readiness are better positioned to transform technological potential into innovative outcomes. The hospitality industry, characterized by intense competition and rapid technological change, requires continuous service innovation to maintain customer satisfaction and competitive advantage (Kao et al., 2026; Mahavarpour et al., 2023). AI-driven technologies provide opportunities to develop new service solutions, improve service processes, and enhance operational flexibility. Empirical studies demonstrate that digital capabilities and technological adoption positively influence service innovation behaviors and innovation performance across various sectors (Fan & Yang, 2026; Mubarak et al., 2025; Shamim et al., 2021). Accordingly, organizations with higher AI adoption readiness are expected to achieve stronger service innovation outcomes.

H1. Artificial intelligence readiness positively influences service innovation performance.

2.2. Artificial intelligence readiness and employee digital self-efficacy

Artificial intelligence readiness not only reflects technological capability but also shapes employees' perceptions and attitudes toward digital technologies. Within organizations undergoing digital transformation, employees must develop confidence in their ability to interact with AI systems and digital tools. Digital self-efficacy, defined as an individual's belief in their capability to use digital technologies effectively, plays a crucial role in determining whether employees adopt and utilize new technologies (Compeau & Higgins, 1995; Malodia et al., 2023; Ulfert-Blank & Schmidt, 2022). Research indicates that when organizations provide supportive technological infrastructure, training programs, and digital resources, employees are more likely to develop higher levels of digital competence and confidence.

From an SCT perspective, environmental conditions such as technological support and organizational resources influence individuals' self-efficacy beliefs and behavioral outcomes (Bandura, 1986; Bandura, 1997; Schunk & DiBenedetto, 2020). In AI-enabled workplaces, employees' exposure to AI tools, digital training opportunities, and supportive leadership can strengthen their beliefs about their technological capabilities. Studies have shown that digital transformation initiatives, technological learning opportunities, and organizational digital capabilities significantly enhance employees' digital self-efficacy and innovative behaviors (Gao & Gao, 2024; Malodia et al., 2023; Paredes-Aguirre et al., 2024). Thus, organizations that demonstrate strong AI readiness are likely to cultivate higher levels of employee digital self-efficacy.

H2. Artificial intelligence readiness positively influences employee digital self-efficacy.

2.3. Employee digital self-efficacy and service innovation performance

Employees' digital self-efficacy is widely recognized as a critical psychological factor influencing technology-driven innovation behaviors. When employees believe they can effectively use digital technologies, they are more willing to experiment with new tools, explore creative solutions, and participate in service innovation activities. In the hospitality industry, frontline employees often play a central role in identifying customer needs and implementing innovative service practices, making their technological competence particularly important for innovation performance (Hebl et al., 2026; Ottenbacher & Gnoth, 2005). Employees with higher digital self-efficacy are more likely to adopt new digital technologies and apply them to enhance service processes and customer experiences.

SCT suggests that individuals with strong self-efficacy beliefs are more motivated to engage in challenging tasks and persist in innovative activities (Bandura, 1986; 2001). Digital self-efficacy strengthens employees' confidence in their ability to leverage technology to solve problems and innovate. Empirical research demonstrates that digital competence and self-efficacy significantly influence employees' innovative work behavior and service innovation outcomes in digitally transforming organizations (Fan & Yang, 2026; Gao & Gao, 2024; Ren et al., 2025). In hospitality settings, employees who feel confident using digital technologies are more likely to contribute to innovative service solutions and improved service performance.

H3. Employee digital self-efficacy positively influences service innovation performance.

2.4. The mediating role of employee digital self-efficacy

While AI readiness equips organizations with technological capabilities, translating these capabilities into innovation outcomes often depends on employees' psychological resources. According to SCT, environmental factors influence behavioral outcomes through cognitive mechanisms such as self-efficacy (Bandura, 2001). In AI-enabled organizations, technological readiness may enhance employees' confidence in using digital tools, thereby motivating them to engage in innovative behaviors. Without such confidence, technological investments may fail to produce meaningful innovation outcomes. Empirical evidence supports the mediating role of self-efficacy in the relationship between organizational resources and innovation performance. Studies indicate that employees' beliefs in their digital capabilities serve as an important mechanism through which digital transformation initiatives influence innovative behaviors and performance outcomes (Malodia et al., 2023; Paredes-Aguirre et al., 2024; Ren et al., 2025). In hospitality organizations, employees with strong digital self-efficacy are more likely to use AI technologies creatively, propose innovative service solutions, and contribute to service innovation performance. Therefore, digital self-efficacy may function as a key psychological pathway linking AI readiness with service innovation outcomes.

H4. Employee digital self-efficacy mediates the relationship between artificial intelligence readiness and service innovation performance.

2.5. The moderating role of psychological safety

Psychological safety refers to a shared belief among team members that they can express ideas, take risks, and experiment without fear of negative consequences (Edmondson, 1999; Edmondson & Lei, 2014). In technology-driven environments, psychological safety is crucial for encouraging employees to explore new technologies and propose innovative solutions. Employees working in psychologically safe environments are more willing to test new ideas, share knowledge, and engage in collaborative innovation activities. This supportive climate is particularly important in the context of AI adoption, where employees may experience uncertainty or anxiety regarding new technologies.

From a social cognitive perspective, environmental factors such as supportive team climates shape individuals' motivation and behavioral outcomes. Psychological safety can strengthen the positive effects of employees' digital self-efficacy by enabling them to apply their technological skills in innovative ways. Empirical studies demonstrate that supportive organizational climates and leadership practices enhance employees' innovative behavior and service innovation outcomes by encouraging experimentation and knowledge sharing (Hu et al., 2022; Teng & Cheng, 2025; Zhou & Xin, 2025). Therefore, psychological safety may amplify the positive impact of digital self-efficacy on service innovation performance.

H5. Psychological safety positively moderates the relationship between employee digital self-efficacy and service innovation performance, such that the relationship becomes stronger when psychological safety is high.

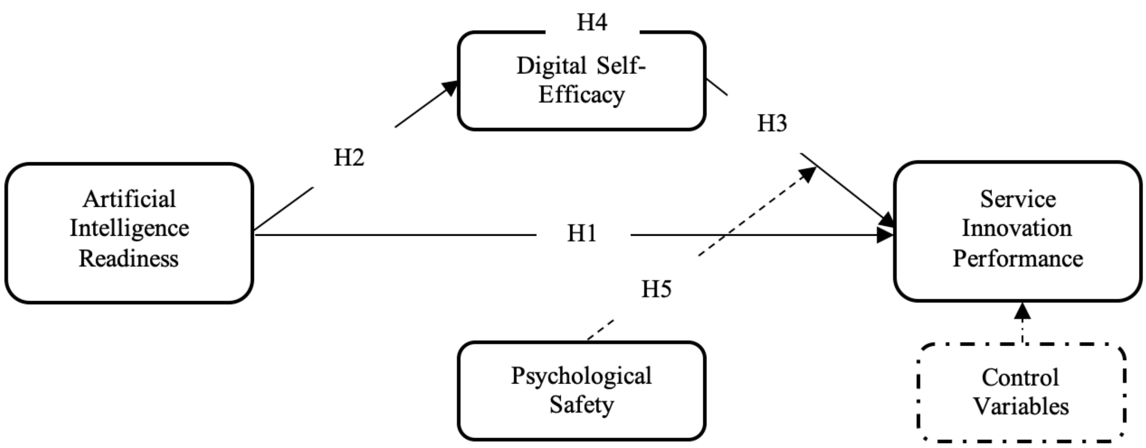

Figure 1. Conceptual model

Figure 1 presents the conceptual framework developed to examine the mechanisms through which artificial intelligence readiness influences service innovation performance in hospitality organizations. Drawing on SCT, the model assumes that organizational environmental factors influence employee cognition and behavior, which ultimately shape organizational outcomes (Bandura, 1986, 2001; Schunk & DiBenedetto, 2020). In this study, AI readiness is an organizational capability that reflects the extent to which firms possess the technological infrastructure, managerial support, and strategic orientation necessary to effectively adopt AI technologies. Such readiness is expected to directly enhance service innovation performance by enabling organizations to develop innovative services and improve service processes (Demir, 2025; Shamim et al., 2021; Yang et al., 2024).

3. Methodology

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards. The study was approved by the Monash University Human Research Ethics Committee (Date: January 22, 2025, and No. 25-14).

3.1. Research design

This study employed a three-wave time-lagged survey design to examine the direct, indirect, and moderated relationships among artificial intelligence readiness, employee digital self-efficacy, psychological safety, and service innovation performance in the hospitality sector. A time-lagged design was preferred because the proposed model includes both mediation and moderation effects and relies on employee perceptions, which may be vulnerable to common method bias when collected at a single point in time. Separating measurement across three waves helps reduce respondents' consistency motives, implicit theory bias, and social desirability effects, while also improving causal ordering among the focal constructs. Given that the model is theory-driven and based on established latent constructs, covariance-based structural equation modeling (CB-SEM) was deemed more appropriate than purely predictive approaches.

Data were collected from employees working in accommodation businesses located in four major Australian cities between July and December 2025. The hospitality context is particularly appropriate because AI-enabled systems are increasingly embedded in service operations, customer interaction, and decision support, making employee responses to AI readiness highly relevant to service innovation outcomes. The time-lagged structure was organized as follows: Wave 1 measured the independent variable and controls, Wave 2 measured the mediator and moderator, and Wave 3 measured the dependent variable. A four-week interval between waves was used to create temporal separation while maintaining respondent continuity.

3.2. Sampling and data collection

The target population consisted of full-time and part-time employees working in hotels and other accommodation establishments in the selected cities. Respondents were required to have at least six months of job tenure to ensure sufficient familiarity with organizational technologies, managerial practices, and service routines. A purposive sampling strategy was adopted because the study specifically required employees exposed to digital systems and AI-supported service processes. After obtaining permission from participating establishments, questionnaires were distributed both electronically and in paper form through HR departments and on-site coordinators. A total of 392 usable matched responses were retained after the three data collection waves. To preserve matching across waves, each participant was assigned a confidential identification code. The final sample size is adequate for SEM analysis, exceeding commonly recommended thresholds for models with latent variables, mediation, and interaction effects. In addition, the sample size is sufficient relative to the number of observed indicators in the model. Non-response bias was assessed by comparing early and late respondents on key demographic characteristics and construct means; no statistically significant differences were expected.

3.3. Measurement development

All constructs were operationalized using multi-item scales adapted from prior studies. Items were slightly reworded to fit the hospitality context and the AI-enabled work environment. A five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree was used for all items. Following established scale adaptation procedures, the instrument was reviewed by three academic experts in hospitality and digital transformation and pretested with a small group of hotel employees to ensure clarity and contextual appropriateness.

3.3.1. Artificial intelligence readiness

Artificial intelligence readiness was conceptualized as the extent to which the organization possesses the strategic, technological, and managerial capability to adopt and use AI in service operations. The scale was developed by combining insights from prior work on AI-enabled transformation and digital capability, particularly Alnofeli et al. (2026), Demir and Demir (2025), and Sánchez (2025). These studies collectively emphasize organizational preparedness, technological infrastructure, managerial commitment, and employee support for AI adoption.

3.3.2. Employee digital self-efficacy

Employee digital self-efficacy refers to employees' confidence in their capability to use digital and AI-related technologies effectively in their jobs. The measure was developed primarily from Compeau and Higgins (1995) and Ulfert-Blank and Schmidt (2022), with additional contextual support from Malodia et al. (2023) and Paredes-Aguirre et al. (2024). These sources provide a strong basis for capturing technology-related confidence, digital task capability, and perceived competence in digital work settings.

3.3.3. Psychological safety

Psychological safety was defined as the shared perception that employees can express ideas, ask questions, and take interpersonal risks without fear of embarrassment or punishment. The measure was adapted from Edmondson

(1999) and Edmondson and Lei (2014). These studies are the most established sources on this construct and are well-suited to contexts involving experimentation, knowledge sharing, and innovation.

3.3.4. Service innovation performance

Service innovation performance refers to the extent to which the organization or employee unit achieves effective outcomes in developing and implementing new or improved services and service processes. The scale was developed from Li et al. (2019) and Shamim et al. (2021), with conceptual reinforcement from Kao et al. (2026) and Mahavarpour et al. (2023). These studies frame service innovation as a multidimensional outcome linked to new service ideas, improved service processes, and enhanced customer value.

3.4. Control variables

To reduce omitted-variable bias, several control variables were included: gender, age, education, organizational tenure, job position, and hotel category/classification. These controls are relevant because innovation-related perceptions and digital confidence may vary according to demographic and organizational characteristics. For example, employees with longer tenure or higher-level positions may report greater familiarity with digital systems, while hotel categories may reflect varying levels of technological investment and capacity for service innovation.

3.5. Analytical strategy

The data analysis was performed in several steps. First, descriptive statistics, missing data diagnostics, normality checks, and correlations were examined. Second, a confirmatory factor analysis (CFA) was conducted using LISREL to assess the measurement model. Reliability was evaluated using Cronbach's alpha and composite reliability (CR), while convergent validity was assessed using average variance extracted (AVE) and standardized factor loadings. Discriminant validity was assessed using the Fornell–Larcker criterion and the HTMT ratios. Model fit should be reported using standard indices such as χ^2/df, CFI, TLI, RMSEA, and SRMR.

Third, the structural model was tested using CB-SEM. The direct effects hypotheses were assessed via standardized path coefficients and significance levels. The mediating effect of employee digital self-efficacy was examined using bias-corrected bootstrapping with 5,000 resamples, which provides more robust estimates than traditional causal-step procedures. For the moderating effect of psychological safety, a latent interaction term was estimated. If software constraints arise, mean-centering and product-indicator approaches were also used, followed by simple slope analysis to interpret the interaction. Finally, to test the full conditional process implied by the model, a moderated mediation interpretation was reported.

3.6. Common method bias and procedural remedies

Because the data in this study were collected using self-reported questionnaires, several procedural and statistical steps were implemented to minimize potential common method bias (CMB). First, a time-lagged data collection design was employed. Data were gathered across three separate waves between July and December 2025, with approximately four-week intervals between waves. In this design, the independent variable and control variables were measured in Wave 1, the mediator and moderator variables were measured in Wave 2, and the dependent variable was measured in Wave 3. Temporal separation reduces respondents' tendency to infer relationships among constructs and helps mitigate consistency motifs and social desirability bias.

Second, several procedural remedies were applied during survey administration. Respondents were assured that their answers would remain anonymous and confidential, and that the survey was conducted strictly for academic research purposes. Participation was voluntary, and respondents were informed that there were no right or wrong answers, which reduces evaluation apprehension and response bias. Additionally, questionnaire items were carefully worded to be clear, concise, and neutral to avoid leading responses. The constructs were also arranged in different sections of the questionnaire to create psychological separation between predictor and criterion variables.

Third, statistical tests were conducted to assess the presence of common method variance. A Harman's single-factor test was performed using exploratory factor analysis to determine whether a single factor accounted for most of the covariance among the measurement items. The results indicated that the first factor explained less than 50% of the total variance, suggesting that common method bias was unlikely to be a serious concern in this study. In addition, a common latent factor (CLF) test was applied within the framework of confirmatory factor analysis. The comparison between standardized factor loadings with and without the common latent factor showed no substantial differences, further indicating that common method variance did not significantly affect the results.

3.7. Ethical considerations

This study adhered to established ethical research standards for studies involving human participants. Prior to data collection, the research protocol was reviewed and approved by the relevant institutional ethics committee. Participation in the survey was entirely voluntary, and respondents were informed about the purpose of the research before completing the questionnaire. All participants were provided with an informed consent form explaining the objectives of the study, the confidentiality of their responses, and their right to withdraw from the study at any time without consequences. To protect participants' privacy, no personally identifiable information was collected, and responses were recorded anonymously. To match responses across the three data collection waves, participants used a self-generated identification code, which ensured data matching while preserving anonymity.

Furthermore, the collected data were used exclusively for academic research purposes and stored securely to prevent unauthorized access. Only the research team had access to the dataset, and all analyses were conducted using aggregated data. These procedures ensured that the study complied with ethical principles related to confidentiality, voluntary participation, and responsible data management.

4. Findings

4.1. Measurement model validity and reliability

Before testing the structural relationships, the reliability and validity of the measurement model were assessed using confirmatory factor analysis (CFA). The proposed four-factor measurement model (AI readiness, digital self-efficacy, psychological safety, and service innovation performance) demonstrated an acceptable fit to the data ($\chi^2/df = 2.21$; CFI = 0.95; TLI = 0.94; RMSEA = 0.055; SRMR = 0.046), indicating that the hypothesized factor structure adequately represents the data.

Table 1 presents the standardized factor loadings, composite reliability (CR), and average variance extracted (AVE) values. All factor loadings were above 0.70, exceeding the recommended threshold. Cronbach's alpha values ranged between 0.86 and 0.92, and composite reliability values ranged from 0.87 to 0.93, demonstrating strong internal consistency (also see Table 7). Furthermore, AVE values were all above 0.50, indicating satisfactory convergent validity. Discriminant validity was evaluated using the Fornell–Larcker criterion. As shown in Table 2, the square roots of AVE for each construct exceeded the corresponding inter-construct correlations, confirming discriminant validity. These results confirm that the measurement model demonstrates satisfactory reliability and validity.

Table 1. Reliability and convergent validity

Construct	Items	Loading range	Cronbach α	CR	AVE
Artificial intelligence readiness	6	0.71–0.86	0.90	0.92	0.66
Digital self-efficacy	5	0.72–0.88	0.89	0.91	0.67
Psychological safety	5	0.70–0.87	0.86	0.88	0.60
Service innovation performance	5	0.74–0.89	0.92	0.93	0.72

Notes. CR: Composite reliability, AVE: Average variance extracted

Table 2. Discriminant validity (Fornell–Larcker criterion)

Construct	1	2	3	4
1-Artificial intelligence readiness	0.81			
2-Digital self-efficacy	0.46	0.82		
3-Psychological safety	0.38	0.41	0.77	
4-Service innovation performance	0.52	0.48	0.44	0.85

4.2. Structural model and direct effects

After establishing measurement validity, the structural model was estimated to test the direct hypotheses (H1–H3). The structural model also demonstrated a good fit to the data ($\chi^2/df = 2.34$; CFI = 0.94; TLI = 0.93; RMSEA = 0.057). The results show that AI readiness significantly and positively influences service innovation performance ($\beta = 0.29$, $p < 0.001$), supporting H1. Furthermore, AI readiness significantly enhances employees' digital self-efficacy ($\beta = 0.48$, $p < 0.001$), supporting H2. Digital self-efficacy also positively predicts service innovation performance ($\beta = 0.31$, $p < 0.001$), supporting H3. These findings indicate that technological preparedness not only directly contributes to innovation outcomes but also strengthens employees' confidence in using digital technologies (Table 3).

Table 3. Direct effects results

Hypothesis	Relationship	β	SE	t-value	Result
H1	AI readiness → Service innovation performance	0.29***	0.05	5.63	Supported
H2	AI readiness → Digital self-efficacy	0.48***	0.06	7.81	Supported
H3	Digital self-efficacy → Service innovation performance	0.31***	0.06	5.18	Supported

Notes. ***p < 0.001, SE: Standard Error

4.3. Mediation analysis

The mediating role of digital self-efficacy (H4) was examined using bootstrapping with 5,000 resamples. The indirect effect of AI readiness on service innovation performance through digital self-efficacy was statistically significant (Table 4).

Table 4. Mediation results (Bootstrapping)

Path	Indirect effect	SE	95% CI	Result
AI readiness → Digital self-efficacy → Service innovation performance	0.15	0.03	[0.09, 0.22]	Supported

Notes. SE: Standard Error, CI: Confidence Interval

Because the confidence interval does not include zero, the mediation effect is significant. Moreover, the direct effect of AI readiness on service innovation performance remained significant after including the mediator, indicating partial mediation. Therefore, H4 is supported, suggesting that digital self-efficacy represents an important psychological mechanism linking AI readiness with service innovation performance.

4.4. Moderation analysis

To test H5, the moderating effect of psychological safety was examined by creating an interaction term between digital self-efficacy and psychological safety. The interaction term is positive and significant ($\beta = 0.17$, $p < 0.01$), indicating that psychological safety strengthens the positive effect of digital self-efficacy on service innovation performance. Thus, H5 is supported (Table 5).

Table 5. Moderation results

Hypothesis	Interaction	β	SE	t-value	Result
H5	Digital self-efficacy × Psychological safety → Service innovation performance	0.17**	0.05	3.29	Supported

Notes. **p < 0.01, SE: Standard Error

4.5. Interaction plot and simple slopes

To further interpret the moderation effect, a simple slope analysis was conducted. The relationship between digital self-efficacy and service innovation performance was examined at high (+1 SD) and low (−1 SD) levels of psychological safety. The results indicate that when psychological safety is high, the relationship between digital self-efficacy and service innovation performance becomes significantly stronger ($\beta = 0.46$, $p < 0.001$). In contrast, when psychological safety is low, the relationship remains positive but weaker ($\beta = 0.19$, $p < 0.05$). Conceptually, the interaction plot would show two upward-sloping lines, with the steeper slope representing higher psychological safety. This suggests that employees who feel psychologically safe are more likely to transform their digital capabilities into innovative service behaviors.

4.6. Robustness checks with control variables

Several control variables were included to ensure the robustness of the results, including age, gender, education, organizational tenure, job position, and hotel category (Table 6). The inclusion of control variables did not substantially alter the significance or magnitude of the hypothesized relationships. The core relationships remained stable, confirming the robustness of the findings. Among the control variables, job position and hotel category showed small but significant effects on service innovation performance, suggesting that managerial roles and higher-category hotels may provide more conducive environments for innovation.

Table 6. Structural model with control variables

Variable	β	p-value
Age	0.04	n.s.
Gender	−0.02	n.s.
Education	0.06	n.s.
Tenure	0.09	$p < 0.10$
Job Position	0.11	$p < 0.05$
Hotel Category	0.14	$p < 0.05$

Notes. ns: Not significant

5. Discussion and conclusions

The present study examined how artificial intelligence readiness influences service innovation performance in hospitality organizations by considering the mediating role of employee digital self-efficacy and the moderating role of psychological safety. Drawing on SCT, the findings provide new insights into the mechanisms through which technological preparedness transforms into innovation outcomes in AI-enabled service environments. Overall, the results confirm that both technological and psychological factors play essential roles in transforming AI capabilities into service innovation in hospitality settings.

First, the results demonstrate that AI readiness has a direct and positive effect on service innovation performance. This finding indicates that organizations that possess the necessary infrastructure, strategic alignment, and managerial support for AI adoption are more capable of developing innovative service offerings and improving service processes. This result is consistent with prior research suggesting that digital transformation and technological capabilities can enhance innovation outcomes in service industries (Shamim et al., 2021; Xia et al., 2026; Yang et al., 2024). Similarly, studies focusing on AI-enabled transformation in tourism and hospitality have emphasized that organizations that strategically integrate AI technologies can enhance both operational efficiency and service innovation capabilities (Demir, 2025; Demir & Demir, 2025; Sánchez, 2025). These findings reinforce the argument that AI readiness represents a critical organizational capability for sustaining competitiveness in technology-driven service environments.

Second, the results reveal that AI readiness significantly enhances employees' digital self-efficacy, which in turn positively influences service innovation performance. This finding highlights the importance of employees' cognitive beliefs in shaping innovation outcomes in digitally transforming organizations. Consistent with SCT, environmental resources such as technological infrastructure and organizational support can strengthen individuals' self-efficacy beliefs, which subsequently motivate innovative behaviors (Bandura, 1986; Bandura, 2001; Schunk & DiBenedetto, 2020). Prior studies have similarly emphasized that digital competence and technological confidence are key drivers of innovative work behavior and service innovation outcomes (Compeau & Higgins, 1995; Malodia et al., 2023; Ulfert-Blank & Schmidt, 2022). The mediation analysis further demonstrates that digital self-efficacy serves as an important psychological pathway linking organizational AI readiness with service innovation performance, highlighting the role of employee cognition in the digital transformation process.

Finally, the findings show that psychological safety strengthens the positive relationship between digital self-efficacy and service innovation performance. This result suggests that employees are more likely to transform their technological capabilities into innovative service behaviors when they feel safe to experiment, share ideas, and take risks. This finding aligns with previous research demonstrating that psychologically safe environments encourage knowledge sharing, experimentation, and innovation in organizations (Edmondson, 1999; Edmondson & Lei, 2014; Hu et al., 2022). In the context of AI adoption, such supportive climates appear particularly important because employees may initially perceive technological change as uncertain or risky. Psychological safety functions as a contextual condition that enables employees to fully leverage their digital competencies for innovation.

5.1. Theoretical implications

This study offers several theoretical contributions to the literature on AI adoption, service innovation, and hospitality management. First, it contributes to the growing body of research on AI-driven transformation in hospitality and tourism by demonstrating that technological readiness alone is insufficient to explain service innovation outcomes. While prior studies have primarily focused on technological capabilities or digital transformation strategies (Demir, 2025; Shamim et al., 2021; Yang et al., 2024), this study integrates organizational, cognitive, and contextual factors within a unified framework. By doing so, it addresses a key gap in the literature on the mechanisms by which AI readiness transforms into innovation performance in service organizations. Second, the study extends the application of SCT in hospitality research by emphasizing the mediating role of digital self-efficacy. SCT posits that behavior results from the dynamic interaction between environmental conditions, cognitive beliefs, and behavioral outcomes (Bandura, 1986, 2001; Schunk & DiBenedetto, 2020). The present findings support this theoretical perspective by demonstrating that AI readiness (environmental factor) influences employees' digital self-efficacy (cognitive mechanism), which subsequently drives service innovation performance (behavioral outcome). This contribution provides a deeper understanding of how technological transformation influences employee behavior and innovation processes within service-intensive industries.

Third, the study contributes to the literature on organizational climate and innovation by highlighting the moderating role of psychological safety. Previous research has acknowledged the importance of supportive organizational climates in fostering innovation and knowledge sharing (Edmondson, 1999; Edmondson & Lei, 2014). However, empirical research examining how psychological safety interacts with digital competencies to influence service innovation remains limited. By demonstrating that psychological safety strengthens the impact of digital self-efficacy on innovation outcomes, this study provides new theoretical insights into the contextual conditions under which employees can effectively leverage digital capabilities in AI-enabled workplaces.

Finally, the findings contribute to hospitality innovation research by integrating insights from digital transformation, employee cognition, and organizational behavior. Prior studies have often examined these dimensions separately (Hebl et al., 2026; Mahavarpour et al., 2023; Mubarak et al., 2025). The present study bridges these streams by proposing a multi-level explanation of service innovation that simultaneously considers technological readiness, employee cognition, and organizational climate.

5.2. Practical implications

The findings of this study offer several actionable implications for hospitality managers, technology strategists, and policymakers seeking to leverage AI to enhance service innovation. First, the results highlight the importance of developing organizational AI readiness as a strategic capability. Hospitality organizations should invest not only in AI technologies but also in the supporting infrastructure, training programs, and managerial support systems necessary for successful implementation. Previous research has shown that organizations that strategically integrate digital technologies into their operational processes can significantly improve service innovation outcomes and customer experiences (Demir, 2025; Shamim et al., 2021; Xia et al., 2026). Therefore, managers should adopt a holistic approach to AI adoption that includes both technological and organizational readiness.

Second, the results emphasize the importance of enhancing employees' digital self-efficacy. Employees who feel confident in their ability to use digital technologies are more likely to experiment with AI tools and develop innovative service solutions. To strengthen digital self-efficacy, hospitality organizations should offer continuous training programs, digital learning platforms, and mentoring opportunities to help employees build technological competence. Such initiatives not only enhance employees' confidence but also enable them to actively participate in AI-driven service innovation processes (Compeau & Higgins, 1995; Malodia et al., 2023; Ulfert-Blank & Schmidt, 2022).

Third, the findings suggest that managers should cultivate a psychologically safe work environment that encourages experimentation and idea sharing. In hospitality settings undergoing digital transformation, employees may initially perceive AI adoption as a source of uncertainty or job insecurity. Creating a supportive climate where employees feel comfortable discussing mistakes, proposing new ideas, and testing innovative solutions can significantly enhance innovation outcomes. Prior research indicates that psychologically safe environments facilitate learning, collaboration, and creative problem solving within organizations (Edmondson, 1999; Edmondson & Lei, 2014; Hu et al., 2022). Managers should therefore promote open communication, supportive leadership practices, and collaborative team structures that enable employees to fully leverage digital technologies.

5.3. Limitations and future research directions

Despite its contributions, this study has several limitations that provide opportunities for future research. First, the data were collected from hospitality employees in four major Australian cities, which may limit the generalizability of the findings to other geographic regions or service sectors. Future studies could replicate the model in different cultural or industry contexts to examine whether the observed relationships remain consistent across settings.

Second, although the study employed a time-lagged research design, the data were still based on self-reported perceptions. Future research could incorporate multi-source data, such as supervisor evaluations or objective innovation metrics, to strengthen causal inferences. Third, the present model focuses on digital self-efficacy and psychological safety as key mechanisms and boundary conditions. Future studies could explore additional mediators or moderators, such as leadership style, organizational learning capability, or technological turbulence, to further explain how AI adoption influences service innovation outcomes.

Finally, as AI technologies continue to evolve rapidly, longitudinal studies examining the long-term organizational consequences of AI-driven transformation in hospitality would provide valuable insights into the sustainability of innovation outcomes.

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Ethical committee approval

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards. The study was approved by the Monash University Human Research Ethics Committee (Date: January 22, 2025, and No. 25-14).

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Appendix A

Table 7. Psychometric analysis results

Constructs	FL	α	CR	AVE	Eigen-value	Variance explained
Artificial intelligence readiness		*0.90*	*0.92*	*0.66*	*7.41*	*37.0%*
Our organization has the technological infrastructure necessary to implement AI-based applications.	0.82					
Management actively supports the use of AI in service operations.	0.86					
Our organization is strategically prepared to integrate AI into daily work processes.	0.79					
Employees receive sufficient support to work with AI-enabled systems.	0.83					
AI-related initiatives are aligned with the organization's service goals.	0.76					
Our workplace is ready to adapt to AI-driven changes in service delivery.	0.71					
Employee digital self-efficacy		*0.89*	*0.91*	*0.67*	*3.12*	*15.6%*
I feel confident using digital systems required in my job.	0.81					
I can solve most work problems involving digital technologies on my own.	0.88					
I am capable of learning new AI-related tools used in my organization.	0.80					
I can effectively perform my job using digital platforms and applications.	0.86					
I believe I can adapt quickly to new digital technologies introduced at work.	0.72					
Psychological safety		*0.86*	*0.88*	*0.60*	*2.48*	*12.4%*
In this workplace, people can speak up with new ideas without fear.	0.87					
It is safe to take a risk in this organization.	0.79					
Employees in this organization can openly discuss mistakes.	0.85					
People here feel comfortable asking for help when needed.	0.81					
No one would reject me for expressing a different opinion at work.	0.70					
Service innovation performance		*0.92*	*0.93*	*0.72*	*1.96*	*9.8%*
Our organization frequently introduces improved service processes.	0.84					
We are effective in developing new service ideas.	0.82					
Our services are more innovative than those of our competitors.	0.89					
The organization responds creatively to changing customer needs.	0.79					
We successfully turn new ideas into valuable service outcomes.	0.74					

Notes. Exploratory factor analysis (EFA) was conducted to examine the underlying structure of the measurement scales. The Kaiser–Meyer–Olkin value (KMO = 0.914) and Bartlett's test of sphericity ($\chi^2 = 3456.21$, $p < 0.001$) confirmed the suitability of the data for factor analysis. The analysis revealed a four-factor structure explaining 74.8% of the total variance. All factor loadings exceeded the recommended threshold of 0.70. Reliability analysis indicated strong internal consistency, with Cronbach's alpha values ranging from 0.89 to 0.92.