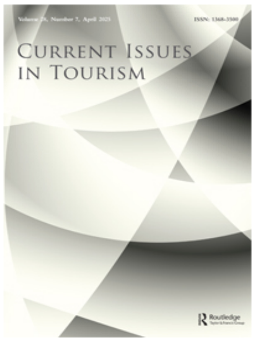

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AI colleagues: how AI influences hotel employees' service performance?

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ABSTRACT

This study examines the impact of employee and AI attributes on hotel employees' service performance. Partial least squares structural equation modelling and necessary conditions analysis were conducted. The study indicates that (1) AI skills and AI understanding significantly and positively affect AI trust and are necessary conditions for AI trust, (2) privacy concerns do not significantly impact AI trust, but uncertainty and creepiness substantially negatively affect AI trust, (3) both perceived supervisor support and AI trust are essential for service performance, (4) perceived supervisor support moderates the linkage between AI trust and improvisation, and between AI trust and role ambiguity, (5) improvisation is significantly and positively related to external and internal service performance, and (6) role ambiguity negatively influences internal and external service performance. These findings contribute to the discourse on sustainable growth in the hospitality industry by highlighting the role of AI in the modern tourism and hospitality workplace.

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Artificial intelligence; hospitality industry; service performance; improvision; employee; tourism employment

1. Introduction

Although AI technology has been used widely in the hospitality industry, its influence on employees' service performance and skills remains uncertain. Many enterprises have started to integrate AI-power technologies into their marketing and management activities, but they lack knowledge about effectively leveraging AI to increase service performance and staff satisfaction by effectively (Fan et al., 2022). In addition, it has been reported that employees lack trust, AI skills, competence, and understanding, which results in a limited knowledge of the influence of AI systems on their jobs (Chowdhury et al., 2022). Some key questions require deeper reflection: can AI technology optimise service performance in the hospitality industry? If so, what are the key factors in realising this process?

Existing literature mainly explores the role of AI technologies in data analysis and prediction (Akter et al., 2023; Bulchand-Gidumal et al., 2024), as well as customer preference recommendation by intelligent recommender systems (d'Angella et al., 2024; Femenia-Serra et al., 2022). Other studies

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have explored factors such as user-friendliness, privacy protection, and technical reliability of AI systems based on the perspective of customer acceptance and satisfaction with AI technologies (Shin & Jeong, 2022; Zhao et al., 2024). Existing research focuses more on the customer application perspective, while the employee perspective is often overlooked. There is little in-depth exploration of how employees collaborate with AI technologies and the impact on employee work environments and roles (Qiu et al., 2022). Yet, employees are important contributors to the hospitality experience (Prayag & Lee, 2019).

Notably, this study argues that building trust is a complex yet crucial undertaking for employees working with AI systems. It remains unknown how AI trust fosters collaboration between hotel employees and AI systems, and its impact on service performance. This study contends that understanding the facilitators (i.e. AI skills and AI understanding) and impediments (i.e. privacy concerns, creepiness, and uncertainty) is crucial in affecting trust.

While research on AI technology in the hospitality industry has confirmed its positive impact on workers' spontaneity and creativity, gaps remain. Specifically, the link between AI trust and employees' capacity for improvisation is underexplored, as is the potential for AI trust to increase job ambiguity. Improvisation can be defined as an employee's capacity to react quickly and imaginatively to difficulties when faced with unforeseen events or unclear instructions (Jun et al., 2022). When employees lack a clear knowledge of their job duties and role expectations, it is known as role ambiguity (Chien et al., 2021). Addressing these gaps is important for optimising AI integration in the tourism and hospitality workplace. Additionally, this study argues that understanding the moderating role of supervisor support is key to fostering a work environment conducive to effective AI integration.

2. Conceptual development

2.1. Theoretical foundation

To build a more holistic and in-depth theoretical framework, this study combines three significant theories. Socio-technical system theory focuses on the mutual dependence between technologies and social structures. The theory suggests that both human competencies and technological attributes must work in tandem in determining organisational outcomes (Davis et al., 2014). The theory provides a foundation for distinguishing people factors (e.g. employees' AI skills and understanding) from technological factors (e.g. AI attributes) and then analysing how they interact (Sony & Naik, 2020).

According to knowledge-based view theory, knowledge, especially knowledge assets, and capabilities, can strengthen the competitive advantage of organisations (Latif et al., 2020). Blanka et al. (2022) contended that competency development at the individual level aggregates into organisational capability throughout the transformation process. The argument reinforces the idea that knowledge resources (e.g. AI-centric skills) underpin digital transformation (e.g. AI collaboration). As a result, we contend that the approach to include AI skills and AI understanding in managing and leveraging AI applications aligns with Chowdhury et al. (2022)'s AI capability framework. In particular, grounded in the knowledge-based view theory, cultivating employees' AI-centric competencies (non-technical resources) is necessary for providing superior, technology-enabled hospitality services, which eventually contributes to strengthening a firm's overall competitive position in the marketplace.

Organisational support theory stresses the close relationship between organisational support and staff performance (Lussier et al., 2022). To explain, employees rely on material and emotional resources from their organisation to manage job demands effectively. In a growingly demanding and stressful work environment, organisational support is a critical resource that enables employees to manage their responsibilities effectively and sustain a positive attitude toward their work (Côté et al., 2021). Based on the theory, we argue that supervisor support may moderate the effects of

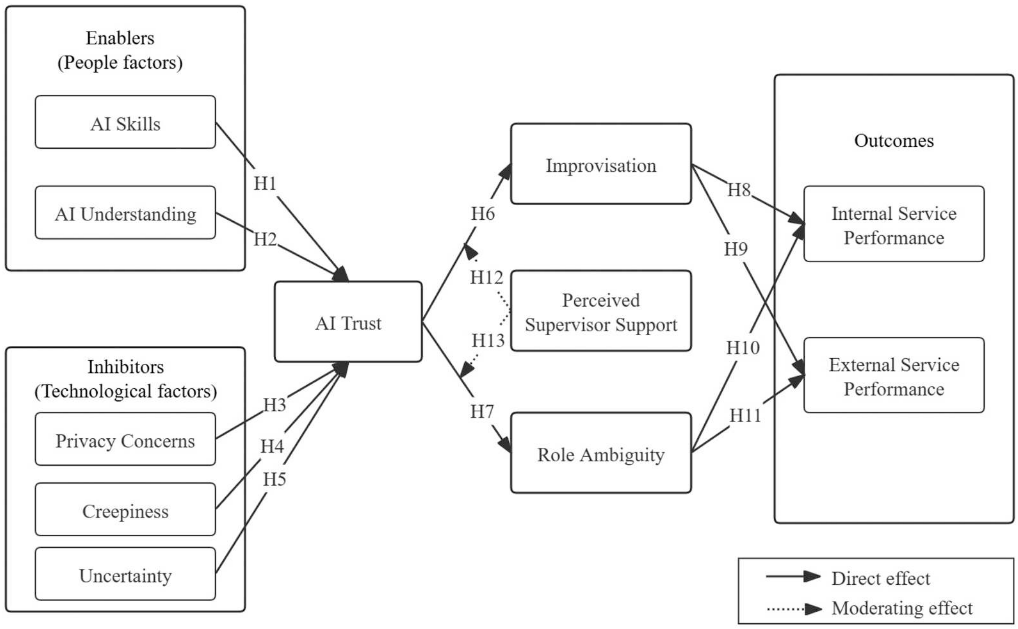

Figure 1. Conceptual framework.

trust because AI implementation requires experimentation and adaptation, which involves risk-taking and guidance. Figure 1 shows the conceptual framework of the research.

2.2. AI competence (AI skill and AI trust)

Knowledge-based theory states that an organisation's internal knowledge and skills are key to its competitive advantage (Bedué & Fritzsche, 2022). This means mastering the skills of AI systems has a significant effect on AI trust. Social cognitive theory (Bandura, 1986) supports the argument concerning the effect of AI skills on AI trust by showcasing that acquiring and refining AI-related competencies can promote self-efficacy and reduce uncertainty, thereby making employees more confident in the technology's functionality. The literature has articulated that AI skills go beyond just operating AI systems. They include the ability to interpret AI outputs and make informed decisions based on AI recommendations (Li & Kim, 2024). When AI skills are improved, workers can learn more about AI systems' functions, abilities, and weaknesses accordingly (Kong et al., 2023). Employees who lack AI skills may misunderstand AI's capabilities and limitations, resulting in skepticism and lower trust in AI. It has been shown that improvement of employees' AI skills promotes trust among employees and confidence in applying new technologies in AI application settings (Bedué & Fritzsche, 2022; Chowdhury et al., 2022; Kaplan et al., 2023).

H1: AI skills positively influence AI trust.

As the knowledge-based view theory outlines, comprehension of knowledge largely impacts its application (Chowdhury et al., 2023). Suppose individuals are aware of the capabilities, limits, and working process of AI systems. In that case, they may evaluate the dependability of the systems more thoroughly and impartially, and will develop a greater degree of trust in the systems (Chowdhury et al., 2022). As demonstrated by von Eschenbach (2021), people can identify and comprehend the logic, algorithms, and workflows of AI systems if they have a thorough understanding of AI. Meanwhile, if employees have a deeper understanding of AI, they are more likely to comprehend the foundation of AI's decisions and avoid information opacity. Subsequently, they will be more inclined to trust and leverage AI systems, and their willingness to engage with AI will increase.

H2: AI understanding positively influences AI trust.

2.3. Privacy concerns, creepiness, and uncertainty

The socio-technical systems theory is crucial in understanding the various technical and social factors that are shaping the practices of AI technology today. Understanding the psychological mechanisms of employees concerning AI integration in the hospitality industry is crucial (Zhao et al., 2023). Major social factors include fraudulent activities, privacy issues, and uncertainty about employees facing new technology (Liu et al., 2022). The public possesses a vastly negative opinion of AI technologies in regard to confidentiality, data security, and control of private information (Chatterjee et al., 2021; Fan et al., 2020). These concerns undermine the public's trust in AI systems' ability to ensure data safety. As a consequence, they become increasingly unwilling to employ AI technologies that could potentially exploit users' private data (Canhoto et al., 2024).

H3: Privacy concerns negatively influence AI trust.

According to Rajaobelina et al. (2021), creepiness is characterised by a feeling of disgust, ill at ease, and disturbance. Creepiness makes AI systems appear less competent and reliable (Dekkal et al., 2024; Raff et al., 2024). There have been numerous recorded incidents during which AI systems display bizarre and worrisome behaviours that users feel compelled to speculate on the technology's safety and even its built-in ethics (Rajaobelina et al., 2021). As the natural response to these doubts, people tend to avoid AI systems that display the creepiness trait. Moreover, after encountering these horrifying or unsettling AI interactions, the users usually share their experiences with more people, creating an even larger panic that dismantles public trust in not just the technology but the organisations behind it (Canhoto et al., 2024).

H4: Creepiness negatively influences AI trust.

The socio-technical systems theory points out that uncertainty regarding the implications and outcomes of AI technology can cause employees to distrust the system (Upadhyay et al., 2022). When employees are concerned and unsure about the future regarding AI, it activates their psychological defense mechanisms. The trust-building process is slowed down due to the intense caution from employees while using AI systems (Gao & Waechter, 2017). The natural response from employees is to comprehend the fundamental decision-making logic behind the system. However, the lack of transparency in many such systems deepens suspicion (Koo et al., 2021). Thus, uncertainty is another major factor that reduces employees' trust in AI technologies (Sun, Lee, et al., 2020; Sun, Wu, et al., 2020).

H5: Uncertainty negatively influences AI trust.

2.4. AI trust and improvisation

Human beings often employ their creativity to search for a thoughtful solution that is not premeditated while facing difficulties, complexity, and ambiguity, known as improvisation (Carlson & Ross, Jr., 2022). When employees trust AI, it becomes a valuable tool that facilitates the generation of new ideas and adaptation to various environments, presenting itself as a robust problem-solving partner (Liao et al., 2023; Sun, Lee, et al., 2020; Sun, Wu, et al., 2020). Trust in AI is crucial because it enables users to confidently incorporate AI's information and recommendations into their decisions and strategies (Kushwaha et al., 2021). AI integration simplifies the adaptation and improvisation in various scenarios, providing abundant aid to employees' decision-making processes (Bhatia et al., 2021). The engendered trust maximises AI systems' outstanding advantages and functions to enhance employees' ability to improvise (Luo et al., 2023).

H6: AI trust positively influences improvisation.

2.5. AI trust and role ambiguity

Employees reject AI because this new technology creates confusion regarding the employees' role in the new environment (Mustafa & Siew Chen Sim, 2023). AI trust is vital in the adaptation process as it creates an optimistic AI culture in the organisation and resolves negative emotions brought by drastic technological change (Mustafa & Siew Chen Sim, 2023). Employees often find it easier to follow an AI system's instructions when they view it as trustworthy. In addition, AI trust creates an environment that is beneficial for the circulation and sharing of information in the workplace, which brings about even more clarity regarding each individual's objectives.

H7: AI trust negatively influences role ambiguity.

2.6. Improvisation and service performance

Internal service performance indicates the effectiveness of an organisation in providing services from one department or team to another. Employees' improvisation capability often dictates their responsiveness, creativity, and flexibility. These qualities can greatly improve the quality of internal services (De Clercq et al., 2021). Employee's improvising ability is demonstrated through their fast reaction and smooth adaptation to all kinds of unexpected changes in the environment (Liao et al., 2023). Another aspect of improvisation is the ability to take various perspectives into account and create unique and targeted services with different approaches (Jun et al., 2022). Improvisation makes employees better team players who can effectively cooperate with their colleagues to deliver excellent services (Sun, Lee, et al., 2020; Sun, Wu, et al., 2020).

H8: Improvisation positively influences internal service performance.

The effectiveness and quality of services delivered to external customers are generally regarded as indicators of an organisation's external service performance. In a more complicated or unusual situation, the service quality often relies on the staff's improvisation and adaptability. The possession of these traits enables employees to deliver personalised and professional service. Service providers can resolve challenges and handle complicated situations if they master the skill of flexibility (Menguc et al., 2020). Flexible responses often leave a professional and friendly impression on customers, who will then rate the service experience positively. It is also an essential element of building customer loyalty and a positive brand image (Secchi et al., 2019). Particularly, employees who are able to respond to unexpected events quickly are always in a better position to maximise customer satisfaction and their service quality.

H9: Improvisation positively influences external service performance.

2.7. Role ambiguity and service performance

Role ambiguity, reflected in unclear tasks and expectations, can significantly affect internal service performance. Employees may feel more anxious and uncertain when they experience role ambiguity in the organisation, which will affect their performance in internal services. Role ambiguity disrupts the internal synergistic effect in an organisation of the communication barriers (Blanco-Donoso et al., 2019). Unclear role boundaries create confusion about responsibilities and tasks, hindering effective communication and collaboration. This uncertainty disrupts internal processes and ultimately reduces service efficiency.

H10: Role ambiguity negatively influences internal service performance.

One of the disadvantages of unclear employee roles is about customer experience. For instance, uncertainties may arise in the service process due to role ambiguity (Jiang et al., 2019). To some extent, this kind of role ambiguity means unclear employee responsibility, leading to suboptimal and discontented customer experiences. As a result, customers view the lack of clarity as unprofessional and incompetent, thereby decreasing their satisfaction toward external service performance. Moreover, role ambiguity negatively impacts service quality and efficiency. Disorganisation and low task performance efficiency occur when employees experience role ambiguity. While providing external service, suboptimal customer interaction arises due to unclear roles and responsibilities (Jiang et al., 2019).

H11: Role ambiguity negatively impacts external service performance.

2.8. Moderating role of perceived supervisor support

It has been indicated that employee confidence in the organisation is strengthened when they sense support from the supervisors. This results in their confidence in trying new and improvised strategies to deal with challenges in the workplace. Supervisor support is not only about emotional holding but also about providing necessary resources and guidance. Moreover, when trust in AI is aligned with the actual backing from supervisors, employees feel more comfortable using AI while demonstrating higher levels of improvisation (Macpherson et al., 2022). Furthermore, supervisor support can reduce employees' uncertainty about AI usage. Under the support and guidance of supervisors, employees are motivated to explore new and improvised working methods without fear of negative outcomes due to uncertain technology (Liu et al., 2023).

H12: Perceived supervisor support moderates the relationship between AI trust and improvisation.

Perceived supervisor support potentially moderates the association between AI trust and role ambiguity. Supportive behaviour is manifested when supervisors clearly show their employees' role expectations. When employees perceived AI trust and received clear guidance from supervisors, they felt easier and more confident in understanding and adopting new role requirements, thereby diminishing role ambiguity. This perceived support makes employees more confident while facing the role ambiguity arising from technology application and integration. In addition, perceived supervisor support helps create a positive work atmosphere and develops trust in supervisors, which plays an essential role in dealing with uncertainty in the workplace (Ziegert & Dust, 2021). Such a conducive work environment may significantly alleviate role ambiguity associated with AI technology.

H13: Perceived supervisor support moderates the relationship between AI trust and role ambiguity.

3. Methodology

3.1. Data collection and sample characteristics

This study used an online questionnaire to collect data, and due to the difficulty of developing a complete sampling frame for frontline employees in the hospitality industry, a purposive sampling technique was employed in this study (Sarstedt et al., 2018). All participants were full-time employees who had worked in the hotels for at least six months in different departments such as front office, guest room, food and beverage, and concierge. An initial sample that meets specific criteria was screened by Ctrip, China's largest online travel agency, to ensure that five-star hotels with customer ratings of more than 4.5 out of 5 and positive responses to customer reviews are selected (Qiu et al., 2022). Also, this study screened hotel reviews and selected hotels with reviews involving the application of two or more AI technologies.

Ultimately, the study identified 50 eligible hotels on Ctrip.com, and this study then contacted the managers of these hotels by phone or email for assistance (Qiu et al., 2022). Hotel managers who agreed to participate shared the link with around 20 frontline staff in their hotels to participate in the survey. The data was collected between November 2023 and January 2024. A total of 554 responses were obtained after removing responses that showed a straight-lining pattern. In terms of the composition of the respondents, 51.1% of the respondents were female, and the majority (60.9%) of them were below 35 years of age. The majority of the respondents had a Bachelor's degree or higher (91.4%) and had been working in hospitality for more than seven years (64.3%). Distribution of positions across various departments was relatively balanced: front office (20.8%), housekeeping (19%), food and beverage (20.9%), recreation and entertainment (19.5%), and sales (19.9%).

3.2. Measures

All constructs used in this study were adapted from the literature and measured on a seven-point Likert scale ranging from 'strongly disagree' to 'strongly agree'. AI skills scale was adapted from Chowdhury et al. (2022). AI understanding was adapted from Chowdhury et al. (2022). The privacy concerns scale was adapted from Dekkal et al. (2024). The creepiness scale was adapted from Dekkal et al. (2024). The uncertainty scale was adapted from Rafferty and Griffin (2006). The AI trust scale was adapted from eleven works of Chowdhury et al. (2022). The improvisation scale was adapted from Magni et al. (2009) and Carlson and Ross, Jr. (2022). The role ambiguity scale was adapted from Carlson and Ross, Jr. (2022). The scale of perceived supervisor support was adapted from Lussier et al. (2022). The internal and external service performance items were adapted from Prentice et al. (2020).

4. Data analysis

This research employed partial least squares structural equation modelling (PLS-SEM) to explore relationships between variables. PLS-SEM is a flexible method that can be used to analyse interconnected variables and multilevel structures; thus, it is extremely useful for examining the possible relations within multivariate variables (Hair et al., 2019). Besides, PLS-SEM is effective in handling complicated modelling and small sample sizes because it does not impose restrictions on data distribution. Thus, it is more suitable for processing non-normally distributed samples or small samples. Additionally, PLS-SEM can effectively explore and deal with the impacts of moderating variables (Hair et al., 2019). In this study, SmartPLS 4 software was applied to perform measurement model assessment, structural model assessment, and necessary condition analysis.

4.1. Common method bias

The Harman single-factor test's result indicated that none of the dominant factors accounted for more than 50 percent of the total variance. Besides, this study employed a variance inflation factor (VIF) approach and found that the VIF values of all constructs in this study range from 1.992 to 2.87, which are lower than 3.3, indicating no significant common method bias.

4.2. Measurement model assessment

According to Table 1, the composite reliability of all structures is higher than 0.7, indicating a robust performance in terms of internal consistency (Hair et al., 2019). Second, the factor loadings of all items exceeded 0.7, while the AVE values of all constructs exceeded the threshold of 0.5, indicating that the items adequately explained most of the variance of the constructs they belonged to (Hair et al., 2019). Finally, in terms of discriminant validity, the HTMT ratio is assessed, and all values are less than 0.9 (Table 2), indicating sufficient discriminant validity.

Table 1. Construct reliability and validity.

Constructs	Items	Loadings	CR	AVE
AI Skills	AS1: I have knowledge about AI systems.	0.796	0.914	0.652
	AS2: I have relevant skills to use AI systems in my work.	0.811		
	AS3: I have the competencies to understand how AI systems will execute.	0.825		
	AS4: I have developed new skills because of AI education.	0.821		
	AS5: I have recognised certifications demonstrating knowledge of AI.	0.795		
	AS6: I have skills to interpret the AI outputs.	0.809		
	AS7: I have skills to prepare inputs for AI systems.	0.795		
AI Understanding	AU1: I have attended training programmers through my organisation to gain AI knowledge.	0.809	0.942	0.651
	AU2: I understand the capabilities of AI systems.	0.802		
	AU3: I understand the limitations of AI systems.	0.809		
	AU4: I understand the context of using AI.	0.797		
	AU5: I understand what to expect from AI systems.	0.810		
	AU6: I understand the purpose of using AI.	0.807		
	AU7: I understand the benefits of using AI for the organisation.	0.800		
	AU8: I understand the benefits of using AI in my daily job activities.	0.822		
	AU9: I understand that AI will enhance the efficiency of my work.	0.813		
	AU10: I understand that AI will enable me to accomplish analytical activities efficiently and effectively in my job.	0.798		
Privacy Concerns	PC1: When AI systems ask me for personal information, I sometimes think twice before providing it.	0.884	0.926	0.736
	PC2: It usually bothers me when AI systems ask me for personal information.	0.804		
	PC3: I'm concerned that AI systems is collecting too much personal information about me.	0.866		
	PC4: I thought that giving out personal information to the AI systems could threaten my private life.	0.876		
Creepiness	CRP1: When using AI systems, I had a queasy feeling.	0.816	0.920	0.670
	CRP2: When using AI systems, I felt uneasy.	0.829		
	CRP3: When using AI systems, I had an indefinable fear.	0.814		
	CRP4: When using AI systems, I somehow felt threatening.	0.810		
	CRP5: When using AI systems, I didn't know exactly how to behave.	0.792		
	CRP6: When using AI systems, I didn't know exactly what to expect.	0.832		
	CRP7: When using AI systems, I didn't know exactly what was happening to me.	0.835		
Uncertainty	UNT1: My work environment is changing in an unpredictable manner.	0.876	0.888	0.745
	UNT2: I often don't know how to cope with the changes brought about by AI.	0.844		
	UNT3: I am often unsure of the impact of the changes brought about by AI on my work unit.	0.869		
	UNT4: I am unsure how severely AI will affect my work unit.	0.862		
AI Trust	AT1: I have confidence in the use of AI technology.	0.792	0.945	0.644
	AT2: I believe AI technology can facilitate routine and trivial tasks through automation.	0.806		
	AT3: I believe my organisation will be able to operate AI technology reliably or consistently without failing.	0.808		
	AT4: I believe that AI technology will consistently operate providing adequate and efficient results within a broad spectrum of processes.	0.797		
	AT5: I believe AI adoption will result in the creation of new jobs.	0.781		
	AT6: I have a positive attitude toward the adoption of AI.	0.778		
	AT7: I believe AI technology can help me develop new skills that will benefit my career development activities.	0.805		
	AT8: I have a positive attitude towards its impact on intra-organisational business operations.	0.827		
	AT9: I believe AI will positively change employee dynamics within the organisation.	0.817		
	AT10: AI adoption won't result in reduced focus on human skills such as creative intellect in my job.	0.816		
	AT11: I believe AI adoption will enhance the quality of my work.	0.800		
Improvisation	IMP1: I deal with unanticipated events on the spot.	0.847	0.903	0.718
	IMP2: I think on my feet when carrying out actions.	0.843		
	IMP3: I respond at the moment to unexpected problems.	0.853		
	IMP4: I try new approaches to problems.	0.845		

(*Continued*)

Table 1. Continued.

Constructs	Items	Loadings	CR	AVE
	IMP5: I take risks in terms of producing new ideas in doing my job.	0.848		
Role Ambiguity	RA1: I receive clear instructions about my job duties. (reverse-coded)	0.854	0.884	0.741
	RA2: I know what my responsibilities are. (reverse-coded)	0.864		
	RA3: I know exactly what is expected of me. (reverse-coded)	0.859		
	RA4: I have divided my time properly. (reverse-coded)	0.865		
Perceived Supervisor Support	PSS1: My manager takes great pride in my accomplishments.	0.831	0.871	0.708
	PSS2: My manager really cares about my well-being.	0.849		
	PSS3: My manager really considers my goals and values.	0.832		
	PSS4: My manager is willing to help me if I need it.	0.852		
Internal Service Performance	ISP1: I adequately complete my assigned duties with my co-workers.	0.876	0.893	0.755
	ISP2: I fulfil the responsibilities specified in my job description when working with my co-workers.	0.853		
	ISP3: I perform all tasks that are expected of me when interacting with my co-workers.	0.885		
	ISP4: I meet the performance requirements that involve teamwork with my co-workers.	0.861		
External Service Performance	ESP1: I consistently show friendliness to customers.	0.802	0.939	0.664
	ESP2: I am always willing to help customers.	0.801		
	ESP3: I demonstrate a concerned and caring attitude toward customers.	0.807		
	ESP4: I provide prompt customer service.	0.812		
	ESP5: I am capable and competent when handling customers' queries and requests.	0.809		
	ESP6: I give customers my undivided attention.	0.826		
	ESP7: I remain consistently courteous to customers.	0.848		
	ESP8: I properly handle any problems that arise.	0.830		
	ESP9: I make sure I understand customers' specific needs for hotel services.	0.794		

4.3. Structural model assessment

Firstly, this study checked for potential multicollinearity problems. The results showed that the highest inner VIF value is 1.352, which is below the recommended threshold of 3.0, suggesting that independent variables are not overly correlated (Hair et al., 2019). Secondly, this study manifested R^2 values ranging between 0.199 and 0.278. Based on Cohen's (1988) classification of endogenous R^2 values based on the thresholds of small (0.02), medium (0.13), and large (0.26), the R^2 in this study falls within a satisfactory range. Furthermore, comparisons with similar studies (Ali et al., 2023; Ling et al., 2025) confirmed that the model effectively predicts the endogenous variable. Q^2 was used to measure how well the model predicts out-of-sample data. Given that the Q^2 value is greater than zero, the result indicates that the model possesses good predictive power (Hair et al., 2019).

This study evaluated the structural model and tested the significance of the path coefficients by running a bootstrap procedure with 5,000 samples (Hair et al., 2019). As shown in Table 3, the results showed that AI skills (β: 0.205, $p < 0.001$) and AI understanding (β: 0.214, $p < 0.001$) exerted a significant positive effect on AI trust. Thus, H1 and H2 were supported. However, privacy concerns had no significant correlation with AI trust (β: −0.025, $p > 0.05$). So, H3 was unsupported. Creepiness (β: −0.176, $p < 0.001$) and uncertainty (β −0.143, $p < 0.01$) showed significant negative correlations with AI trust. Thus, H4 and H5 were supported. AI trust had a positive effect on improvisation (β: 0.289, $p < 0.001$) and a negative effect on role ambiguity (β: −0.321, $p < 0.001$). Thus, H6 and H7 were supported. Improvisation showed a significant positive correlation with internal service performance (β: 0.263, $p < 0.001$) and external service performance (β: 0.266, $p < 0.001$). Therefore, H8 and H9 were supported. Role ambiguity showed a significant negative correlation with internal service performance (β: −0.296, $p < 0.001$) and external service performance (β: −0.273, $p < 0.001$), respectively. Hence, H10 and H11 were supported.

This study found a significant moderating effect of perceived supervisor support in the linkage between AI trust and improvisation (β: 0.353, $p < 0.001$). Therefore, H12 was supported. This study also identified a significant moderating effect of perceived supervisor support in the linkage

Table 2. Discriminant validity.

	AS	AT	AU	CRP	ESP	IMP	ISP	PSS	PC	RA	UNT
AS	**0.808**										
AT	0.399 (0.370**)	**0.803**									
AU	0.272 (0.252**)	0.404 (0.381**)	**0.807**								
CRP	0.363 (−0.332**)	0.412 (−0.384**)	0.448 (−0.416**)	**0.818**							
ESP	0.357 (0.331**)	0.453 (0.427**)	0.390 (0.366**)	0.407 (−0.377**)	**0.815**						
IMP	0.341 (0.309**)	0.416 (0.383**)	0.342 (0.315**)	0.408 (−0.372**)	0.396 (0.364**)	**0.847**					
ISP	0.374 (0.337**)	0.444 (0.407**)	0.383 (0.351**)	0.436 (−0.394**)	0.425 (0.389**)	0.414 (0.372**)	**0.869**				
PSS	0.301 (0.266**)	0.310 (0.279**)	0.297 (0.268**)	0.302 (−0.268**)	0.307 (0.276**)	0.234 (0.206**)	0.361 (0.316**)	**0.841**			
PC	0.181 (−0.163**)	0.145 (−0.134**)	0.230 (−0.210**)	0.135 (0.122**)	0.212 (−0.194**)	0.162 (−0.145**)	0.171 (−0.152**)	0.189 (−0.165**)	**0.858**		
RA	0.343 (0.307**)	0.444 (0.405**)	0.358 (0.327**)	0.464 (−0.418**)	0.406 (0.370**)	0.414 (0.369**)	0.442 (0.392**)	0.239 (0.208**)	0.123 (−0.109*)	**0.861**	
UNT	0.396 (−0.356**)	0.370 (−0.338**)	0.302 (−0.276**)	0.386 (0.348**)	0.397 (−0.362**)	0.351 (−0.314**)	0.410 (−0.365**)	0.308 (−0.269**)	0.115 (0.102*)	0.335 (−0.296**)	**0.863**

Note: Off-diagonal elements: HTMT values, HTMT < 0.90. Diagonal elements (bold): Squared root of AVEs. Brackets: Inter-construct correlations, *$p < 0.05$, **$p < 0.01$. AS = AI skills, AU = AI understanding, PC = Privacy concerns, CRP = Creepiness, UNT = Uncertainty, AT = AI trust, IMP = Improvisation, RA = Role ambiguity, PSS = Perceived supervisor support, ISP = Internal service performance, ESP = External service performance.

Table 3. Results.

Hypothesis	Relationships	β	*T*-Value	*P* Values	Decision
H1	AI Skills → AI Trust	0.205	5.125	0.000	Supported
H2	AI Understanding → AI Trust	0.214	5.313	0.000	Supported
H3	Privacy Concerns → AI Trust	−0.025	0.708	0.479	Not Supported
H4	Creepiness → AI Trust	−0.176	4.153	0.000	Supported
H5	Uncertainty → AI Trust	−0.143	3.418	0.001	Supported
H6	AI Trust → Improvisation	0.289	7.394	0.000	Supported
H7	AI Trust → Role Ambiguity	−0.321	8.023	0.000	Supported
H8	Improvisation → Internal Service Performance	0.263	6.629	0.000	Supported
H9	Improvisation → External Service Performance	0.266	6.829	0.000	Supported
H10	Role Ambiguity → Internal Service Performance	−0.296	7.696	0.000	Supported
H11	Role Ambiguity → External Service Performance	−0.273	6.856	0.000	Supported
H12	Perceived Supervisor Support × AI Trust → Improvisation	0.353	9.441	0.000	Supported
H13	Perceived Supervisor Support × AI Trust → Role Ambiguity	−0.302	7.796	0.000	Supported

between AI trust and role ambiguity (β: −0.302, $p < 0.001$). Therefore, H13 was supported. To investigate the interaction terms further, this study performed a simple slope analysis. As shown in Figure 2 and Figure 3, for high-level perceived supervisor support (+1SD), the positive linkage between AI trust and improvisation is stronger than for low-level perceived supervisor support (−1SD). Meanwhile, the negative link between AI trust and role ambiguity is also stronger in the condition of high-level perceived supervisor support.

4.4. Necessary condition analysis

This study further conducted a necessary condition analysis (NCA) analysis (Dul et al., 2020). As presented in Table 4, the results show that AI skills and AI understanding are meaningful ($d \geq 0.1$) and significant ($p \leq 0.05$) necessary conditions of AI trust (Richter et al., 2020). Moreover, perceived

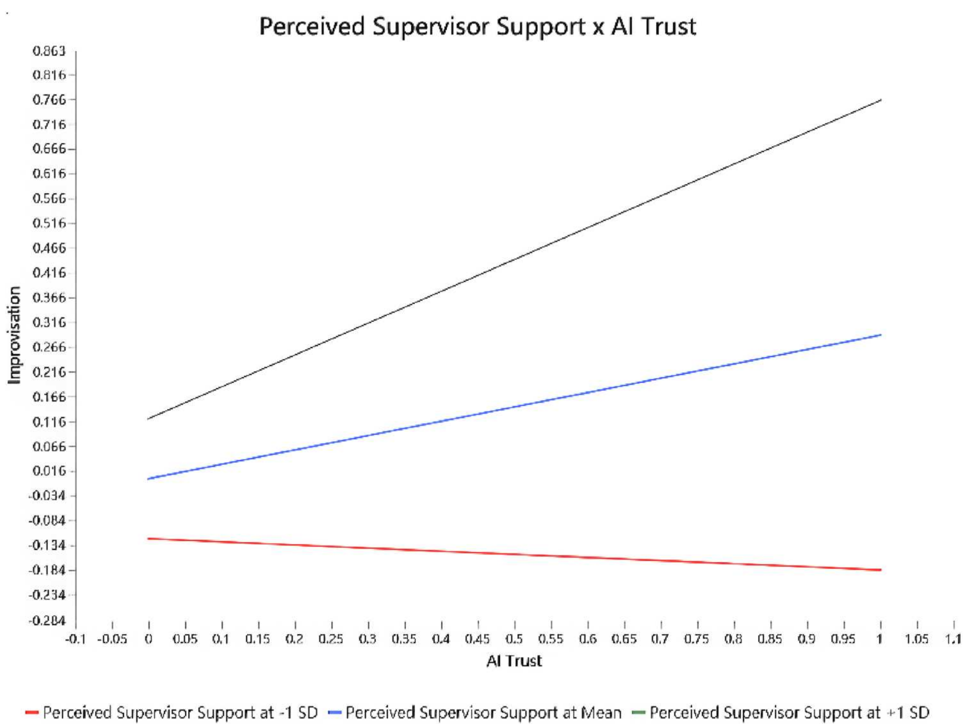

Figure 2. Moderating effect of perceived supervisor support in the relationship between AI trust and improvisation.

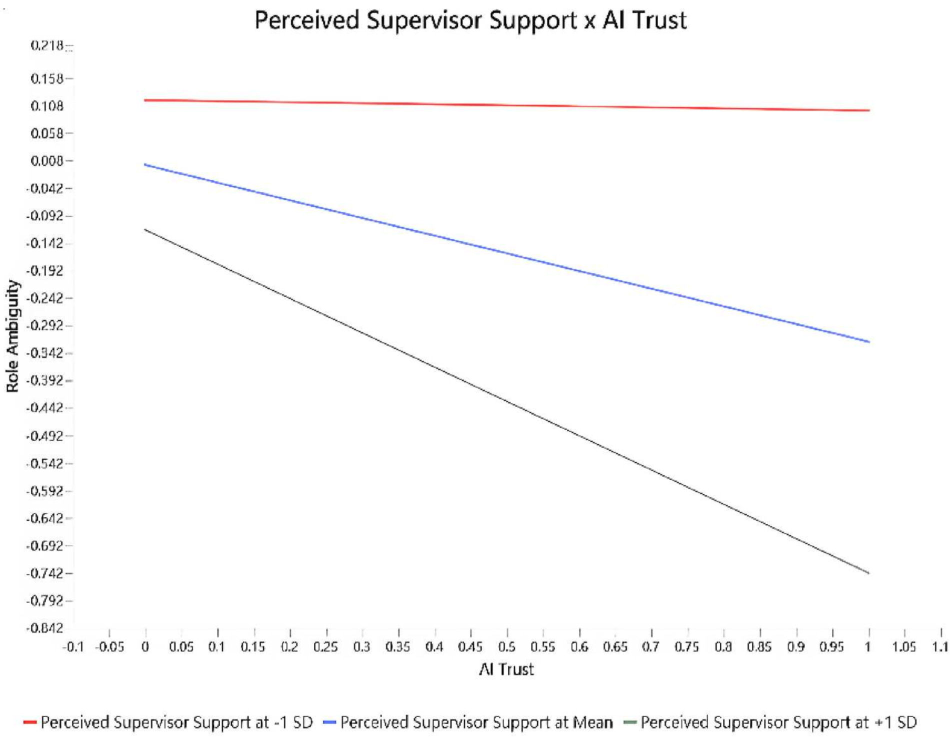

Figure 3. Moderating effect of perceived supervisor support in the relationship between AI trust and role ambiguity.

Table 4. NCA effect sizes.

	AI Trust		Internal Service Performance		External Service Performance	
Construct	CE-FDH	*p*-value	CE-FDH	*p*-value	CE-FDH	*p*-value
AI Skills	0.102	0.000				
AI Understanding	0.132	0.000				
Privacy Concerns	0.042	0.974				
Creepiness	0.004	0.003				
Uncertainty	0.001	0.972				
AI Trust			0.058	0.133	0.112	0.002
Improvisation			0.071	0.000	0.074	0.026
Role Ambiguity			0.000	0.000	0.004	0.978
Perceived Supervisor Support			0.056	0.071	0.116	0.001

supervisor support and AI trust can significantly affect external service performance. For a more in-depth exploration, this study conducted a bottleneck analysis, and the results were shown in Table 5. To achieve a high level of AI trust (90%), employees must attain at least 25.63% in AI skills and 31.95% in AI understanding. This implies that if these minimum skill thresholds are not met, a high level of AI trust cannot be achieved. Similarly, for high external service performance (90%), employees must have at least 25.99% in AI trust and 50.54% in perceived supervisor support.

5. Discussion

5.1. Theoretical contribution

The first contribution of this study is that it extends the theoretical framework related to AI collaboration by combining multiple theoretical perspectives. Existing research on employee perspectives

Table 5. Bottleneck table (percentages).

	AI Trust					Internal Service Performance				External Service Performance			
Percentage	AS	AU	PC	CRP	UNT	AT	IMP	RA	PSS	AT	IMP	RA	PSS
0%	NN	NN	NN	NN	NN	NN	NN	NN	NN	NN	NN	NN	NN
10%	NN	NN	NN	NN	NN	NN	NN	NN	NN	NN	NN	NN	NN
20%	0.18	0.36	NN	NN	NN	NN	NN	NN	NN	NN	NN	NN	NN
30%	0.18	1.08	NN	NN	NN	NN	0.18	NN	NN	NN	NN	NN	NN
40%	0.18	1.08	NN	NN	NN	NN	0.18	NN	NN	NN	NN	NN	NN
50%	0.18	1.08	NN	NN	NN	NN	0.18	NN	NN	1.63	NN	NN	NN
60%	0.18	1.81	NN	NN	NN	NN	0.18	NN	NN	1.63	NN	NN	NN
70%	7.40	3.25	NN	NN	NN	0.90	0.18	NN	NN	3.07	0.36	NN	0.72
80%	13.18	25.63	NN	NN	NN	0.90	8.66	NN	0.903	3.07	0.36	NN	2.17
90%	25.63	31.95	NN	NN	NN	0.90	13.36	NN	8.303	25.99	40.79	NN	50.54
100%	94.22	55.96	83.21	19.31	29.06	42.24	47.29	NN	37.726	97.11	76.35	7.04	69.13

of AI adoption in hotels focuses on factors such as perceived ease of use (Vorobeva et al., 2024), perceived usefulness (Liu et al., 2024), AI awareness (Liu & Cheng, 2025), and job insecurity (Leong et al., 2025). Research on the consequences of AI adoption, on the other hand, has focused on AI acceptance (Lu et al., 2025; Rawal et al., 2022), job satisfaction (Huang et al., 2024), intention to turnover (Li, 2023), and AI readiness (Jerez-Jerez, 2025). To understand how AI technologies impact employees' service performance, this study utilises three theories, namely socio-technical systems theory, organisational support theory, and the knowledge-based view.

The second contribution is that this study enriches the literature on human–computer collaboration in the tourism and hospitality industry and the employee AI trust framework. Existing studies have examined outcomes like turnover intention, job satisfaction, and job insecurity (Huang et al., 2024; Koo et al., 2021; Kumawat et al., 2025; Li, 2023), but they have not comprehensively integrated the formation and impact of AI trust on frontline service performance outcomes. This study explores the application of AI technologies in the hotel industry from the perspective of employees, holistically discussing the inhibitors and enablers in employees' AI trust. The approach taken addresses an overlooked aspect in prior consumer-centric research (Sthapit et al., 2024). Moreover, this framework clarifies the inter-relationships between role ambiguity, improvisation, and AI trust, thereby offering a multifaceted perspective on employee experiences in an AI-integrated work environment.

The third contribution of this study is the pioneering demonstration of a moderating mechanism of perceived supervisor support on the relationship between AI trust, role ambiguity, and improvisation. While earlier research acknowledges supervisor support as a key driver of different employee outcomes, its moderating role in influencing employees' AI trust's effects has remained underexplored. Nguyen and Malik (2022) advocated that future research should consider examining moderators such as supervisor support to comprehend the impact of AI in workplace settings. By demonstrating that strong supervisory support not only reinforces employees' AI trust's effects in mitigating role ambiguity and enhancing improvisation, this study extends the current understanding of the different roles of perceived supervisor support.

5.2. Managerial contribution

Hotels can provide employees with training programmes focused on the practical applications of AI systems. These programmes should cover AI principles, application scenarios, and operational processes. Such training can encourage employees to better understand AI systems and develop AI skills more efficiently (Jabeen et al., 2022). It is essential to recognise that investing in employee training is not a waste of resources but a critical requirement for maximising AI system performance. Secondly, hotel managers must address employees' concerns regarding discomfort and uncertainty when interacting with AI technology. To mitigate these concerns, managers should consider the optimal design of AI interface, enhance transparency in AI operations, and clearly communicate AI's role and ethical guidelines to ensure responsible AI use. According to Okumus et al. (2020), it is crucial for hotel managers to develop appropriate strategic management strategies in the context of AI technology applications. This requires supervisors to communicate with employees to help them clarify their tasks and responsibilities and division of roles. This can reduce the negative impact on service performance due to employee role ambiguity. Lastly, hotel supervisors should create a positive and easy learning atmosphere for their employees and take the initiative to encourage learning and using AI technologies among employees.

6. Limitations and future research suggestions

First, this research used a cross-sectional design. Therefore, it is challenging to find out the evolving changes in employee perception in different periods. Therefore, future studies could adopt a longitudinal or experimental research design to verify causality and temporal changes. Secondly, this research primarily emphasises AI technologies' effects on workers, failing to consider organisational-level causes. To better grasp how organisational-level factors affect the application of AI technologies, it is suggested that other variables like leadership style and organisational culture be considered in future studies.

Disclosure statement

No potential conflict of interest was reported by the authors.

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