



Employee agility and technology self-efficacy: A framework for AI-HRM adoption in Malaysian hotels

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ABSTRACT

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The growing adoption of artificial intelligence in human resource management is changing the way things are done in the hospitality industry. While customer-facing AI technologies have been widely addressed in previous studies, the adoption of AI-integrated HRM (AI-HRM) systems by employees has not received much attention. To bridge this gap, this conceptual paper synthesized relevant literature and combined the Stimulus-Organism-Response model with Social Cognitive Theory to describe employees' adoption of AI-HRM. Grounded in these theories, this study positioned work-related use of enterprise social media (ESM) as a technological stimulus and employee agility as an organismic adaptive capability that turns digitally mediated work conditions into adoption behavior. Additionally, technology self-efficacy is suggested as both a direct predictor of AI-HRM adoption and a moderating cognitive boundary that influences the strength of the agility-adoption link. To ensure conceptual clarity, this paper defined AI-HRM as an umbrella term that captures the integration of AI into HRM functions, recognizing the variation in terminologies used in past literature. Theoretically, this paper suggests five propositions on how these identified constructs interact. Although no primary data were collected in this study, a moderated-mediation framework is presented to guide future empirical validation in the hotel context. The implications suggest that successful AI-HRM adoption may be achieved by developing employee agility and technology self-efficacy through capacity-building training and supportive digital collaboration conditions.

Contribution/Originality: By synthesizing Stimulus-Organism-Response and Social Cognitive Theory, this paper clarifies an internal capability-belief mechanism for AI-integrated HRM adoption in hotels. It adds practical value by providing an empirically testable model through a suggested sampling strategy and respondent screening criteria, an implementation detail often not presented in conceptual papers.

1. INTRODUCTION

The onset of the Fourth Industrial Revolution (4IR) has redefined how industries work worldwide. Central to this transformation are advanced 4.0 technologies such as Big Data, virtual reality, artificial intelligence (AI), and Internet of Things (IoT) that have heightened the shift towards digital innovation and sustainability of business operations (Budhwar, Malik, De Silva, & Thevisuthan, 2022; Casais & Ferreira, 2023). In the hospitality sector, AI has become one of the most transformative factors in helping organizations automate complicated processes, increase operational efficiency, and optimize strategic decision-making (Jayawardena, Ahmad, Valeri, & Jaharadak, 2023; Yawised, Apasrawirote, Chatrangsan, & Muneesawang, 2023). Industry evidence implies that the global AI market

in hospitality and tourism is booming at an accelerated pace, rising above a 30% annual growth rate, reflecting rapid integration of AI in both guest-facing and internal organizational practices (Liu & Zhang, 2026). Similarly, the Malaysian tourism and hospitality sector has contributed around 15.1 % of the Gross Domestic Product (GDP), generating RM102.2 billion in revenues and creating an estimated 3.5 million employment opportunities in 2024 (MBSB Research, 2025).

Despite its relevance to the economy, the hotel industry is grappling with workforce challenges, including high employee turnover, difficulties in recruiting employees, and decreasing employee engagement, which all contribute to a lack of operational efficiency and low service quality (Bakir, Ayoun, Wei, & Bilgihan, 2025; Kendricks, 2024; Malaysia Digital Economy Corporation, 2022). In response to these workforce challenges, 38% of companies across industries resorted to digital transformation and automation as one of the top three strategic solutions (United Overseas Bank, 2025). In the case of hotels, this transition is particularly valuable since human capital is heavily involved in the delivery of services. As such, AI-integrated human resource management (AI-HRM) is becoming one of the digital initiatives to facilitate recruitment, training, performance management, and workforce analytics, offering organizations the opportunity to make their processes more efficient, accurate, and strategic (Ali & Rafi, 2024; Madaan, Singh, Rabby, Arora, & Niyompuhwe, 2025). AI-HRM systems through machine learning, and process automation would simplify the recruitment process, personalize training programs, provide real-time feedback on performance and predict employee turnover risks (Kurek, 2021; Prentice & Nguyen, 2020; Ramachandran et al., 2022) allowing for more effective work, better performance results, and acquisition of new abilities (Mo, Liu, Chark, Zeng, & Song, 2025).

In spite of these potential benefits, the integration of AI in HRM has also raised employee-level challenges that can impede successful implementation. As AI-HRM may change the job descriptions and working processes, employees are required to continuously rely on new digital tools and upgrade their technical skills (Prentice & Nguyen, 2020; Varshney, 2020). This persistent demand has resulted in uncertainty, decreased confidence, and doubt about perceived competence in interaction with the AI technologies (Cao, Duan, Edwards, & Dwivedi, 2021), thereby potentially preventing meaningful use of the system regardless of the level of technological preparedness within the organization. In this regard, variations in adaptability and employees' self-belief in using the digital systems have become the key parameters of the comprehension of the digital transformation in the work setting today (Kim & Kim, 2024; Maran et al., 2022). This emphasizes the need to investigate the role of employees' psychological factors, particularly agility and technology self-efficacy, in defining the uptake of AI-HRM in the hotel sector.

Nonetheless, the past research in tourism and hospitality industry were mainly centered around the customer-facing technologies that focused on how AI improves service processes, enables touchless services, and enhances operational performance (Bulchand-Gidumal, William Secin, O'Connor, & Buhalis, 2024; Chen, Tzeng, Tham, & Chu, 2021; Dwivedi, Pandey, Currie, & Micu, 2024; Mariani & Borghi, 2024). This signifies that the extant literature is predominantly studied from the perspective of hotel guests, delving into their experience and satisfaction (Kumawat, Datta, Prentice, & Leung, 2025; Wang, 2025). Additionally, while prior literature has largely investigated the adoption of advanced technology for organizational-level value generation (Kraus, Schiavone, Pluzhnikova, & Invernizzi, 2021; Mele, Capaldo, Secundo, & Corvello, 2024) little is known about what makes adoption successful at the employee level (Malik, Andargoli, Ali, & Chavez, 2024) and how they react to AI in HRM context (Shin, Choi, & Kim, 2025). Therefore, this paper proposes an employee-centered perspective to address the current emphasis on organizational and customer-focused streams of hospitality AI research.

2. THEORETICAL BACKGROUND AND CONSTRUCT CONCEPTUALIZATION

When it comes to the topic of digitalization and digital transformation, it has been observed that a larger stream of research within hotel context has concentrated on customer facing technologies, among others, include self-service systems (Kumawat et al., 2025; Wang, 2025) chatbots and virtual assistants for guest support (Bulchand-Gidumal et

al., 2024) and blockchain technology for reservation assistance (Puri, Mondal, Das, & Vrana, 2023). Although such studies have made a significant contribution to the knowledge about technology-facilitated service encounters, the attention has now shifted from customer-centric to employee-centric, particularly regarding the circumstances under which employees actually use or interact with digital technologies in their work practices (Liu & Zhang, 2026).

With the continued integration of AI in organizational processes, especially in the functions of HRM, it is imperative to know how employees act and engage with these systems. Even though AI-HRM systems are aimed at aiding workforce management, the effectiveness depends on whether the employees are willing to adopt and use these systems in their working routine (Dwivedi et al., 2022). Therefore, understanding the factors that contribute to employee adoption and use of AI-HRM is crucial to improve digital transformation research within the hospitality and tourism industry. To explain these mechanisms, this study synthesizes the Stimulus-Organism-Response (S-O-R) model and Social Cognitive Theory (SCT) for a deeper insight into how the technological environment interacts with employee cognition in influencing behavioral response.

2.1. Stimulus-Organism-Response Theory (S-O-R)

The Stimulus-Organism-Response (S-O-R) theory was first introduced to environmental psychology by Mehrabian and Russell (1974). It provides a framework that illustrates how external or contextual stimulus (S) shapes the internal psychological states of people, otherwise known as the organism (O), which then causes behavioral responses (R) (Manresa, Sammour, Mas-Machuca, Chen, & Botchie, 2025; Mehrabian & Russell, 1974; Perez-Vega, Kaartemo, Lages, Razavi, & Männistö, 2021; Pham, Le, Dinh, & Pham, 2024; Raj, Singh, & Lascu, 2023). According to this framework, the organism explains the internal processes in cognitive assessment, emotional responses, and motivational orientations that mediate the connection between the environmental conditions and behavioral consequences (Duong, Dao, Vu, Ngo, & Tran, 2024).

S-O-R has been commonly used to investigate how technology-enabled environments affect employee and consumer reactions through internal psychological processes (Ibrahim, Hazzam, Qalati, & Attia, 2025; Rather, 2025). However, the system mainly offers a structural rationale, explaining the links between the stimulus and response, but does not clearly define the organism component (Bai, 2025). Consequently, researchers have tended to incorporate the interdisciplinary theoretical views to enhance their conceptual modeling of the internal mechanisms that connect the environmental stimuli with behavioral consequences. This flexibility allows scholars to adjust the model to various technological contexts and use other theoretical lenses to describe internal psychological processes in a more accurate manner (Jacoby, 2002; Talwar, Kaur, Nunkoo, & Dhir, 2023).

2.1.1. Work-Related Use of Enterprise Social Media (ESM) as Technological Stimulus (S)

In today's digitally transformed working environments, enterprise social media (ESM) platforms like Microsoft Teams, Yammer, IBM Connections and Workplace by Meta have become a significant infrastructure through which employees receive real-time information, coordinate work activities, and exchange knowledge across organizations (Cai, Huang, Liu, & Wang, 2018; Huang & Zulkifli, 2023; Olfat, Shokouhyar, Ahmadi, & Ghaderi, 2023; Sun, Mengyi, & Jeyaraj, 2025). The existing body of knowledge commonly differentiates ESM usage into two purpose-driven patterns, specifically work-related use and social-related use (Chen & Wei, 2019).

Beyond distinguishing the usage patterns, previous studies indicate that each type of use may yield distinct, and at times, contradictory effects on employee behaviors and psychological states (Deng & Zhu, 2023; Liang, Xin, Yan, & Jianxiang, 2021; Ma, Yu, Zhang, & Hao, 2025; Zhu, Li, Gao, & Zuo, 2024). To maintain theoretical alignment with the proposed model, this study concentrates on work-related ESM usage, which is referred to as employees' use of the organization's internal digital platforms for communication, collaboration and knowledge sharing (Bulgurcu, Van Osch, & Kane, 2018; Deng & Zhu, 2023; Leonardi, Huysman, & Steinfield, 2013). It captures the use of ESM to clarify task goals, coordinate assignments, monitor progress, and share task-relevant information with coworkers (Deng,

Liu, Huang, & Ding, 2021). More broadly, it involves accessing and sharing work-related content such as policies, procedures, and project updates (Chen & Wei, 2019; Li & Liu, 2025).

From the S-O-R lens, work-related use of ESM makes a focal stimulus as it signifies external work conditions that continuously shape how employees obtain and translate information on an ongoing basis. According to this theory, environmental input as stimuli triggers changes in internal conditions, including cognitive processing, which reflects how individuals attain, process, and retrieve information (Jacoby, 2002; Mehrabian & Russell, 1974). Through its technological affordances, including accessibility, visibility, editability, persistence, and association (Shi, Zhao, Li, Zhang, & Leung, 2024; Sun, Zhong, Jeyaraj, & Zhu, 2024; Treem & Leonardi, 2013), ESM structures the way information and interactions are encountered and reused in day-to-day work. The significance of ESM as an internal digital transformation effort is further supported by the fact that more than 90% of 500 global companies have adopted ESM (Shi et al., 2024). Most importantly, national evidence also indicates that ESM platforms are progressively being used in Malaysian business operations, with 21% adopting Google Suite and 14% using Microsoft 365 (Malaysia Digital Economy Corporation, 2022). Due to the fact that ESM is being increasingly implemented throughout organizations and that ESM usage has diverse effects on employees' internal conditions (Sun et al., 2024), the selection of ESM as a technological and environmental stimulus is contextually timely and theoretically relevant.

2.1.2. Employee Agility as an Organism Adaptive Capability (O)

While ESM acts as a technological stimulus, the S-O-R framework underscores that those behavioral responses rely on organisms' internal capabilities. In this study, employee agility is conceptualized as the organismic adaptive mechanism. It portrays employees' capability and competency to react speedily to unexpected changes in both internal and external environments (Alavi, 2016; Doeze Jager, Born, & van der Molen, 2022). The concept of employee agility is frequently explained through three dimensions, particularly adaptability, resilience, and proactivity (Alavi, Abd Wahab, Muhamad, & Arbab Shirani, 2014; Breu, Hemingway, Strathern, & Bridger, 2002). Adaptability denotes an employee's ability to adjust to environmental change; resilience refers to an optimistic attitude towards unforeseen situations; and proactivity reflects initiatives in resolving issues arising from change and fostering work improvement (Talwar et al., 2023; Wei, Pitafi, Kanwal, Ali, & Ren, 2020).

This multidimensional concept of employee agility is particularly significant in a technology-enabled environment where employees need to manage disruption and also respond positively to new information and evolving work demands. Scholars highlighted that agile employees are more flexible in reacting to environmental shifts, therefore contributing to organizational development (Pitafi & Ren, 2021). Similarly, the adaptive behaviors demonstrated due to the implementation of digital technologies are argued to influence the post-adoption behavior, affecting both routine and advanced performance (Zhang, Xu, & Ma, 2024). This suggests that technology adoption and continuance of use depend on employees' internal ability, justifying the positioning of employee agility as an organismic component in the proposed model. Within the service-intensive sectors such as hospitality itself, the importance of agility is further intensified by operational unpredictability, rapid technological evolution and ever-changing customer expectations (Sackey et al., 2025). Even though organizations invest in innovative systems or infrastructure, the execution of new practices in daily work hinges upon employees (Ali, Li, & Qiu, 2022). This is also extended to HR practitioners, as being agile will not only allow them to adapt to shifting business trends but also effectively leverage innovative technology to streamline HR processes (Madakam, Holmukhe, & Jaiswal, 2019; Mehrajunnisa, Jabeen, Faisal, & Mehmood, 2022). Taken together, employee agility is an appropriate organismic mechanism for understanding adoption of AI in HRM in digitally transforming organizations.

2.1.3. AI-HRM Adoption as Behavioral Response (R)

The implementation of AI in HRM has brought about significant changes in how HR practices and procedures are being delivered. Across the existing literature, scholars use various terms to describe this phenomenon, including

AI in HRM (Nawaz, Arunachalam, Pathi, & Gajenderan, 2024), AI-driven HRM (Do, Chu, & Shipton, 2025), and AI-augmented HRM (Prikshat et al., 2023), among others.

While these terminologies vary, they share a similar understanding regarding the integration of AI technologies into HRM functions. For example, Do et al. (2025) defined AI-driven HRM as a combined system that facilitates employees in acquiring knowledge, skills, and motivation to work with AI tools. Along the same line, Prikshat et al. (2023) described AI-augmented HRM as the integration of AI technologies within HRM through a business intelligence system to support better problem-solving and decision-making in operational, relational and transformational outcomes. In view of the overlapping scope in definition as well as to ensure terminological consistency, this paper uses the umbrella term AI-integrated HRM (AI-HRM) hereafter to refer to the integration of AI technologies into HRM functions that augment HR decision-making, problem-solving, and delivery of HR procedures and practices.

Within the S-O-R framework, employee adoption of AI-HRM represents the behavioral response (R) that follows from employees' internal capability and beliefs. Zhang and Hao (2025), in their study on AI virtual assistance adoption, highlighted that technology adoption can be characterized as initial adoption and continuous adoption. While initial adoption refers to initial acceptance and utilization, continuous adoption implies ongoing use that relates to attitude and intention to continue using the technology, comprising continuity, routinization, and integration following initial adoption (Venkatesh, 2022). Likewise, Oeij, Hulsege, and Preenen (2022) pointed out that employee innovation adoption involves the preparation to accept an innovation, which entails the actual use of it in their work beyond mere intention to use. Building on this view, this study suggests that adoption reflects employees' engagement with and use of AI-HRM in work-related activities, including learning new system routines, applying system output and integrating AI-supported processes into daily work practices.

2.2. Social Cognitive Theory (SCT): Technology Self-Efficacy

In order to enhance the explanatory value of the S-O-R framework, this paper will use Social Cognitive Theory (SCT) which focuses on how cognitive beliefs contribute to behavior. Being one of the most influential theories for explaining human behavior (Chen, Cao, & Liang, 2023), SCT can be used as a powerful basis to understand how employees react to digital transformation. According to SCT, behavior develops through two-way interactions of the personal factors, environmental factors, and behavior patterns as opposed to technological availability or organizational initiatives (Bandura, 1986). This view has found extensive use in the explanation of different types of technology- and media-related behavior, such as media adoption, constant use, and habitual use of digital platforms (Pizzi, Vannucci, Mazzoli, & Donvito, 2023). In organizational settings that are undergoing digital transformation, SCT thus becomes very applicable in the context of explaining the way in which the employees understand and react to the new technological systems brought about within their workplace.

Self-efficacy, as the beliefs of individuals in their ability to accomplish certain tasks, is considered to be one of the central constructs in SCT (Bandura, 2001). An extensive number of studies conducted in the technology-related fields, such as computer use, e-learning, and interaction with the digital platform, continuously show that self-efficacy is a very strong predictor of behavioral intentions as well as real technology use (Al-Dokhny, Drwish, Alyoussef, & Al-Abdullatif, 2021). Self-efficacy has also been identified as an important factor that determines the willingness of employees to use the new digital tools and systems in the context of information systems and human resource management (Kesharwani, 2020). These findings underscore the relevance of efficacy beliefs in the explanation of employee reactions to AI-integrated HR technologies.

Notably, self-efficacy may be modeled on various levels of specificity. General self-efficacy is a deep and comparatively constant conviction of one having the capability to handle various circumstances in a proficient manner, and this indicates a trait-based orientation (Chen, Gully, & Eden, 2001). On the other hand, domain or task-specific self-efficacy is the belief in the ability to carry out specific tasks or learn specific skills within a particular situation

(Abele & Spurk, 2009; Broos & Roe, 2006). Since task-specific efficacy is the concept that is more pertinent to behavioral aspects, it is especially helpful in elucidating the technology adoption processes, in which individuals are expected to acquire and perform certain system-related actions (Hatlevik, Throndsen, Loi, & Gudmundsdottir, 2018).

Grounded in SCT, this study establishes technology self-efficacy as organism cognitive boundary within the S-O-R framework that shapes employees' adoption of AI-HRM systems in hotels. In the context of this study, technology self-efficacy is interpreted as the confidence of employees in the ability to utilize digital resources and systems in order to undertake new, complicated, or changing technology-related tasks (Al-Hattami, 2023; Falebita & Kok, 2025; Pan, 2020). The paper has combined both SCT with S-O-R to elaborate how ESM as digitally mediated working conditions influence the adoption behavior of employees through their adaptive abilities and cognitive perceptions. In summary, Table 1 shows the conceptual roles of the study constructs to elucidate how each construct is theoretically grounded within the suggested framework.

Table 1. Theoretical Grounding and Constructs Conceptualization.

Construct	Theoretical lens	Conceptual role in the model	Operationalization	Key references
Work-related use of ESM	S-O-R	Stimulus (S)	The extent to which employees exchange work-related information, coordinate tasks, and engage in knowledge sharing through a digitally mediated communication and collaboration platform within organizations.	Cai et al. (2018); Chen and Wei (2019); Deng et al. (2021) and Liang et al. (2021)
Employee agility	S-O-R	Organism (O) mediator	Employees' adaptive behavioral capacity (e.g., proactivity, flexibility, resilience) that enables them to anticipate change, adjust behaviors quickly, and remain effective under uncertainty in technology-intensive work settings.	Verma and Singh (2022) and Alavi et al. (2014)
Technology self-efficacy	SCT	Organism (O) moderator	Employees' belief in their expertise and capabilities to successfully use technology to effectively execute a technology-based task.	Al-Hattami (2025), Kaqinari et al. (2022), and Pan (2020)
AI-HRM adoption	S-O-R	Response (R)	Employees' willingness to engage with and use AI-integrated HR tools for HR-related functions (e.g., recruitment, training, performance management, workforce analytics)	Ali and Rafi (2024); Madaan et al. (2025) and T. Wang, Cheng-Xi Aw, Wei-Han Tan, Sthapit, and Li (2025)

Note: S-O-R= Stimulus-Organism-Response Theory, SCT= Social Cognitive Theory.

3. PROPOSITIONS DEVELOPMENT

3.1. Work-Related Use of ESM, Employee Agility, and AI-HRM Adoption

As a technological stimulus, work-related application of ESM influences the organization of work and the involvement of employees in sense-making and informal learning by facilitating the flow of information and collaborative problem-solving (Cai et al., 2018). ESM-enabled environments are especially pertinent to the development of employee agility as they allow for numerous and timely access to information sources and rapid knowledge exchange. This matters because employee agility, which refers to the ability of an individual to effectively learn and adapt to emerging challenges and changing market conditions (Salmen & Festing, 2022; Sun et al., 2025), requires the acquisition of adequate information and the capacity to process diverse information efficiently, so they can sense and act quickly in response to external changes (Bathaei et al., 2019).

This claim is further reinforced by empirical findings that the intensive use of ESM promotes active behavior and the ability to combine knowledge that is core to agile performance in technology-based settings (Petermann & Zacher, 2021). In consonance with the extant literature, Wei et al. (2020) suggest that ESM usage promotes employee agility by enhancing employee meta-knowledge. Similarly, Pitafi, Rasheed, Kanwal, and Ren (2020) and Sun et al. (2025) pointed out that the link between ESM usage and employee agility is observed to be higher as employees are constantly involved in coordinating, sharing, and discussing job-related information. This supports the view that with digitally mediated interactions, employees get to know more about digital working processes and therefore become familiar with digital tools. Such exposure can make employees more flexible and willing to work with more sophisticated technological systems, for instance, AI-HRM software. Therefore, this study advances the following proposition.

Proposition 1: Work-related use of ESM positively influences employee agility.

Notably, agility is not a product of digitally mediated work alone but also an ability that determines whether employees transfer digital work conditions into new technology utilization. Within this study's conceptual framework, employee agility is positioned as an internal mechanism or resource that promotes proactive alteration to changing work circumstances (Aggarwal & Stanley, 2025). Prior research claimed that an agile workforce has been connected to improved innovation outcomes and greater project achievement (Sheffield & Lemétayer, 2013). Likewise, this view is further supported by Muduli and Choudhury (2025) that agile behavior facilitates the adoption of digital technology by promoting values of learning, risk-taking, innovativeness, and flexibility.

Although earlier studies discuss digital technology adoption more generally, a similar concept can be extended and applied to the AI-HRM adoption process as it requires employees working with the new workflow, understanding the outputs produced by an algorithm, and modifying the expectations placed on tasks. These demand lifelong learning and adaptability to change, which correlate with agile behavioral abilities (Verma & Singh, 2022). As such, agile employees or agile behavior that aids digital technology adoption should be more likely to increase employees' willingness to embrace and use the AI-HRM system in practise. Accordingly, this study proposes that:

Proposition 2: Employee agility positively influences employee adoption of the AI-HRM system.

3.2. Mediating Role of Employee Agility

Within the S-O-R framework, the organism component acts as intermediary states through which individuals obtain, process, and interpret external stimuli, including environmental sources (Jacoby, 2002; Mehrabian & Russell, 1974). This cognitive process enables individuals to understand these stimuli and act accordingly (Dalvi-Esfahani, Mosharaf-Dehkordi, Leong, Ramayah, & Kanaan-Jebna, 2023).

Reflecting this internal mechanism, employee agility is deemed crucial for effective digital transformation, particularly in responding to the adoption and incorporation of advanced technologies into the business environment (Alavi et al., 2014; AlNuaimi, Singh, Ren, Budhwar, & Vorobyev, 2022; Franco, Guimarães, & Rodrigues, 2023; Hillmann & Guenther, 2021; Vial, 2019). Such an optimistic response towards unexpected change in the workplace is possible when employees regularly communicate and collaborate with others across the organization (Chen, Wei, & Rice, 2020). This clarifies the role of ESM for work related purpose as it increases employee's exposure to latest information which facilitates the discussion of alternative solutions, and contributes to the high-quality decision-making in process improvement and innovation (Bathaei et al., 2019; Cao, Guo, Vogel, & Zhang, 2016; Sun, Zhou, Jeyaraj, Shang, & Hu, 2019; Wu, Zhang, Huang, & Yuan, 2021).

Although employee agility has been acknowledged as an enabler of employee innovation (Abrishamkar, Abubakar, & Mitra, 2021), the impact can be varied depending on contextual aspects that allow employees to capitalize on their agility (Jo & Hong, 2022). Taken together, the application of this logic to AI-HRM is relevant as employees need sufficient information to flexibly adjust to new work practices and proactively experiment with AI-HRM

functions. Hence, this study suggests that work-related use of ESM indirectly influences AI-HRM adoption through employee agility. This mediation relationship is illustrated by the following proposition.

Proposition 3: The relationship between work-related use of ESM and AI-HRM adoption is mediated by employee agility (Work-related use of ESM → employee agility → AI-HRM adoption).

3.3. Technology Self-Efficacy and AI-HRM Adoption

The notion of self-efficacy in AI learning is built upon Bandura's SCT. It implies that an individual's confidence in his or her talents affects the person's motivation, actions and accomplishments in a certain area (Kim & Lee, 2024). Although prior studies do not directly investigate technology self-efficacy within the context of AI-HRM adoption, the technology adoption literature as a whole suggests similar findings. Past findings highlighted that efficacy beliefs play a substantial role in turning individuals' intention into prolonged use of technology.

More than just beliefs and perceptions, efficacy appears to influence implementations. Previous studies suggested that professionals with higher technology self-efficacy are more inclined to use new digital methods, such as automating regular work, applying analytics to achieve more accurate data, and using digital tools to facilitate decision-making (Al-Hattami, 2023; Odonkor, Kaggwa, Uwaoma, Hassan, & Farayola, 2024). Increased level of self-efficacy in individuals allows them to complete technology-enabled tasks more speedily and effectively (Lee, Chuang, Lee, & Israeli, 2022), demonstrating that confidence can translate into more competent and continuous system use.

Extending this reasoning to AI-integrated work processes, employees who believe they can use digital systems effectively are more likely to engage in adaptive behaviors and persist through the learning curve associated with AI-supported workflows (He, 2025), thereby increasing the likelihood of adopting and using AI-HRM. Even though this evidence does not involve AI-HRM directly, it can be applied to the said context as AI-HRM adoption similarly requires employees to engage with complicated systems, learn different workflows, and incorporate advanced technology into their daily routine at work. Thus, this study proposes that:

Proposition 4: Technology self-efficacy positively influences employee adoption of AI-HRM.

3.4. Technology Self-Efficacy as a Moderator

Beyond its direct role, technology self-efficacy is likely to function as a boundary condition that determines whether employees' adaptive capability translates into actual AI-HRM use. In AI-HRM contexts, employee agility may influence employees to respond proactively to change; however, agile tendencies may not translate into adoption when employees doubt their ability to operate an AI-integrated system effectively. When employees face challenging situations, those who have confidence in their capabilities to learn AI will be better able to adapt to changing job requirements, take advantage of AI's opportunities and feel competent and in control (Kim & Kim, 2024; Kim & Lee, 2024; Sharma, Pandher, & Prakash, 2024).

Supporting this contingent logic, prior research shows that higher self-efficacy encourages not only adoption but also deeper engagement behaviors such as exploring system features, experimenting with new applications, and adapting digital tools to meet growing demands (Al-Hattami, 2023; Venkatesh, Morris, Davis, & Davis, 2003). Although these studies do not examine employee agility explicitly, the described behaviors like exploration, experimentation, and adaptive use reflect the proactive and adaptive work responses commonly associated with employee agility in technology-mediated environments. Accordingly, technology self-efficacy is expected to amplify the positive relationship between employee agility and AI-HRM adoption. Consequently, this study proposed that:

Proposition 5: Technology self-efficacy positively moderates the relationship between employee agility and AI-HRM adoption, such that the relationship is stronger when technology self-efficacy is higher.

All in all, Figure 1 illustrates the conceptual framework whereby the work-related use of ESM represents the environmental stimulus that affects the agility of the employees, which in turn impacts AI-HRM adoption. In addition,

technology self-efficacy is positioned as a moderator that reinforces the connection between the agility of the employees and the use of AI-HRM.

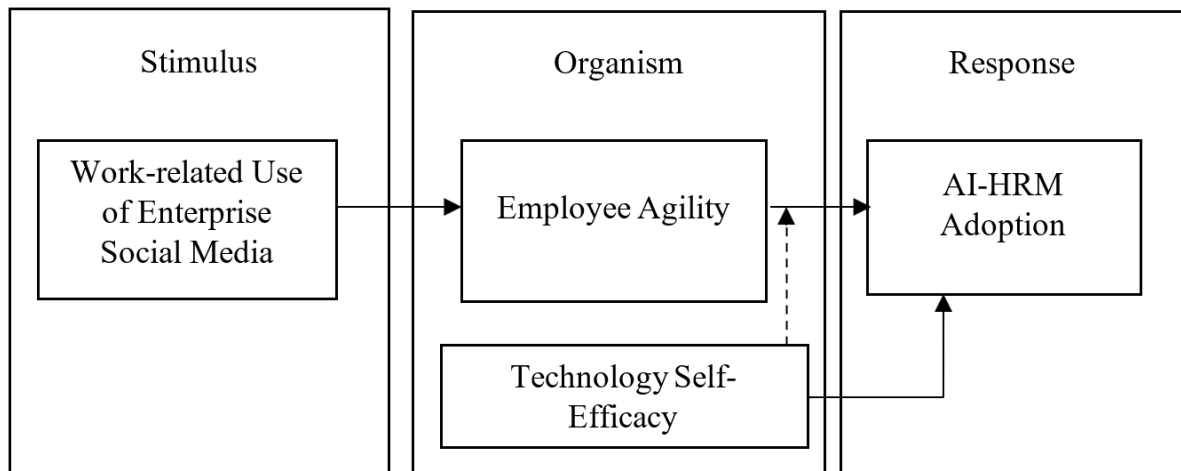


Figure 1. Conceptual framework of employee adoption of AI-HRM.

4. PROPOSED METHODOLOGY FOR EMPIRICAL VALIDATION

4.1. Proposed Research Design

To guide empirical validation of the suggested moderated-mediation framework, this study may apply a quantitative, survey-based research design. A cross-sectional approach could be utilized in investigating the relationships between work-related ESM usage, employee agility, technology self-efficacy, and AI-HRM adoption in Malaysian hotels, especially when the AI-HRM system is already in place. Although such cross-sectional data cannot be used to draw a causal link over time, it is a practical and widely adopted approach in theory testing.

Since the proposed conceptual model involves mediation and moderation, structural equation modeling (SEM) could be used to test the relationships concurrently. In particular, agility among employees could be measured as a mediating variable that connects the work-related use of ESM and AI-HRM adoption, while technology self-efficacy could be the moderator that affects the strength of the agility-adoption link. SEM is suitable for estimating direct, indirect, and conditional impacts at the same time while considering measurement error.

4.2. Proposed Population and Sampling

This subsection outlines the recommended population and sampling strategy to conduct future empirical validation of the conceptual model. The target population includes employees in Malaysian hotels who have access to AI-HRM tools.

This encompasses HR professionals and non-HR staff whose scope of work involves HR-related duties (e.g., supervisors dealing with appraisal inputs or department heads who participate in the staffing process). In order to achieve conceptual consistency, inclusion criteria could be utilized to screen out respondents with exposure to AI-HRM applications like recruitment analytics, AI-assisted screening, performance dashboards, learning recommendation systems, or HR chatbots.

This type of screening is essential to prevent the sampling of respondents who assess the AI-HRM adoption but do not experience AI-HRM functions in practice. In line with the future testing approach, Table 2 sums up the inclusion and exclusion criteria of targeted respondents.

Table 2. Proposed inclusion and exclusion criteria for empirical validation.

Category	Criteria
Inclusion criteria	1. Employed in a four- or five-star hotel operating in major Malaysian hotel markets. 2. Direct involvement in HR-related tasks (e.g., recruitment/selection, training and development, appraisal, payroll/HR analytics) 3. Meaningful exposure to at least one AI-enabled HRM tool or AI-supported HR process (e.g., AI-assisted screening, recruitment analytics, performance dashboard, learning recommendation system, HR chatbot). 4. Minimum six months of employment to ensure adequate familiarity with HR processes and system routines. 5. Aged 18 years or older and able to provide informed consent.
Exclusion criteria	1. Employed in budget hotels, homestays, boutique properties, or properties rated below four stars. 2. No involvement in HR-related tasks and no exposure to HR systems or AI-enabled HR practices. 3. Interns, trainees, or part-time students with minimal operational experience. 4. Employed for less than six months, limiting familiarity with HR processes and technology routines.

Note: AI-HRM exposure screening may be implemented as a short eligibility check prior to administering the main questionnaire.

Building on these criteria, a purposive sampling approach may be used to target only hotels that already integrate AI-HRM in practice, along with a response-level filtering to gauge respondents with AI-HRM system exposure. Since the operations of a hotel are organized in a departmental structure, and the application of digital HR tools can be unevenly distributed among the departments, the sampling strategy could seek to capture variation across role categories and functional areas. With adequate organizational participation, analysis could also address hierarchical effects (i.e., respondents nested within hotels) using multilevel modelling, as adoption and efficacy beliefs may be influenced by common organizational circumstances.

5. RESULTS

This conceptual paper did not produce empirical results as no primary data were collected. The main outputs of this paper are the development of a conceptual framework that signifies AI-HRM adoption as a behavioral response and five propositions resulting from the synthesis of S-O-R and SCT. The developed framework positions work-related use of ESM as a technological and work condition stimulus while employee agility serves as the focal organismic mechanism. Within this developed framework, technology self-efficacy represents an organismic cognitive confidence that conditions the agility-adoption link. These conceptual outputs, especially the five propositions, are explained in the Propositions Development section.

6. THEORETICAL AND PRACTICAL IMPLICATIONS

This conceptual framework offers several theoretical and practical implications for understanding the adoption of AI-HRM by employees in the hotel industry. First, this study contributes to the growing literature on AI adoption, particularly in the HRM context, because it incorporates employee agility and technology self-efficacy as the main behavioral and cognitive predictors of AI-HRM adoption.

Although previous studies of technology adoption have paid more attention to the technological nature or organizational aspects, this framework underlines the personal abilities of employees, especially their adaptive behavior and self-confidence to work with digital technologies. Positioning employee agility as a fundamental determinant of AI-HRM implementation, the framework expands the knowledge on how employees react to digital transformation within service-based forms of industries like hospitality.

Second, the model enhances the current study by postulating that the relationship between employee agility and AI-HRM adoption is moderated by technology self-efficacy. This shows the significance of cognitive beliefs in empowering agile employees to convert their adaptive behaviors into useful technology use. As such, the framework

helps to explain the technology adoption process through the combination of agility and social cognitive orientation. Finally, this theoretical work gives a basis for future empirical studies in exploring the impact of behavioral skills and psychological preparedness on AI-HRM practices.

From a managerial perspective, the framework proposed can provide the HR managers and organizational leaders in the hospitality industry with a number of practical insights. The organizations are advised to aim at creating employee agility through the creation of a culture that promotes continuous learning, a proactive approach to problems, and flexibility in everyday work practices.

These initiatives may assist the employees to react better to the technological changes and the changing HR processes. Moreover, technology self-efficacy in employees is critical to strengthen in an effort to reduce the resistance to AI-HRM systems. Organizations can do it with the help of well-organized training sessions, practical workshops, mentorship programs, and unceasing technical support that will increase the confidence of the employees to work with AI-enabled tools.

7. CONCLUSION

This conceptual paper advanced a testable moderated-mediation model to clarify employee adoption of AI-HRM in Malaysian hotels. Through the integration of S-O-R and SCT, the model proposes that work-related use of ESM enhances employee agility (P1) by improving information visibility, collaboration, and knowledge exchange in daily tasks. In turn, employee agility is anticipated to improve employees' adoption of AI-HRM (P2). By suggesting these associations, the model signifies that AI-HRM adoption should be treated as an enacted behavioral process instead of a direct effect of organizational implementation.

Beyond these direct relationships, this paper also proposes a mediating pathway in which employee agility serves as a mechanism in translating ESM-enabled work conditions into adoption behavior (P3). The framework further identifies technology self-efficacy not only as a direct predictor of adoption (P4) but also as a form of cognitive boundary that strengthens the agility-adoption interaction, inferring that agility is more likely to encourage adoption as employees believe in their capacity to use innovative tools (P5). Together, these propositions create a sound moderated-mediation logic that provides a roadmap for empirical validation for future research.

8. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

This paper has some limitations that should be acknowledged. The first limitation of this study lies in its conceptual nature. Even though the conceptual framework was founded within the established theories, it does not test the proposed relationship empirically. Therefore, future research should empirically validate the proposed propositions using primary data from HR professionals with proven exposure to AI-HRM functions.

Secondly, the intended empirical approach relies on a self-reported cross-sectional survey that captures employees' perceptions at a single point in time. Since AI technologies and employees' familiarity continue to evolve, longitudinal designs can be applied to provide causation in investigating the role of agility and self-efficacy in enhancing AI adoption in the long-term.

Lastly, the model concentrates on a restricted mechanism that links the digital work environment to adoption behavior through employee agility and technology efficacy. Other factors, such as the organizational culture, the leadership style, or the learning orientation of employees, might also be studied to comprehend the AI adoption dynamics in a better way.

Additionally, while Malaysian hotel contexts provide a meaningful setting due to labor intensity and ongoing digital transformation, cross-cultural comparisons across different institutional environments could be investigated to increase the generalizability.

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