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Employee agility and technology self-efficacy in smart HRM 4.0 adoption: A pilot study in the Malaysian manufacturing industry

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ABSTRACT

The integration of Industry 4.0 technologies into human resource management (HRM) has accelerated the emergence of Smart HRM 4.0 practices within organizations. Despite growing investments in digital transformation, the successful implementation of Smart HRM 4.0 remains a challenge as organizations grapple with workforce-related obstacles, particularly those related to employees' readiness and capability to embrace new ways of working. This is notably critical in the manufacturing industry, where HR professionals play a central role in adopting innovative HR technologies to support workforce adaptation in an increasingly complex, safety-critical, and technology-driven environment. Prior research on technology adoption has largely focused on technological and organizational factors, while emphasis on employees' capabilities remains limited. Grounded in the microfoundations of Dynamic Capability Theory and Social Cognitive Theory, this pilot study addresses the gap by examining how employee agility and technology self-efficacy influence Smart HRM 4.0 adoption among HR professionals in the Malaysian manufacturing sector. Quantitative research was conducted through an online survey platform involving 30 respondents. The findings demonstrated that employee agility and technology self-efficacy were positively correlated with the adoption of Smart HRM 4.0. The study also established satisfactory reliability for all measurement constructs, indicating the appropriateness of the instrument for use in full-scale data collection. Overall, this research offers preliminary empirical evidence of the significance of employee agility and technology self-efficacy in facilitating the adoption of Smart HRM 4.0. Additionally, this research advances the innovative HRM literature while supporting digital transformation initiatives aligned with Sustainable Development Goal (SDG) 8 and 9.

Contribution/Originality: This pilot study provides initial evidence of Smart HRM 4.0 adoption among Malaysian manufacturing HR professionals. It expands applications of the microfoundational perspective of Dynamic Capability Theory and Social Cognitive Theory by positioning employee agility and technology self-efficacy within the Smart HRM 4.0 adoption framework as complementary capability- and motivation-based mechanisms.

1. INTRODUCTION

Innovative 4.0 technologies, particularly artificial intelligence (AI), are no longer trends of the future but part of the current business environment, transforming work processes at all levels. Propelled by the advent of Industry 4.0, this technological revolution has continued to accelerate across various industries (Agarwal, Swami, & Malhotra, 2024; Ekuma, 2024), offering advanced and intelligent features that can improve business performance, efficiency, and

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competitiveness (Li et al., 2023). Subsequently, the integration of these innovative technologies into organizational management has modified organizational structures, management functions, and employee dynamics (Abhari, 2025; Al-Kharabsheh, Attiany, Alshawabkeh, Hamadneh, & Alshurideh, 2023).

The Human Resource Management (HRM) function is no exception. It has also undergone a significant shift, from a typical administrative role focused on transactional and repetitive activities, such as record-keeping and personnel administration, to a more strategic, agile, and technology-driven (Agarwal, 2023; Gupta, Arora, & Chakrabarti, 2024; O'Brien, Li, Adotey, & Yohuno, 2025). HRM practices have evolved into what is termed Smart HRM 4.0, in which advanced digital technologies are adopted and integrated into HR functions (da Silva et al., 2022; Ogbeibu, Pereira, Emelifeonwu, & Gaskin, 2021; Pillai & Srivastava, 2024). Remarkably, Smart HRM 4.0 is not tied to one specific technology but is instead an integrated system that incorporates multiple Industry 4.0 technologies, such as the Internet of Things (IoT), cloud computing, big data, and artificial intelligence (AI) (Jain & Sharma, 2024; O'Brien et al., 2025; Pillai & Srivastava, 2024). This integration empowers organizations to leverage smart systems to undertake strategic functions, such as workforce analytics, talent acquisition and management, performance evaluation, and retention processes, thus revolutionizing the way human capital is managed (Ferreira-Oliveira, Keating, & Silva, 2020). Additionally, progress in AI, machine learning, and big data analytics enables HR professionals to generate actionable insights from large datasets, which can be used to make informed decisions and complement HRM processes (Garg, Sinha, Kar, & Mani, 2022).

Although increased productivity is achieved with the rise of digital solutions in HRM, human intervention is still necessary to foster creativity, teamwork, and innovation in organizations (Alqudah et al., 2024; Marion & Fixson, 2021; Šebestová & Popescu, 2022). This human-centric perspective is especially relevant to the Malaysian context, as companies still grapple with workforce issues. According to the United Overseas Bank (2025), two out of five organizations have been identified as being impacted by manpower-related challenges, such as attracting skilled talent (48%) and motivating and retaining employees (44%). Digital transformation and automation have, in turn, been listed among the three most strategic initiatives implemented by organizations to address workforce-related challenges (United Overseas Bank, 2025). This means that digital transformation is not considered technological upgrading alone but is gradually perceived as a strategic tool for better workforce management.

Within the Malaysian economy, this transformation is particularly important in the manufacturing industry, as it contributes significantly to national development and employment creation. Nationally, it is evident that the manufacturing sector received approximately RM131 billion in total approved investments and created over 100,000 employment opportunities, underscoring the critical role of the manufacturing sector in promoting Malaysia's economic growth (Malaysian Investment Development Authority, 2026b). With manufacturers still coping with workforce pressures and the demands of digital transformation, Smart HRM 4.0 has gained even greater relevance. In addition to serving as a strategic tool for enhancing workforce management, Smart HRM 4.0 can also contribute to the United Nations Sustainable Development Goals (SDGs), namely SDG 8 (Decent Work and Economic Growth) through better workforce productivity and SDG 9 (Industry, Innovation and Infrastructure) through the enhancement of industrial digital transformation and innovation.

Regardless of its growing importance, Malaysia's digital transformation journey seems to be inhibited by various issues, including low employee readiness and a lack of engagement (Lee, 2025). It is reported that 33% of employers are less confident that employees can successfully incorporate advanced technologies into work practices and decision-making (Lee, 2025). Similarly, scholarly literature suggests that organizational digital transformation requires employees' active dedication, including a willingness and eagerness to share insights on digital participation programs (Rubel, Kee, & Rimi, 2023). This highlights that the adoption of Smart HRM 4.0 depends not only on technological infrastructure but also on employees' willingness to use advanced HR systems. To this extent, differences in employees' adaptability and self-confidence in utilizing digital systems have become key aspects of digital

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transformation in modern workplaces (Kim & Kim, 2024; Maran et al., 2022), and the psychological factors associated with employees are significant to consider.

Even though prior research has examined technology acceptance and digital literacy (Panagoulias, Virvou, & Tsihrintzis, 2024; Schiavo, Businaro, & Zancanaro, 2024), the majority of studies have focused on the adoption and preparedness of AI at the organizational or system level (He, Pham Thi, Phan, & Duong, 2026). This represents an important gap, especially from a capability-driven and motivational perspective (He et al., 2026), as employees are not passive users of technology but active agents who contribute to the accomplishment of digital transformation initiatives. By acknowledging that employees are among the most important users, whose adoption behaviors and attitudes can influence overall organizational results, this study seeks to answer the following research questions: (1) What is the level of employee agility and technology self-efficacy among HR professionals? and (2) what is the association between employee agility and technology self-efficacy and Smart HRM 4.0 adoption?

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

This section elaborates on the concept of Smart HRM 4.0 adoption and its role in transforming HRM functions. Then, the theoretical underpinnings are discussed to further explain the employee-level capabilities influencing the adoption of Smart HRM 4.0. Specifically, Dynamic Capability Theory (DCT) and Social Cognitive Theory (SCT) are employed as supplementary theoretical approaches to describe the nexus between employee agility and technology self-efficacy in enabling employees to adopt and use smart HR systems. Based on these theoretical foundations, the relationships between the variables are discussed, and the hypotheses are formulated.

2.1. Smart HRM 4.0 Adoption

Having passed through numerous stages shaped by evolving organizational priorities, technological growth, and market needs, HRM has developed significantly over the years (O'Brien et al., 2025). Consequently, the evolution of digital technologies and Industry 4.0 innovations has progressively turned HRM into a more strategic, technology-oriented, and data-focused function. The integration of new 4.0 technologies, including AI, machine learning (ML), IoT, chatbots, and big data analytics, enhances the effectiveness of many HR functions, including workforce planning and recruitment, employee development, and exit management (Sivathanu & Pillai, 2018).

This practice, referred to as Smart HRM 4.0, has largely helped organizations develop high-performance work teams and implement more effective talent management (Sivathanu & Pillai, 2018). For example, recruitment and talent acquisition processes are becoming more automated through AI technologies, enhancing efficiency and reducing human error throughout the recruitment lifecycle, including employer branding, candidate attraction, evaluation, selection, and onboarding (Pillai & Sivathanu, 2020). Employee performance and talent management are also being supported by AI technologies to reduce bias and enhance the accuracy of performance-related appraisals (Pillai & Srivastava, 2024). In addition to automation, Smart HRM 4.0 enables businesses to use HR analytics for strategic decision-making. HR analytics supports data visualization, dynamic reporting, workforce forecasting, and evidence-based HR planning (Bahuguna, Srivastava, & Tiwari, 2024). With these capabilities, companies can benchmark HR functions, strengthen HR capabilities, and enhance overall HR performance (da Silva et al., 2022; Singh, Agrawal, & Modgil, 2022). Consequently, Smart HRM 4.0 is increasingly acknowledged as a strategic mechanism that helps organizations remain competitive and responsive in a rapidly changing business milieu (Pillai & Sivathanu, 2020; Sivathanu & Pillai, 2018).

Despite the increased relevance of Smart HRM 4.0, the use of innovative HR practices remains uneven across organizations. Evidently, many organizations still rely on traditional HR procedures, such as job portals, paper-based evaluations, and conventional interview techniques, instead of utilizing advanced technology-powered HR practices (Pillai & Srivastava, 2024). Other HR managers feel that they lack the competence to utilize advanced technologies

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in managing HR (Pillai & Srivastava, 2024). This shows that the adoption and use of Smart HRM 4.0 go beyond technological availability and infrastructure, as successful adoption also requires employees' readiness and capability.

2.2. Employee Dynamic Capability as Microfoundation of Dynamic Capability Theory

First introduced in strategic management, Dynamic Capability Theory (DCT) is a model that explains how companies can survive in rapidly changing environments by continuously integrating, developing, and reconfiguring internal resources and capabilities (Liu et al., 2026; Teece, 2007; Yoshikuni et al., 2024). These dynamic capabilities refer to organizations' ability to identify and exploit new opportunities by leveraging and reorganizing internal resources and capabilities (Al Wali, Muthuveloo, Teoh, & Al Wali, 2023; Ramdhan et al., 2026; Teece, 2007). They enable companies to remain innovative and competitive as technology and market dynamics evolve (Bornay-Barrachina, López-Cabrales, & Salas-Vallina, 2025). Nonetheless, research on dynamic capabilities has focused mostly on the macro level, even though individuals also exhibit adaptive capabilities that enable them to adapt, learn, and innovate in response to technological and environmental changes (Ellström, Holtström, Berg, & Josefsson, 2022; Helfat & Martin, 2015; Leso, Cortimiglia, Ghezzi, & Minatogawa, 2024).

While employees are regarded as an organization's primary resources, dynamic capabilities are hardly discussed from their perspective (Bieńkowska & Tworek, 2020; Subramaniam, Dorasamy, & Malarvizhi, 2025). Bieńkowska and Tworek (2020) pointed out that, to navigate transformation in the workplace, it is crucial for employees to have flexibility, adaptability, and tolerance for the ambiguities caused by these changes. This is in line with the microfoundational perspective, which suggests that organizational dynamic capabilities are ultimately ingrained in individual-level behaviors, interactions, and competences (Apascaritei & Elvira, 2022; Salvato & Vassolo, 2018). To simplify, organizational capabilities do not emerge on their own but are constructed by the capabilities and actions of employees, which together contribute to organizational adaptation and transformation.

Based on this microfoundational perspective, employee dynamic capability has emerged as an employee-level generalization of Dynamic Capability Theory that describes employees' capacity to integrate, innovate, and reorganize their skills to fit changing workplace environments (Bieńkowska, Koszela, & Tworek, 2021; Bieńkowska & Tworek, 2020). At the individual level, dynamic capabilities are broadly characterized by three basic elements: sensing, seizing, and reconfiguring (Teece, 2007). Such abilities clarify how people recognize environmental changes, respond effectively to new threats and opportunities, continuously update their knowledge and abilities, and integrate innovations to fulfill future workplace demands (He et al., 2026; Subramaniam et al., 2025). These competencies are particularly useful in digitally transforming organizations, as employees must not only adjust to changing work requirements but also learn to use new technologies, such as Smart HRM.

It is against this background that this study proposes that employee agility may be considered a behavioral expression of employee dynamic capability, since they both focus on the adaptability, proactivity, and resilience of employees in their responses to dynamic organizational and technological environments. Thus, the microfoundational perspective of DCT highlights the contribution of employee-level capabilities to facilitating changes in workforce management. In this view, employee dynamic capability provides the conceptual framework for analyzing the correlation between employee agility and Smart HRM 4.0 adoption.

2.3. Employee Agility and Smart HRM Adoption

Numerous studies have revealed that agility is a management concept that emerged as an appropriate response, especially to complex and dynamic working environments (Menon & Suresh, 2022). Employee agility, which is synonymously referred to as workforce agility (Lim, Halim, & Thurasamy, 2022) is described as the personal capability to perceive environmental changes and react promptly by gathering resources, processes, and knowledge (Alavi, 2016). The academic literature on the topic consistently characterizes employee agility in three behavioral areas, namely, proactivity, adaptability, and resilience (Alavi, 2016; Zhu, Sun, Jeyaraj, & Hao, 2021). Proactivity

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indicates that employees take various initiatives to address problems associated with change and promote changes in their work activities (Abbas, 2025; Zhu et al., 2021). Adaptability is associated with the speed at which workers adapt to changes in the environment, whereas resilience is a positive attitude toward adapting to unforeseen and new circumstances (Talwar, Luqman, Kaur, Srivastava, & Mishra, 2023).

Since Smart HRM requires workers to change their manual and time-consuming duties to data-driven and technology-enabled work practices, agile employees are better suited to handling this shift in responsibilities. Also, proactive workers tend to seek new digital solutions and strategies for addressing complex business situations, thus making the actual utilization and implementation of Smart HRM tools in the organization easier. Concurring with Zhang, Xu, and Ma (2024), these adaptive behaviors demonstrated through the implementation of digital technology have been identified as affecting employees' post-adoption behavior regarding the use of technology.

Even with the growing recognition of employee agility as an essential capability in digital transformation efforts, research examining workforce and employee agility within digital transformation remains inadequate and fragmented (Muduli & Choudhury, 2025). Existing research has mainly concentrated on understanding the antecedents of employee agility, including digital literacy (Chong & Zainal, 2024), transformational leadership (Chong & Zainal, 2024), performance coaching (Srigouri & Muduli, 2024), task autonomy and task interdependence (Lai, Pitafi, Hasany, & Islam, 2021), and workforce spirituality (Srivastava & Gupta, 2022). Additionally, while existing research has focused more on organizational practices that foster workforce agility, only a few studies have focused on employees' personal factors (Janani & Vijayalakshmi, 2023). Similarly, although the influences of workforce agility have been explored in performance aspects such as task performance, citizenship behavior, job satisfaction (Petermann & Zacher, 2022), employee creativity (Rasheed, Pitafi, Mishra, & Chotia, 2023), and well-being (Srivastava & Gupta, 2022), relatively little attention has been given to examining the implications of employee agility for technology adoption. This suggests that the role of employee agility in enabling technology adoption, particularly Smart HRM 4.0 adoption, is insufficiently understood. Consequently, further investigation is warranted to determine whether employee agility contributes to employees' adoption of Smart HRM 4.0, especially within the Malaysian manufacturing sector.

Although research that specifically examines the relationship between employee agility and Smart HRM 4.0 implementation is limited, previous research offers analytical evidence of the importance of agility in technology-based change environments. For example, Muduli and Choudhury (2025) proposed that agile behavior can facilitate digital technology adoption by promoting learning, risk-taking, innovativeness, and flexibility. Similarly, Abrishamkar, Abubakar, and Mitra (2021) found that greater agility has an impact on successful innovation implementation, suggesting that agile workers can be more helpful in supporting transformation efforts. Additional reinforcement may also be found in literature exploring the connection between workforce agility and employees' innovative behavior. In research on internal marketing orientation, Sackey et al. (2025) characterized workforce agility as having a positive influence on employees' innovative behavior. This behavior involves the intentional invention, introduction, and use of new ideas, technologies, and practices by employees to improve organizational performance (Janssen, 2000). These behaviors include discovering new technologies, recommending alternative methods for achieving work goals, implementing improved work processes, and acquiring resources to support new initiatives (Yuan & Woodman, 2010).

These results imply that agile workers are more likely to embrace change and actively participate in innovation-driven activities in the workplace. Within the framework of Smart HRM 4.0, this behavioral tendency is particularly applicable because implementing new HR systems may require employees to experiment with new technologies, adapt to new HR processes, and engage in organizational digital transformation activities. Based on DCT, employee agility is a dynamic capability that allows workers to sense changes in technology and take advantage of digital transformation opportunities (Ajgaonkar, Neelam, & Wiemann, 2022; Deepa, Sekar, Malik, Kumar, & Attri, 2024),

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especially during Smart HRM 4.0 adoption and utilization. Thus, based on this evidence, the present study hypothesizes that:

H_1: Employee agility is associated with Smart HRM 4.0 adoption.

2.4. Social Cognitive Theory

Complementing DCT, Social Cognitive Theory (SCT) by Bandura (1986) offers a significant perspective for explaining employees' cognitive beliefs, attitudes, and behavioral responses toward technology adoption and use (Kimiagari & Baei, 2024; Osakwe, Hudik, Říha, Stros, & Ramayah, 2022). This theory specifically highlights self-efficacy as a key construct representing people's confidence that they can successfully perform certain tasks (Bandura, 2001). The antecedent literature on technology-related areas, such as computer use, e-learning, and interaction on digital platforms, continues to show that self-efficacy is a robust predictor of behavioral intention and actual technology use (Al-Dokhny, Drwish, Alyoussef, & Al-Abdullatif, 2021). SCT has thus received substantial empirical support in technology-related research (Demirel, 2022; Wu, Khan, Chien, & Wen, 2022). Self-efficacy has also been recognized as a significant variable influencing employees' willingness to use innovative digital tools and systems within information systems and HRM frameworks (Kesharwani, 2020).

Since self-efficacy is affected by changes in task demands, personal involvement, and the presence of resources needed to carry out tasks (Gist & Mitchell, 1992), it may be described in different ways depending on its specificity. As a general trait-oriented concept, general self-efficacy depicts a general and enduring belief in a person's capacity to cope successfully with different environments (Chen, Gully, & Eden, 2001). Comparatively, domain-specific self-efficacy refers to individuals' beliefs in their ability to perform certain duties or acquire specific competencies in a given situation (Abele & Spurk, 2009; Broos & Roe, 2006). Because domain-specific efficacy more closely resembles behavioral performance under certain conditions, it is considered more applicable to explaining technology adoption processes, particularly when people must learn and engage in specialized tasks associated with technology use (Hatlevik, Throndsen, Loi, & Gudmundsdottir, 2018).

2.5. Technology Self-Efficacy and Smart HRM 4.0 Adoption

Although self-efficacy has been acknowledged as an important factor in technology adoption, empirical findings remain inconsistent across technological contexts. Tripathi, Upadhyay, and Das (2022) pointed out that self-efficacy did not significantly influence technology adoption. In a generative AI adoption study, Shata and Hartley (2025) found that self-efficacy significantly improved the perceived ease of use of technology but did not directly influence attitudes or behavioral intentions toward its adoption. These findings suggest that general self-efficacy alone may not sufficiently explain technology adoption behavior, as contextual factors and the specific technological domain may shape its influence. Following the proposition of Bandura (2018) and Hatlevik et al. (2018) that self-efficacy should be examined in relation to specific tasks and domains, the present study therefore focuses on technology self-efficacy as a domain-specific form of self-efficacy reflecting employees' confidence in utilizing digital technologies within digitally transforming workplaces. Accordingly, further examination is required to determine whether technology self-efficacy explains Smart HRM 4.0 adoption in the Malaysian manufacturing context.

Within these circumstances, technology self-efficacy has increasingly become relevant as employees continuously have to work in an ever-changing environment due to advancements in digital technologies. This development implies that technologies considered advanced today can become obsolete in the future (Hanelt, Bohnsack, Marz, & Antunes Marante, 2021). In such a dynamic environment, having technical knowledge alone may not be adequate to support successful technology deployment. Rather, employees are increasingly required to exhibit continuous learning capacity, flexibility, and confidence in their interactions with new technologies (Dabić, Maley, Švarc, & Poček, 2023). In this respect, organizations are called upon to adopt a holistic perspective when evaluating employee

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skills by taking into account not only technical skills but also psychological factors such as employees' motivation and confidence to successfully adopt digital technologies (Palmer, Niemand, Stöckmann, Kraus, & Kailer, 2019).

In the framework of this research, technology self-efficacy refers to employees' belief in their abilities to use digital resources and systems to accomplish new, complex, or changing technology-related tasks (Al-Hattami, 2025; Falebita & Kok, 2025; Pan, 2020). With organizations increasingly adopting sophisticated digital technologies in HR operations, employees are expected to engage constantly with new innovations and upgrade their knowledge and skills for new digital work environments.

Past research has stressed the role of technology self-efficacy in positive experiences of using technology and attitudes towards digital systems. For example, Winarno, Mas'ud, and Palupi (2021) highlighted that technology self-efficacy increased system usage practices by facilitating the completion of work tasks to a greater extent. Likewise, Yeşilyurt, Ulaş, and Akan (2016) described technology self-efficacy as having a positive effect on users' attitudes towards the application of computer-supported services. Recent empirical studies have pointed out that professionals with greater technological self-efficacy are more likely to experiment with up-to-date technologies, automate routine tasks, use analytics tools, and employ digital platforms in financial decision-making processes (Al-Hattami, 2023; Odonkor, Kaggwa, Uwaoma, Hassan, & Farayola, 2024).

Although some of these discoveries were studied in the context of accounting-related environments, they can be applied to Smart HRM 4.0 adoption because both situations involve employees working with digitally empowered systems and technology-based work processes. This suggests that employees who are more confident in using technology are likely to have more positive attitudes towards innovative HR technologies and contribute to digital transformation in organizations. Therefore, this research hypothesizes that:

H_2: There is a significant association between technology self-efficacy and Smart HRM 4.0 adoption.

3. METHODOLOGY

3.1. Research Design

This study employed a quantitative cross-sectional survey design to test the association between technology self-efficacy, employee agility, and the adoption of Smart HRM 4.0 in the Malaysian manufacturing sector. The quantitative method was suitable because the research involved quantifying structured responses from similar respondents and analyzing statistical relationships among pre-set constructs. The cross-sectional design involved capturing responses at one time. Thus, the results represent correlations rather than causal relationships.

3.2. Population and Sampling

Focusing on employees working in manufacturing firms across various subsectors, the sample for this study was collected using purposive sampling. As purposive sampling depends on the researcher's judgment when selecting respondents who fit the study context, criteria that closely align with the objectives of the study should be stipulated (Andrade, 2021). As such, respondents were targeted among employees in Malaysian manufacturing companies who were either in HR jobs or had HR-related duties. They must also have had first-hand experience with technology-based HR practices.

These criteria were used to ensure that the respondents were relevant in terms of their exposure to HR practices, digital HR systems, and Smart HRM 4.0 features. The questionnaire also contained screening questions pertaining to involvement in HR roles, HR-related tasks, the size of the HR department, the use of digital HR systems, and the availability of smart features, including the use of AI, automation, or data analytics in HR functions. Table 1 shows the criteria applied in selecting the respondents.

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Table 1. Inclusion and exclusion criteria for selecting respondents.

Category	Criteria
Inclusion criteria	1. Employed in a small, medium or large manufacturing firm.
	2. Job responsibilities involved HR-related tasks or functions.
	3. Exposed to at least one innovative HR process that incorporates smart features such as AI-assisted screening, recruitment analytics, automated payroll, etc.
	4. Minimum of six months of employment to ensure satisfactory knowledge about HR processes and system routines.
Exclusion criteria	1. Employed in other establishments than a manufacturing firm.
	2. No involvement in HR-related tasks or functions
	3. No exposure to smart HR systems or practices.
	4. Employed for less than six months, limiting understanding of HR processes and system routines.

3.3. Sample Size

The sample size of a pilot study must be determined based on the purpose of the pilot study and the type of analysis conducted at the preliminary stage (Memon, Ting, Ramayah, Chuah, & Cheah, 2017). Pilot studies are not conducted to test hypotheses or produce generalizable outcomes; instead, they are conducted to assess the practicability of the research design, recognize potential issues, and provide initial empirical evidence before undertaking the full-scale study (van Teijlingen & Hundley, 2002).

Given that the present pilot study involved calculating the internal consistency of the measurement scales using coefficient alpha and identifying preliminary associations among the study variables, a sample of 30 respondents was considered appropriate (Memon et al., 2017). Similarly, Johanson and Brooks (2010) also highlighted that 30 respondents can provide sufficient grounds for estimating initial reliability. Based on this, the total of 30 responses gathered in this study is sufficient to achieve the purpose and objectives of this pilot study, which include preliminary reliability testing and correlation analysis.

3.4. Measurement of Construct

A structured, self-administered online questionnaire was used to collect the data. The questionnaire consisted of two sections. The initial part gathered demographic, screening, and organizational data, such as gender, age, education, job role, experience in HRM, organization size, HR department size, the use of digital HR software, and the availability of Smart HRM 4.0 features. The second part measured the main constructs: employee agility, technology self-efficacy, and Smart HRM 4.0 adoption. Each construct item was measured using a seven-point Likert scale (1 = strongly disagree, 7 = strongly agree).

There were 17 items based on Pitafi and Ren (2021) to measure employee agility. The construct consisted of three dimensions: proactivity, adaptability, and resilience. Five-item measures of proactivity, five-item measures of adaptability, and seven-item measures of resilience were used to measure these traits. These dimensions reflected employees' capacity to take initiative, adapt to changing work demands, and perform well in challenging environments. Technology self-efficacy and Smart HRM 4.0 adoption were assessed using four items based on the Al-Hattami (2025) adaptation. Technology self-efficacy items evaluated respondents' confidence in learning, using, and implementing advanced HRM systems or software in their work-related activities.

Regarding Smart HRM 4.0 adoption, the items addressed employees' actual use of innovative 4.0 technologies, specifically cloud computing, data analytics, artificial intelligence, and connected digital systems, to support HRM functions. In this research, Smart HRM 4.0 adoption was conceptualized as employees' actual use of these technologies. This is in consistent with Oeij, Hulsegge, and Preenen (2022) interpretation, that employee innovation adoption includes the preparation to accept an innovation, which involves the actual use of it in daily work more than just intention to use.

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3.5. Data Collection Procedure

A structured questionnaire was prepared and sent to the respondents of interest with a formal cover letter outlining the purpose and objectives of the study. After receiving ethical approval from Universiti Kebangsaan Malaysia (reference number UKM PPI/111/8), the data collection procedure began by inviting participation from selected manufacturing firms. The organizations were primarily identified from the 54th Federation of Malaysian Manufacturers (FMM) Directory, which served as the sampling frame for identifying qualified manufacturing firms. The questionnaire was distributed in Selangor because it is the main industrial centre in Malaysia (Malaysian Investment Development Authority, 2026a). The data collection process lasted approximately four months, from July 2025 through November 2025.

The Human Resource (HR) departments of the selected firms were first contacted via email. These emails contained a concise description of the research purposes and ethical aspects, as well as a Google Form link to the online questionnaire. Follow-up calls were also made to provide additional clarification about the study when necessary. Upon providing consent to participate, the HR departments then assisted in distributing questionnaires to qualified HR personnel in their firms. To improve participation and facilitate communication with potential respondents within the selected firms, professional networks such as LinkedIn were also utilized as recruitment channels. Of the 50 questionnaires distributed, 30 usable responses were obtained, representing a 60% response rate. Even though the study attained a response rate of 60%, the possibility of non-response bias is acknowledged. Employees who did not participate may have had different attributes or perceptions from those who responded, which may have influenced the results. However, since this pilot study mainly intended to evaluate the measurement instrument and provide preliminary evidence of the relationships among the study variables, the findings should be interpreted as exploratory rather than generalizable to the broader population.

Participation in this study was completely voluntary. The respondents were informed that any information gathered would be treated as confidential and utilized only for academic purposes. The questionnaire was self-administered, allowing respondents to complete the survey at their convenience. Informed consent was obtained electronically from all participants prior to data collection. Organizational permission was obtained through email correspondence, while individual participants provided informed consent by selecting the 'Agree to Participate' checkbox in the online questionnaire administered through Google Forms before proceeding with the survey.

3.6. Common Method Bias (CMB)

Common method bias (CMB) has become a crucial methodological concern in quantitative studies because it may compromise research rigor (Memon et al., 2023). CMB may occur when all inputs are obtained from the same respondents through a single measurement method (Chatterjee, Rana, Dwivedi, & Baabdullah, 2021; Jordan & Troth, 2020). As this study utilized a cross-sectional survey design with self-reported data collected through a single online survey, several procedural controls were undertaken to lessen the likelihood of CMB.

Procedural controls signify measures or remedies aimed at minimizing common method bias through a carefully designed questionnaire. Consistent with current methodological recommendations, this study prioritized procedural remedies, as preventing CMB during questionnaire design and data collection is deemed more effective than relying exclusively on post-data-collection statistical assessments (Kock, Berbekova, & Assaf, 2021; Memon et al., 2023). In this study, a cover letter was provided to ensure that respondents were well informed about the purpose of the study (Su, Baird, & Tung, 2022). They were then assured that their participation was voluntary and that all responses would remain anonymous and confidential (Chatterjee et al., 2021). The questionnaire was designed with clear and concise instructions indicating that there were no right or wrong answers (Kock et al., 2021; Memon et al., 2023) to encourage honest and unbiased responses. Additionally, brief descriptions and relevant examples of each construct were provided to improve respondents' comprehension and reduce the possibility of misinterpretation. Established measurement items adapted from previous studies were also utilized to improve content validity and measurement consistency.

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Overall, these procedural remedies were applied to reduce evaluation apprehension, social desirability, and method-related bias.

Statistical remedies, on the other hand, are complementary techniques implemented after data collection to assess the potential presence of CMB. Although Harman's single-factor test was dominant among statistical assessment techniques (Kock et al., 2021), recent evidence suggests that Harman's single-factor test may be influenced by sample size, the number of factors, the number of indicators, and other research design characteristics; thus, it should not be interpreted as a standalone assessment of CMB (Howard, Boudreaux, & Oglesby, 2024). Considering the pilot nature of this study and its relatively small sample size, greater emphasis was therefore placed on applying appropriate procedural controls. Nevertheless, in the subsequent full-scale study, these procedural measures will be supplemented with appropriate statistical controls, such as the marker-variable method, to allow for a more comprehensive assessment of the potential presence of CMB.

4. DATA SCREENING AND ANALYSIS

Prior to analysis, the responses were first screened for completeness. In addition, only those that met the study's inclusion criteria were retained. The statistical analysis was conducted using IBM SPSS Statistics version 31.0.2.0. The demographic and organizational profiles of the respondents were summarized using descriptive statistics. The internal consistency of the measurement scales was determined using Cronbach's alpha to assess reliability. In preliminary research, alpha values of 0.70 or higher are typically considered acceptable, implying that the items in each construct are reliable enough to measure the same underlying concept (Hair et al., 2021).

Since the sample size used was preliminary, more sophisticated methods of measurement validation, such as confirmatory factor analysis, composite reliability, and average variance extracted, were not implemented at this point and should be utilized in later studies with larger samples. The direction and strength of the relationships between technology self-efficacy and employee agility and Smart HRM 4.0 adoption were analyzed using Pearson correlation analysis. This form of analysis was suitable because the purpose of the study was to evaluate preliminary bivariate relationships between the key constructs.

5. RESULTS AND DISCUSSION

This section offers preliminary evidence of the associations among employee agility, technology self-efficacy, and Smart HRM 4.0 adoption. In line with the objectives of a pilot study, the analysis is restricted to descriptive statistics, reliability analysis, and Pearson correlation analysis to assess the measurement instrument and examine the initial associations among the study variables. Regression analysis is not conducted at this stage, as hypothesis testing will be carried out in the full-scale study.

5.1. Respondents Profile

The demographic profile of the respondents involved in this study is shown in Table 2. The sample comprised 30 respondents, of whom 56.7% were female and 43.3% were male. With respect to age, the majority of respondents were aged 30–39 years (43.3%), followed by those aged 40–49 years (30.0%). The remaining 16.7% of respondents were aged between 20 and 29 years, while 10.0% were aged 50–59 years. Concerning education, most respondents held bachelor's degrees (66.7%), reflecting that the majority had received formal tertiary education in the relevant field. Moreover, 20.0% of respondents had already received a master's degree. Only one in ten had diploma- or certificate-level education, while an even smaller percentage had STPM or pre-university education (3.3%).

In terms of professional experience in the field of HRM, most respondents were formally engaged in HR jobs (83.3%). The remaining 16.7% indicated that they were not employed in HR jobs but were responsible for HR-related activities in their organizations. Regarding their current job positions, 30.0% of the respondents were HR executives or HR managers, followed by senior HR officers at 26.6%. Administrative staff accounted for the lowest proportion,

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at only 13.4%. Finally, the respondents also indicated a significant level of experience in the HR field. Half of the respondents (46.7%) had more than ten years of work experience, while the remainder had between four and six years of experience (23.3%). This shows that the sample largely comprised experienced HR professionals who were qualified to provide informed insights into Smart HRM 4.0.

Table 2. Respondents' demographic profile.

Variables	Frequency	Percentage
Gender		
Male	13	43.3
Female	17	56.7
Age		
20 – 29 years	5	16.7
30 – 39 years	13	43.3
40 – 49 years	9	30.0
50 – 59 years	3	10.0
Education Level		
Pre-University	1	3.3
Diploma / Certificate	3	10.0
Bachelor's Degree	20	66.7
Master's Degree	6	20.0
HR Role Involvement		
HR position	26	83.3
Non-HR position with HR responsibilities	4	16.7
Current HR Position		
HR Executive	9	30.0
Senior HR Officer	8	26.6
HR Manager	9	30.0
Administrative staff	4	13.4
HRM Work Experience		
1 – 3 years	3	10.0
4 – 6 years	7	23.3
7 – 9 years	6	20.0
More than 10 years	14	46.7

5.2. Characteristics of Participating Firms

Table 3 shows the characteristics of the participating firms represented by the respondents. The organizations include various manufacturing subsectors. The chemical and chemical products sector had the greatest representation (20%), followed by electrical and electronics (16.7%) and transportation technology (16.7%). Food technology (13.3%), agriculture (10%), and machinery and equipment (10%) were also reported, while smaller proportions of the sample were represented by building technology (6.7%), medical technology (3.3%), and military equipment manufacturing (3.3%). This distribution suggests that the respondents span a wide range of manufacturing industries.

Regarding the size of the HR department, most of the manufacturing firms involved indicated that they had either two to five HR employees (46.7%) or more than five HR employees (46.7%), meaning that most of the manufacturing firms maintained dedicated HR personnel. In terms of the presence of Smart HR features in HRM systems, 93.3% of respondents indicated that their organizations utilized HR software with smart functionalities, such as artificial intelligence, automation, or data analytics. A very small proportion of respondents indicated that they were uncertain whether these smart features were available (6.7%), suggesting that Smart HRM systems were predominant in the firms involved.

Additional discussion of HR functions utilizing Smart HR features shows that payroll, compensation, and benefits management were fully digitalized in all the participating organizations. Other systems that often incorporate smart capabilities are time and attendance management (86.7%), performance management (70%), HR planning (66.7%), and employee relations systems (60%). In contrast, the application of smart technologies in the occupational safety

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and health (OSH) function was rather limited (16.7%). These results show that most of the manufacturing companies in the sample have adopted Smart HR technologies in some fundamental HR functions, namely administrative and performance management practices. This provides a suitable organizational setting for exploring the role of employee agility and technology self-efficacy in facilitating the adoption and use of Smart HRM 4.0.

Table 3. Firm characteristics.

Variables	Frequency	Percentage
Manufacturing subsector		
Agriculture	3	10.0
Building Technology	2	6.7
Chemical and Chemical Products	6	20.0
Electrical and Electronics	5	16.7
Food Technology	4	13.3
Machinery & Equipment	3	10.0
Medical Technology	1	3.3
Military equipment	1	3.3
Transportation Technology	5	16.7
HR Department Size		
< 2 employees	2	6.7
2 – 5 employees	14	46.7
> 5 employees	14	46.7
Presence of Smart HR Features in HR Systems		
Yes	28	93.3
Not Sure	2	6.7
HR Functions Using Smart HR Features		
Time & Attendance Management	26	86.7
Performance Management	21	70.0
HR Planning & Workforce Analytics	20	66.7
Employee Relations	18	60.0
Health & Safety (OSH)	5	16.7
Payroll, Compensation & Benefit	30	100.0

Note: Frequencies for 'HR Functions Using Smart HR Features' represent the number of participating organizations reporting the use of Smart HR features in each HR function (N = 30). Multiple responses were permitted. Therefore, percentages do not total 100%.

5.3. Reliability Assessment of Constructs

To determine the internal consistency of the measurement constructs used in this study, a reliability analysis was conducted. Cronbach's alpha coefficients were determined for each construct and dimension of employee agility. All constructs demonstrated high internal consistency, as shown in Table 4, with Cronbach's alpha values exceeding the recommended threshold of 0.70 (Hair et al., 2021).

The three dimensions of employee agility, namely, proactivity ($\alpha = 0.911$), adaptability ($\alpha = 0.922$), and resilience ($\alpha = 0.900$), all exhibited strong reliability. When combined as an overall construct, employee agility demonstrated excellent internal consistency, with a Cronbach's alpha value of 0.951. Similarly, the constructs of technology self-efficacy ($\alpha = 0.961$) and Smart HRM 4.0 adoption ($\alpha = 0.947$) also exhibited high reliability levels. These findings show that the measurement scales applied in this pilot study are valid and can be applied to full-scale data gathering in the research study.

Table 4. Construct reliability.

Construct	Dimension	Items	Cronbach's Alpha, α
Employee Agility (EA)	Proactivity	5	0.911
	Adaptability	5	0.922
	Resilience	7	0.900
	Overall Employee Agility	17	0.951
Technology Self-Efficacy (TSE)	–	4	0.961
Smart HRM 4.0 Adoption (SHRM)	–	4	0.947

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5.4. Level of Employee Agility and Technology Self-Efficacy and Their Relationships with Smart HRM 4.0 Adoption

Table 5 shows the descriptive statistics and correlations of the study variables to answer Research Questions 1 and 2. Technology self-efficacy reported the highest mean value of 5.92 (SD = 0.74), followed by employee agility, with a mean score of 5.82 (SD = 0.67). The results indicate that the respondents perceived themselves as having a high level of technology self-efficacy and believed that they were highly agile. Specifically, the high mean score for technology self-efficacy suggests that HR professionals are highly confident in their ability to work with smart HR tools and systems. Likewise, the relatively high mean score for employee agility demonstrates that HR professionals are capable of responding effectively to a shifting work environment, adjusting to changes in work demands, and remaining resilient when facing challenging circumstances. Regarding Smart HRM 4.0 adoption, the mean score was also comparatively high, at 5.64 (SD = 0.86), implying that the adoption of digitally enabled HR practices is already being realized in the participating organizations. This signifies that Smart HRM efforts have already transcended the awareness phase and proceeded to actual application in the workplace.

The Pearson correlation analysis further revealed that employee agility exhibited a positive correlation with the adoption of Smart HRM 4.0 ($r = 0.507$, $p < 0.01$). The coefficient of determination, $r^2 = 0.257$, demonstrates that 25.7% of the variance in Smart HRM 4.0 adoption is explained by employee agility, suggesting a meaningful association between these two constructs. This finding highlighted that employees with higher agility are more inclined to adopt Smart HRM 4.0. This result is consistent with the findings of Awwad, Anouze, and Elbanna (2026), which revealed a strong positive association between workforce agility and sustainable green product innovation. Even though their study investigated workforce agility within the green product innovation context, their findings imply that agile employees are more likely to support organizational innovation efforts. This applies to the present study, given that Smart HRM 4.0 characterizes innovation in HR practices.

The findings of this study also showed that technology self-efficacy had a stronger positive association with the adoption of Smart HRM 4.0 ($r = 0.661$, $p < 0.01$). With an r^2 value of 0.437, technology self-efficacy accounted for 43.7% of the variance in Smart HRM 4.0 adoption. This suggests that, although employee agility is a contributing factor, confidence in using digital technologies has a greater influence on the initial adoption of Smart HRM 4.0. The result aligns with recent research by Al-Hattami (2025), who pointed out that technology self-efficacy was positively associated with innovation in digital accounting tools. While the study examined a different technological context, a comparable finding was that agile employees with higher confidence in using digital technologies are more likely to embrace innovative work practices. Consistently, previous research by Al-Hattami (2023) and Venkatesh, Morris, Davis, and Davis (2003) also highlighted the importance of self-efficacy in influencing technology adoption and innovation-related behaviour.

The implications of these findings are that employees who believe in their ability to utilize digital technologies are more likely to discover and accept technology-based systems in the workplace. This means that employees may be able to adapt to change, but their readiness and capacity to interact with Smart HRM systems depend more on how competent they feel when utilizing such technologies. Therefore, H1 and H2 were both accepted.

Table 5. Mean, standard deviation (SD) and correlation.

Construct	Mean	SD	1	2	3
1. TSE	5.92	0.74	1		
2. EA	5.82	0.67	0.691**	1	
3. SHRM	5.64	0.86	0.661**	0.507**	1

Note: **Correlation is significant at the 0.01 level (2-tailed).

6. CONCLUSION

This study investigated the associations among employee agility, technology self-efficacy, and Smart HRM 4.0 adoption among HR professionals in the Malaysian manufacturing sector. The findings provide preliminary evidence

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that both employee agility and technology self-efficacy are positively associated with Smart HRM 4.0 adoption, with technology self-efficacy showing a stronger relationship. These findings imply that successful Smart HRM 4.0 adoption depends not only on the availability of digital HR technologies but also on employees' readiness and capability to embrace new ways of working.

From a theoretical perspective, the positive relationship between employee agility and Smart HRM 4.0 adoption provides preliminary empirical support for the individual-level extension of DCT, suggesting that employees' adaptive capabilities enable them to respond effectively to technological and environmental change (Helfat & Martin, 2015). In particular, employees' proactiveness allows them to sense emerging digital opportunities, adaptability enables them to seize these opportunities, and resilience permits them to reconfigure their behaviors in response to growing technological demands. Consistent with the sensing, seizing, and reconfiguring processes underpinning DCT (Teece, 2007), this pilot study extends the application of the microfoundational perspective of DCT to the context of Smart HRM 4.0 adoption by positioning employee agility as an important individual adaptive capability among HR professionals in the Malaysian manufacturing sector.

Likewise, the positive relationship between technology self-efficacy and Smart HRM 4.0 adoption also supports the utilization of SCT. Consistent with Bandura's proposition that self-efficacy beliefs are task- and domain-specific (Bandura, 2018), the results reveal that employees' self-assurance in performing technology-related tasks plays an important motivational role in facilitating Smart HRM 4.0 adoption. As such, this study extends the application of SCT by emphasizing the relevance of technology self-efficacy as a domain-specific form of self-efficacy in explaining employee-level Smart HRM 4.0 adoption among HR professionals in the Malaysian manufacturing sector. Together, these findings imply that successful Smart HRM 4.0 adoption is shaped by both employees' adaptive capabilities and their confidence in using digital technologies.

From a practical perspective, the findings indicate that organizations should complement investments in Smart HRM technologies with initiatives that strengthen employee agility and technology self-efficacy. HR practitioners should provide continuous digital skills development, practical hands-on training, mentoring, and opportunities for employees to gain experience using AI-enabled, cloud-based, and data-driven HR systems. At the same time, organizations should cultivate work environments that encourage proactive behaviour, adaptability, and resilience, helping employees respond effectively to the changing demands of digital HR transformation. At the policy level, the findings suggest that Malaysia's digital transformation efforts should place greater emphasis on reinforcing employee-level capabilities alongside technological investments. National programs such as the PACE initiative by the Human Resource Development Corporation (HRD Corp), particularly DIGITAL (Developing an Inclusive Generation for Innovation, Technology & Advanced Learning), provide a fitting platform for improving HR professionals' digital competencies, adaptability, and confidence in using innovative technologies. Expanding such initiatives to include Smart HRM-related competencies, including AI-enabled HR systems, cloud-based HR platforms, and HR analytics, among others, could better prepare HR professionals to support successful Smart HRM 4.0 adoption within the manufacturing sector.

7. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

Despite contributing the initial evidence regarding the connections among employee agility, technology self-efficacy, and the adoption of Smart HRM 4.0, a number of limitations must be acknowledged. Firstly, as this is a pilot study, the results are based on a small sample of HR professionals, which restricts the generalizability of the findings. Future research should validate these preliminary findings using a larger and more representative sample across different industries and organizational settings.

Secondly, the research employed a cross-sectional research design that represents the respondents' perceptions at a particular time. Future studies might utilize a longitudinal design to investigate how employee agility and

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technology self-efficacy influence Smart HRM 4.0 adoption in the long run, as employees' capabilities and technology adoption may change during the digital transformation process.

Thirdly, since the present study adopted a cross-sectional design and relied on self-reported data, it may be prone to common method bias. To further minimize this risk, future studies are encouraged to implement additional procedural and statistical remedies, including collecting data from multiple sources and separating the independent and dependent variables through temporal separation (different time points or time lags between measures) (Jordan & Troth, 2020), as well as post-hoc statistical assessments such as the marker variable technique (Miller & Simmering, 2023).

Finally, future studies should incorporate relevant demographic and organizational control variables to provide a comprehensive understanding of Smart HRM 4.0 adoption. In addition, a subsequent full-scale study could adopt multilevel modelling to examine the proposed relationships by considering both employee- and organization-level factors. Multicollinearity diagnostics, including the variance inflation factor (VIF), should also be conducted before model estimation to ensure robust findings.

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Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
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