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AI-enabled human resource practices and organizational agility: The mediating role of employee voice and the moderating effect of AI-readiness culture in ASEAN countries

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Abstract

Our study examines how AI-HR management practices, including fair algorithms, analytics maturity, legal ethics and employee participation, can boost the retention rate of workforces and the agility of businesses in Southeast Asian countries. It further studies workforce retention as an intermediary mechanism and AI-motivated culture as an environmental moderator on this relationship. Based on Resource-Based View, Socio-Technical Systems theory, and the Dynamic Capabilities approach, this study employs a cross-national quantitative research design. Data collected from organizations in Indonesia, Malaysia, Thailand and Singapore were analyzed using partial least squares structural equation modeling in SmartPLS software to test direct, mediating (indirect), and moderating effects. Our research discovers that algorithmic fairness and digital ethics can directly and significantly promote employee voice; also importantly, an employee's voice contributes not marginally but greatly to workforce retention, and indirectly promotes organizational agility as well. HR analytics maturity indirectly reinforces corporate agility by supporting decision-making that is informed and staff engagement. Moreover, the relationship between employee voice and organizational agility is positively moderated by AI-ready culture--an earlier conclusion which confirms the effectiveness of these new HRM practices. The paper progresses the AI-HRM literature by providing a unified model of several different countries which details that ethical, analytical and "distributed" AI practices serve to enhance the sustainability of workforce and enterprise-wide agility. This study provides new evidence to support theory on Southeast Asia, bringing valuable insights and guides to the establishment of sustainable, and future-oriented AI-HRM systems.

Keywords

artificial intelligence in HRM; algorithmic fairness; HR analytics maturity; digital ethics; employee voice; workforce retention; organizational agility; AI-readiness culture

INTRODUCTION

The proliferation of Artificial Intelligence (AI) within Human Resource Management (HRM) is reshaping organizational talent systems by enabling data-driven decision-making, predictive analytics, and automated HR processes. These technologies promise substantial gains in efficiency and strategic alignment (Rodgers et al., 2022). Yet, the rapid integration of AI has also intensified questions regarding algorithmic fairness, digital ethics, and the extent to which employees are granted voice and participation in AI-mediated decision environments. These concerns are particularly salient in Southeast

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Asia, where AI adoption is accelerating but institutional safeguards remain uneven across countries (Căvescu & Popescu, 2025; Du, 2024; Kayusi et al., 2025). Governments in the region have introduced a range of AI governance initiatives aimed at balancing innovation with responsible use. Singapore's Model AI Governance Framework emphasises fairness, transparency, and accountability in organizational AI applications, including HRM (Huriye, 2023). Malaysia's National AI Framework similarly highlights ethical implementation of analytics-driven talent systems (Busuioc et al., 2022; Cath, 2018) Indonesia's Making Indonesia 4.0 agenda encourages the deployment of AI in workforce development, though questions persist regarding algorithmic bias and opaque HR decision-making (Basnet, 2024). Thailand's "Thailand 4.0" strategy promotes AI-based recruitment and workforce analytics, yet vulnerability to privacy concerns and limited employee participation remains (Agu et al., 2024; Cheong, 2024; Chukwunweike et al., 2024; Faheem, 2024; Weiner et al., 2025).

Despite these institutional efforts, organizations continue to confront critical challenges in ensuring fairness and ethicality in AI-driven HRM. Algorithmic decision systems—often operating as complex and opaque "black-box" mechanisms—can produce biased or unexplained outcomes that undermine employee trust (Dastmalchian et al., 2020). In high power-distance work cultures, where upward feedback is commonly constrained, employees may have limited opportunities to question or influence AI-based HR decisions (Basnet, 2024; Dr Jolly Masih, 2023). A lack of employee voice is therefore not merely a procedural deficit but a substantive barrier to ethical and sustainable AI integration. (Khan et al., 2024; Madanchian & Taherdoost, 2025; Park et al., 2021).

Khan (2025) highlights the role of integrated organizational practices in enhancing business excellence. Beside this a growing body of research indicates that organizations capable of embedding fairness, transparency, and participatory practices into their AI-HRM systems enhance psychological contract fulfillment, strengthen workforce retention, and build the adaptive capabilities necessary for organizational agility (Harrington & Lee, 2014; Böhmer & Schinnenburg, 2023). The concept of an AI-readiness culture—reflecting organizational openness to digital transformation, responsible governance, and employee involvement—plays a crucial moderating role in shaping employees' perceptions of fairness and inclusion in AI-mediated environments. (Căvescu & Popescu, 2025; Fenwick et al., 2024; Jia & Hou, 2024; Madanchian & Taherdoost, 2025).

Although research on AI-enabled HRM is expanding, several key gaps remain. First, existing studies tend to isolate variables such as algorithmic fairness, digital ethics, and analytics maturity, offering limited insight into how these foundational elements jointly influence employee behavioral responses—specifically employee voice—within AI-mediated HR environments. Second, the mediating role of employee voice in linking AI-HRM practices to workforce retention and organizational agility is theoretically acknowledged but remains empirically underdeveloped. Third, while workforce retention has been widely studied in traditional HR contexts, its role within AI-intensive environments is not well understood. Fourth, the moderating influence of AI-readiness culture—an essential socio-technical construct—has not been systematically examined in relation to the employee voice–organizational agility nexus. Finally, comparative evidence across Southeast Asian contexts is scarce, despite the region's diversity in regulatory frameworks, cultural norms, and AI adoption trajectories. These gaps necessitate a comprehensive, multi-country investigation incorporating fairness, ethics, analytics capability, voice, retention, and agility within a single integrative model.

Against this backdrop, the present study examines how algorithmic fairness, digital ethics, and HR analytics maturity drive employee voice in AI-enabled HRM systems, and how employee voice subsequently shapes workforce retention and organizational agility. The study further explores the moderating role of AI-readiness culture and provides comparative insights across Indonesia, Malaysia, Singapore, and Thailand. This approach offers a comprehensive and theoretically integrated examination of AI-HRM within a rapidly transforming region.

Research objectives

RO1: To examine how algorithmic fairness, digital ethics, and HR analytics maturity shape employee voice in AI-enabled HRM systems

RO2: To analyse the effects of employee voice on workforce retention and organizational agility, including its mediating role between AI-HRM practices and organizational outcomes

RO3: To evaluate how AI-readiness culture moderates the influence of employee voice on organizational agility across Southeast Asian contexts

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

We base this study in Organizational Justice Theory which describes how people assess the fairness and ethicality of decision-making systems (Greenberg, 1987; Colquitt, 2001). In the context of AI-based HR, employees evaluate algorithmic social justice, digital ethics/security and data transparency via perceptions of justice which influence trust and behavior responses. Existing research has informed us that fair and explainable algorithmic procedures improve process justice and employees' tendency to speak-up or to offer suggestions in technological mediated environment (Leventhal, 1980; Kirkman & Shapiro, 2001). Therefore, Four, algorithmic justice proper, and responsible data processing and a developed HR analytics can be regarded as justice-based antecedents of employee voice and then retention outcomes in AI-empowered workplaces. To account for the process by which these behavioral mechanisms relate to strategy-making outcomes, we consider Dynamic Capabilities Theory, which emphasizes an organization's capacity to sense and seize resources in a fast-moving environment (Eisenhardt & Martin, 2000; Teece, Pisano & Shuen, 1997). Employee voice is a bottom-up source for sensing the early warning of challenges, and workforce continuity sustains organizational knowledge required for rapid reshapings. Existing studies were found to indicate that agility increases when the company incorporates personnel's decisions into its process of choice, especially among high-tech firms (Teece, 2007; Alsaif & Sabih Aksoy, 2023). Culture of AI-readiness serves as a complementary capability, which improves the extent to which organizations can utilize employee involvement in order to build organizational agility in AI-driven HR systems. (T et al., 2024).

Algorithmic fairness impact on Employee voice

Fairness in algorithms for AI has turn into a significant issue in HR decision making and relates to how far among other factors, the AI systems can be depended on to deliver judgements which are fair, transparent and explainable. Previous studies consistently indicate that fairness perceptions enhance voice behaviors, because employees express their opinions more safely when organizational practices are fair and predictable (Colquitt, 2001; Greenberg, 2011). Dealing specifically with non-AI environments, procedural and distributive justice have been shown to be positively related to employee voice as the former is associated with psychological safety that facilitates constructive upward communication (Grimmelikhuijsen, 2022; Yu & Li, 2022; Zerilli et al., 2018). This pattern was recently confirmed by specific AI studies, but their findings also focus on limitations. Kellogg, Valentine and Christin (2020) demonstrate that algorithmic transparency enhances trust and litigation with respect to automated decision-making. Similarly, Raghavan et al. (2020) shows that bias in hiring processes diminishes expectations of fairness, which restrict engagement and erect barriers to employees raising concerns. Conversely, some research indicates that even fair AI may be perceived as opaque or in questionable and this reduces individuals' will to speak up (Wang & Siau, 2019; Lee, M. K. (2018). This dichotomy highlights that simply being fair is not enough, unless it brings with it understandability and an openness to feedback. Taken together, the literature suggests that fairness always enhances voice, but it is enhanced to a greater extent when AI systems are transparent, accountable and perceived as being modifiable. In such environment, employees trust the AI-powered

HR system and feel that they can suggest or complain. Therefore, we propose:

H1: Algorithmic fairness is positively related to voice

Digital ethic impact on employees' voice

The field of digital ethics addresses the responsible creation and application of digital technology, especially in respect to privacy, transparency, accountability, and data governance. Some previous studies suggest that ethical treatment of employee data will support trust in the organization and lead to effectual communication (Căvescu & Popescu, 2025; Du, 2024; Owolabi et al., 2024; Pickering, 2021; Stahl et al., 2016). Information systems research also shows that employees perceive less risk and are more likely to voice concern or provide constructive feedback when they believe that their organizations are ethical stewards of data (Martin & Murphy, 2017). In the context of HR analytics, Newell and Marabelli (2015) maintain that ethical use of data is crucial for maintaining credibility and ensuring employees feel respected in technology-enabled evaluations. AI-specific research strengthens this argument. According to Boddington (2017), supportive ethical constructs like fairness, explainability and privacy protection build legitimacy while lessening fear of surveillance from which employees draw their involvement with digital systems. Contrary, we know from research that if AI is perceived to be unfair or opaque it results in silence and withholding of input (van den Broek, Sergeeva, & Huysman, 2019). Workers, who suspect their data could be used in exploitative or unfair ways, will be less likely to make a suggestion, dispute a decision or speech up. (Zuboff, 2019; Căvescu & Popescu, 2025; Du, 2024; Ismail & Ahmad, 2025; Le-Nguyen, 2024). Drawing from these perspectives, the findings suggest that digital ethics not only increases trust but also decreases psychological and privacy risks when speaking up in AI-powered HR contexts. Ethical digital governance is, thus, the base condition facilitating and supportive of employee voice. Therefore, we propose:

H2: Digital ethics is positively associated with employee voice

HR analytics maturity impact on employee voice

Human Resources analytics maturity can be defined as an organization's ability to systematically collect, analyze and use the data for workforce decision making (Marler & Boudreau, 2016). It is the established analytics systems that are in combination related with more procedural consistency, data-based decision-making and less managerial prejudgment, which enhance employees' perception of credibility and fairness. Previous studies indicate that when staff perceive HR analytics to be transparent and managed with expertise, they are more willing to trust the system and communicate openly (Huselid, 2018; Van den Heuvel & Bondarouk, 2017). This trust creates psychological safety, which is an important precursor to employee voice. Conversely, low-maturity analytics — an environment of inconsistent data practices and insights of poor quality — introduces uncertainty and can result in resistance or silence (Marler & Boudreau, 2017; Milliken et al., 2003). Levenson (2018) notes that immaturity can cause embarrassment on the part of workers as they challenge HR decisions thus dampening their disposition to contribute input. Likewise, research on algorithm-assisted HRM warns that analytics that do not work properly can be seen as surveillance rather than support and decrease voice behavior (Davenport et al., 2010; Mateescu & Nguyen, 2019). Integrating these two conflicting perspectives, it is concluded that: the more mature HR analytics is in an organization, the more positive perceptions of HR system competence, predictability and trustworthiness will be. These perceptions may increase their willingness to voice tensions and engage in decision making. Therefore, analytics maturity serves as a facilitation condition that amplifies employee voice in AI-augmented HR work contexts. Therefore, we propose:

H3: Maturity in HR analytics is positively related to employee voice

Employee voice impacts workforce retention

Employees sharing their thoughts, complaints or suggestions voluntarily — not under the threat of punishment as shown by contemporary research — is highly influential to fostering organizational commitment and retention. Existing research demonstrates that voice behaviors build inclusion, respect, and psychological safety and contribute to the commitment employees have to their organizations (Detert & Burris, 2007; Morrison, 2014). Employees will have higher satisfaction and stronger sense of belonging to the organization when they believe that their voice is listened and acted upon by management, which results in lowering intention to leave (Kim & Fernandez, 2017). Conversely, when employees' voices are repressed or ignored in an organization, they frequently encounter disengagement and increasing turnover. Dyne, Ang, & Botero 2003 contend that silence, particularly of the nature caused by anxiety or despair, leads to frustration and emotional burden which in turn may increase avoidance responses. Similarly, the work climate in which employees perceive themselves as not being listened to is related to increased levels of voluntary turnover, as staff look for working cultures where their opinions are taken into consideration (Gyensare et al., 2016; Moon et al., 2024; Ponnu & Chuah, 2010). Building on these observations, literature review shows that employee voice opportunity and their perception of voice legitimacy reinforce organizational commitment and attenuate the intention to quit. Voice would serve as a procedural retention enhancer through increased trust, psychological safety and perceived organizational support. Therefore, we propose:

H4: Employee voice will lead to higher levels of employee retention

Workforce retention relation with organizational agility

Organizational agility is dependent on a strong foundation of human capital capable of learning quickly, solving complex problems together, and making rapid decisions. Indeed, empirical evidence highlights that retaining senior staff members facilitates the retention of tacit knowledge, team cohesiveness and operational stability – all precursors for agile sensing and responding capabilities (Teece et al., 2016; Doz & Kosonen, 2010). On the other hand, high employees' turnover hinders social capital, impedes organizational learning and lowers adaptive capacity in adapting to environmental turbulence (Muduli, 2015). This viewpoint is even more clearly supported by recent studies. Moreover, higher retention of employees strongly promotes the firm's ability to quickly reconfigure its processes. The firms with a low level of stability of workforce have higher levels of strategic agility because of more accumulated experience as well as faster spread-out knowledge. Other scholars posit that moderate turnover could even stimulate new thinking and innovative agility. Although it becomes weakened in volatile environments where stable knowledge is more important. (Basnet, 2024; Buchan, 2010; Ludviga & Kalvina, 2023; Rafi et al., 2021; Tripathi, 2024) Taken together, the evidence strongly suggests that continued retention of employees develops the knowledge base, coordination capability and responsiveness required for organisational agility. Therefore, we propose:

H5: Retaining employees has a positive influence on organizational agility

Employee voice relation with organizational agility

Organizational agility refers to the ability to perceive change in the environment and react quickly by maintaining efficient forms of organizing, learning and adaptation networks. This is consistent with the literature that has documented employee voice as a major driver of agility given that it delivers organizations with immediate bottom-up access to knowledge about operational problems, customer needs and process waste (Doz & Kosonen 2010; Knoll et al., 2020; Teece Peteraf Leih 2016). Getting employees to be more vocal helps organizations create richer information flows and better learning routines, which allow them to respond rapidly in times of shock. Research has also demonstrated that agility gains are unlikely unless voice is integrated or acted upon (Bakhash et al., 2025; Mdhlalose, 2024; Sulistiawan et al., 2022). For example, Milliken et al. (2003) demonstrated that silence based on fear in organizations can prevent organizations from accessing vital information needed for adaptation and responsiveness. According to Carmeli, Schaubroeck and Tishler (2011), as voice is suppressed or not brought forth in organizations, it leads the reduction of knowledge-sharing which impedes agility capability. Overall, these findings suggest that voice promotes accelerated learning, better problem solving and the organization's ability to anticipate and react on change. Employee voice is thus a key precursor of agility, serving as an information and learning device in dynamic contexts. Therefore, we propose:

H6: Organizational agility is positively related to employee voice

AI readiness culture role as a moderation

Organizations with a robust AI-readiness culture —characterized by openness to digital innovation, supportive leadership, and willingness of employees to interact with AI tools— are more prepared to optimally use HR practices enabled by AI (Raisch & Krakowski, 2021). When employees perceive their organization as technologically advanced and supportive, they report greater trust in AI, willingness to give control over decisions to the technology, and comfort with its use. The role of organizational innovativeness on R& D work (Prikshat et al., 2023; Hmoud & Várallyai, 2020; Jöhnk et al., 2020). Such culture readiness minimizes anxiety about AI systems and increase employees' willingness to use or accept digital HR processes, which in turn reinforces favourable HR outcomes (Arora & Mittal, 2024; Polisetty et al., 2023).

In contrast, studies show that in low-readiness cultures, AI adoption tends to evoke resistance, threat and mistrust in algorithmic judgment leading to a restricted exploitation of the full potential of AI-enhanced HRM (Siradhana & Arora, 2024; Watts & Munir, 2025). In such workplaces, employees might regard AI systems as opaque or unfair and fail to realise the benefits of digital HR practices for retention and organizational agility. This difference suggests that AI-readiness culture serves as a boundary condition: at high readiness, employees react more positively to AI-HR systems and experience greater alignment with organizational goals. Building on these findings, AI-readiness culture is anticipated to enhance providing the impact of AI-augmented HR practices on organisational agility. Therefore, we propose:

H7: AI-readiness culture as a moderating factor plays role between employee's voice and organisational agility

Conceptual framework for this research

Given the proposed hypotheses and theory arguments, we have proposed conceptual framework for this study as follows. It shows the connections between main constructs and factors, such as algorithmic fairness, HR analytics maturity, digital ethics and workforce retention for AI decision making with employee's voice as a central mediator and organizational agility as the ultimate result. AI-readiness culture is also included as a moderator, affecting the strength between main constructs, especially antecedents with employee voice. The framework is based on the Organizational Justice Theory and Dynamic Capabilities theory, and it is customised to fit into the peculiar context of sociotechnical and regulatory landscapes in Southeast Asia.

METHODS

Research design

The current study follows a quantitative, cross sectional research design in order to understand the impact of AI-augmented HRM practices on both retention and organizational agility within organizations in Southeast Asia. Built upon OJT, DCT and STS lenses, the model combines both technical (algorithmic fairness, AI analytics maturity, digital ethics) and HR mechanisms (employee voice), alongside AI-readiness culture as a situational moderator. This theoretical synthesis enables analysis of how AI-empowered HR systems influence strategic workforce outcomes in emerging digital economies. The sample was

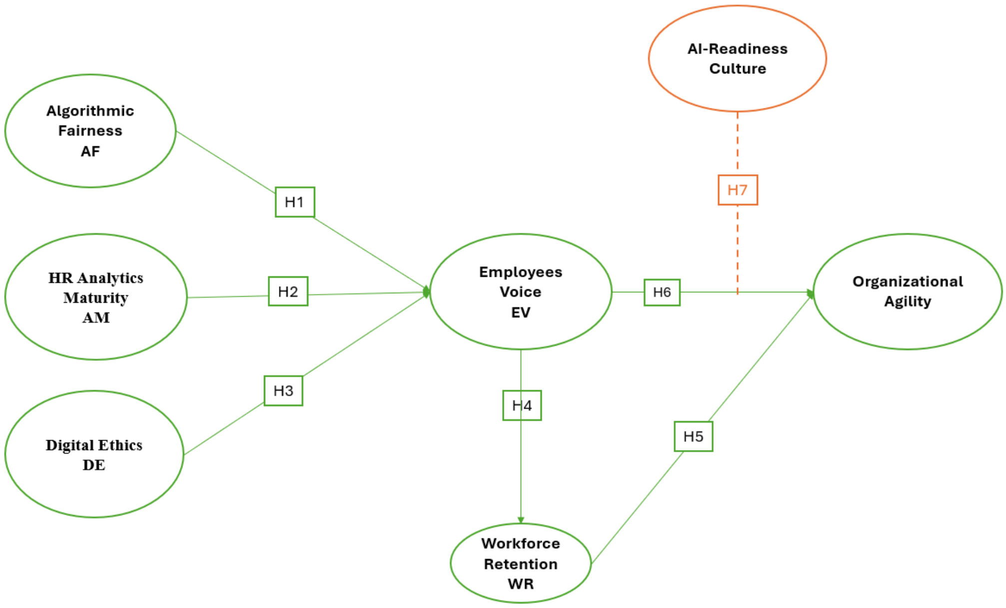

Figure 1.
Conceptual framework

drawn from HR professionals, middle-level and senior managers, as well as employees who involve with or are impacted by the AI-based HRM practices in Indonesia, Malaysia, Singapore and Thailand. These countries have been chosen due to their different levels of AI adoption, digital governance, and the readiness of organizations. Participants' exposure to AI-based HR moved up and down on continuous scale, therefore a purposive, non-probability sampling technique was used to have an adequate sample of participants with varying degrees of exposure. Five hundred on-line questionnaires were released within 10 weeks over professional HR networks, LinkedIn groups spread and institutional partners. A total of 246 useful responses were left after excluding the incomplete and poor-quality responses, which reached a usable response rate of 49.2%.

Construct measurement and development

All constructs were operationalized using multi-item measures adapted from the established literature. Algorithmic Fairness (AF) captures employees' perceptions of fairness, consistency, and bias reduction in AI-driven HR decisions, drawing on algorithmic fairness and organizational justice research (Colquitt, 2001; Cowgill, 2019; Raghavan et al., 2020; Lee, 2018). Analytics Maturity (AM) reflects organizations' HR analytics capabilities, including workforce planning,

Table 1.
Construct reliability and validity

Variable	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)	P Values
AF	0.874	0.878	0.905	0.614	0.348
AIRC	0.848	0.852	0.891	0.622	0.001
AM	0.900	0.907	0.923	0.667	0.000
DE	0.947	0.947	0.957	0.789	
EV	0.926	0.929	0.942	0.730	
OA	0.827	0.829	0.874	0.536	
WR	0.895	0.899	0.919	0.655	

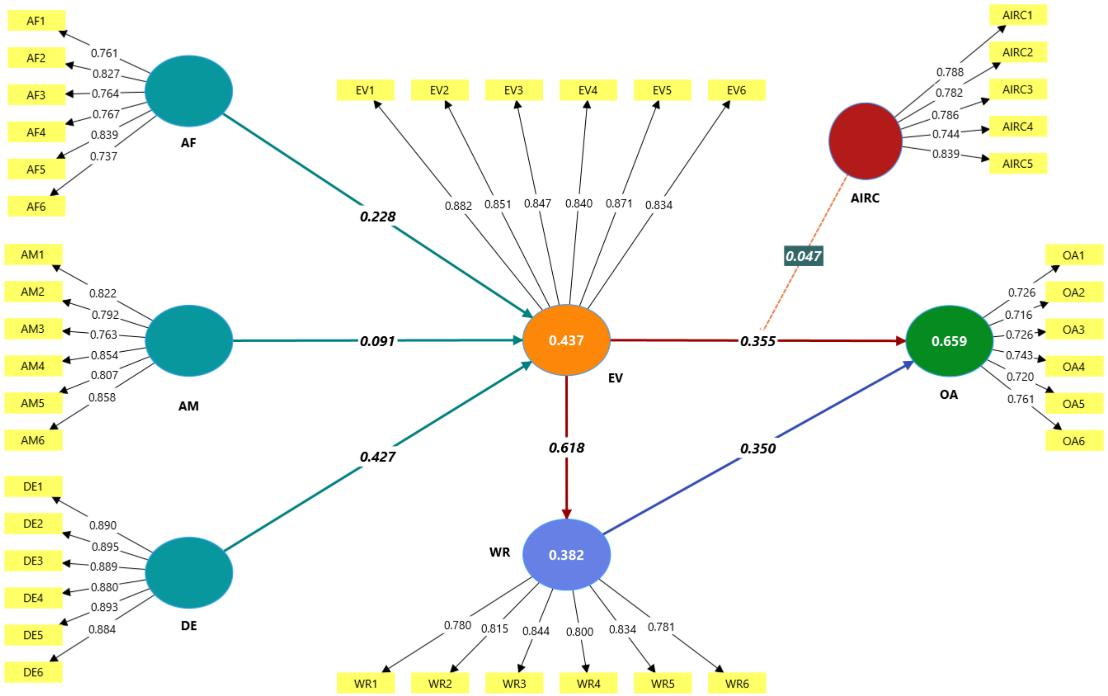

Figure 2.
Outer loading PLS

decision support, and analytics expertise, based on the HR analytics literature (Marler & Boudreau, 2016; Huselid, 2018; Levenson, 2017; Davenport et al., 2010). Digital Ethics (DE) represents employees' perceptions of ethical governance in AI-driven HR systems, including privacy, explainability, and accountability (Mittelstadt et al., 2016; Floridi et al., 2018; Jobin et al., 2019; Stahl et al., 2016). Employee Voice (EV) refers to behaviors through which employees express concerns about AI-enabled HR practices, adapted from the voice literature (Van Dyne & LePine, 1998; Detert & Burris, 2007; Morrison, 2014; Milliken et al., 2003). Workforce Retention (WR) measures employees' intention to remain with the organization (Allen et al., 2010; Hom et al., 2017; Kim & Fernandez, 2017). Organizational Agility (OA) captures the ability to adapt to change through flexible HR processes and decision-making (Doz & Kosonen, 2010; Sambamurthy et al., 2003; Teece et al., 2016; Warner & Wäger, 2019). AI-Readiness Culture (AIRC) represents an organizational mindset supporting AI adoption, including awareness, openness to change, and integration of AI (Westerman et al., 2014; Jöhnk et al., 2020; Raisch & Krakowski, 2021; Kane et al., 2017).

Table 2.
FLC result obtain from PLS

Variables	AF	AIRC	AM	DE	EV	OA	WR
AF	0.783						
AIRC	0.653	0.788					
AM	0.651	0.399	0.817				
DE	0.693	0.731	0.418	0.888			
EV	0.583	0.552	0.418	0.623	0.854		
OA	0.535	0.643	0.342	0.709	0.708	0.732	
WR	0.653	0.615	0.487	0.695	0.618	0.719	0.809

Table 3.
R^2 value by PLS analysis

Variables	R-square	R-square adjusted
EV	0.437	0.430
OA	0.659	0.653
WR	0.382	0.380

Data analysis and interpretations

Data were analyzed with SmartPLS 4.0 software that Is ideal PLS path modeling and complex models encompass mediation/moderation analysis. There were two major components to the analysis. After, measurement model testing was conducted in terms of internal reliability using Cronbach's Alpha and Composite Reliability, followed by tests of convergent validity with the AVAG extracted (AVE ≥ 0.50). Discriminant validity was verified based on the Fornell–Larcker criterion as well as the HTMT ratio, whereas multicollinearity of latent and indicator variables was tested with VIFs in order to guarantee indicator stability. Second, we tested the structural model to determine fit against all direct, indirect, and moderating pathways that were posited. T-statistics, confidence intervals and p values were estimated by using a bootstrapping method with 5,000 resamples. Further, effect sizes (f^2), predictive relevance (Q^2) and model fit indices like SRMR were considered to test the stability and explanatory power of the model. For cross-regional generalizability, multi-group analysis (MGA) was used to test whether the structural relationships in the model differed across China, India, South Korea and Vietnam along with sensitivity analyses to verify that the result held when applied on subsamples.

RESULTS AND DISCUSSION

The reliability and convergent validity of the measurement model were evaluated using Cronbach's alpha, composite reliability (ρA and ρC), and average variance extracted (AVE), as shown in Table 1 and Figure 2. The findings revealed that all constructs exhibited strong internal consistency reliability. Specifically, the values of Cronbach's alpha and rho_A for all constructs surpassed the recommended threshold of 0.70, affirming the stability and consistency of the measurement scales. Additionally, the composite reliability (ρC) values ranged from 0.874 to 0.957, exceeding the minimum acceptable level of 0.70, thereby providing further evidence of the robustness of the measurement model. Regarding convergent validity, the AVE values for all constructs were above the recommended threshold of 0.50, indicating that each construct accounted for more than 50% of the variance in its respective indicators. Overall, these results offer strong empirical support for the adequacy of the measurement model, confirming that the constructs are reliable and valid. Consequently, the measurement properties were satisfactory, permitting the study to advance to the structural model analysis.

Discriminant validity *Fornell-Larcker criterion*

Discriminant validity was evaluated using the Fornell–Larcker criterion, as shown in Table 2. According to this criterion, discriminant validity is confirmed when the square root of the Average Variance Extracted (AVE) for each construct—indicated in bold along the diagonal—surpasses the corresponding inter-construct correlations in the same row and column. The results indicate that all constructs met the Fornell–Larcker criterion. Specifically, the square root of the AVE for each construct (AF = 0.783; AIRC = 0.788; AM = 0.817; DE = 0.888; EV = 0.854; OA = 0.732; WR = 0.809) exceeds its correlations with all other constructs. For instance, Algorithmic Fairness (AF) has a square root of AVE of 0.783, which is greater than its highest correlation with Digital Ethics (0.693). Similarly, Workforce Retention (WR) displayed a diagonal value of 0.809, which was higher than its correlations with Organizational Agility (0.719), Employee Voice (0.618), and the other constructs. Overall, these findings affirm that each construct is empirically distinct, providing

Table 5.
Specific indirect effect

Variables	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	Tstatistics (|O/STDEV|)	P values
AF -> EV -> OA	0.081	0.081	0.029	2.760	0.006
AF -> EV -> WR	0.141	0.143	0.049	2.859	0.004
AM -> EV -> OA	0.032	0.033	0.019	1.733	0.083
EV -> WR -> OA	0.216	0.221	0.038	5.749	0.000
AM -> EV -> WR	0.056	0.058	0.032	1.779	0.075
DE -> EV -> OA	0.152	0.151	0.031	4.832	0.000
DE -> EV -> WR	0.264	0.264	0.040	6.621	0.000
AF -> EV -> WR -> OA	0.049	0.051	0.020	2.471	0.014
AM -> EV -> WR -> OA	0.020	0.020	0.011	1.740	0.082
DE -> EV -> WR -> OA	0.092	0.094	0.021	4.482	0.000

robust evidence of discriminant validity and supporting the adequacy of the measurement model for subsequent structural analyses.

Coefficient of determination (R^2)

The explanatory power of the structural model was evaluated using the coefficient of determination (R^2) for endogenous constructs, as presented in Table 3. The findings demonstrate that the model possesses moderate-to-substantial explanatory power across key outcomes. Specifically, the model accounted for 43.7% of the variance in Employee Voice (EV) ($R^2 = 0.437$), 65.9% of the variance in Organizational Agility (OA) ($R^2 = 0.659$), and 38.2% of the variance in Workforce Retention (WR) ($R^2 = 0.382$). According to widely accepted PLS-SEM benchmarks, these values indicate moderate (EV and WR) to substantial (OA) explanatory power. The adjusted R^2 values closely aligned with the corresponding R^2 estimates, suggesting that the model maintained a balanced level of explanatory strength without inflation due to multiple predictors. Overall, these results imply that the proposed model is theoretically coherent and empirically robust, providing sufficient explanatory capability to support subsequent hypothesis testing and structural-path analysis.

Structural model results: Direct effects

Table 4 and Figure 3 shows the structural path analysis results via SmartPLS, indicating significant associations among constructs and supporting the hypothesized model. Algorithmic Fairness (AF) positively impacts Employee Voice (EV) ($\beta = 0.228$, $t = 2.951$, $p = 0.003$), showing employees are more likely to express concerns when AI-driven HR decisions appear unbiased. Digital Ethics (DE) strongly influences Employee Voice ($\beta = 0.427$, $t = 7.605$, $p < 0.001$), highlighting how ethical AI governance fosters psychological safety and encourages employee expression in AI-enabled HR settings. Analytics Maturity (AM) shows marginal significance on Employee Voice ($\beta = 0.091$, $t = 1.810$, $p =$

Table 4.
Specific direct effect smart PLS analysis

Variables	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AF -> EV	0.228	0.230	0.077	2.951	0.003
AIRC x EV -> OA	0.047	0.049	0.036	1.310	0.190
AM -> EV	0.091	0.093	0.050	1.810	0.070
DE -> EV	0.427	0.425	0.056	7.605	0.000
EV -> OA	0.355	0.355	0.053	6.716	0.000
EV -> WR	0.618	0.620	0.033	18.746	0.000
WR -> OA	0.350	0.355	0.055	6.418	0.000

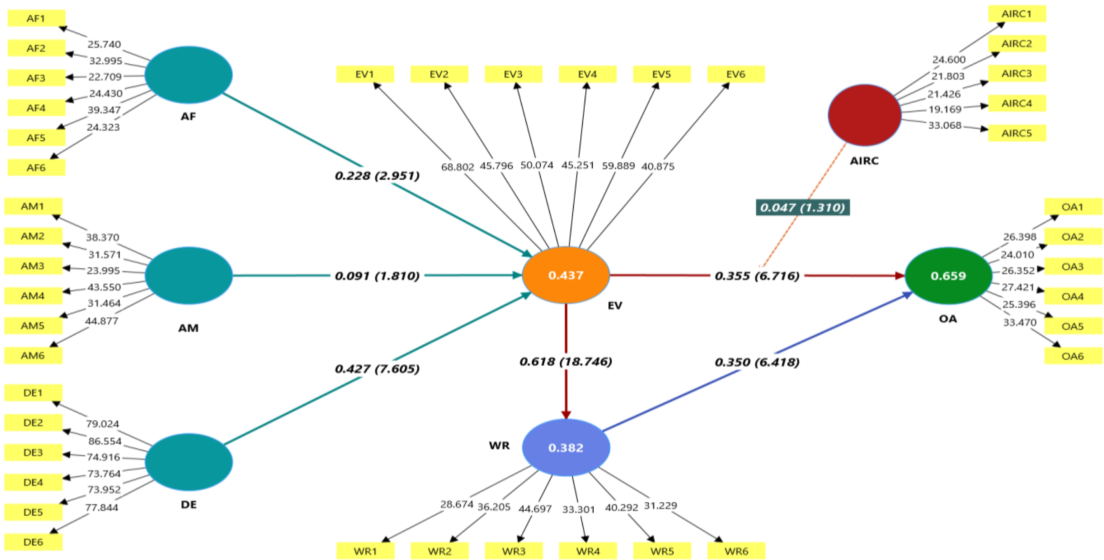

Figure 3.
Structural model results: Employee voice, AI-ready culture, and organizational agility

0.070), suggesting analytics alone cannot fully activate voice behavior without ethical safeguards. The interaction effect of AI-Readiness Culture (AIRC) on Employee Voice and Organizational Agility (EV × AIRC → OA) is not significant (β = 0.047, t = 1.310, p = 0.190), indicating AI-readiness culture does not significantly affect agility outcomes. Employee Voice enhances Organizational Agility (β = 0.355, t = 6.716, p < 0.001) and strongly affects Workforce Retention (β = 0.618, t = 18.746, p < 0.001). Workforce Retention positively influences Organizational Agility (β = 0.350, t = 6.418, p < 0.001), supporting that retained employees enhance organizational responsiveness. The results demonstrate that ethical AI-enabled HR practices foster employee voice, which mediates workforce retention and organizational agility, supporting the proposed framework.

Structural model results: Direct effects

Table 5 presents the results of the mediation analysis using bootstrapping. The findings confirm that Employee Voice (EV) and Workforce Retention (WR) act as key mediating mechanisms linking AI-enabled HR practices to organizational agility. Employee Voice significantly mediates the relationships between Algorithmic Fairness (AF) and Organizational Agility (OA) (β = 0.081, p < 0.01), as well as between Digital Ethics (DE) and Organizational Agility (β = 0.152, p < 0.001). Similarly, EV significantly mediates the effects of AF (β = 0.141, p < 0.01) and DE (β = 0.264, p < 0.001) on Workforce Retention. In

Table 6.
Effect size (f^2) of structral relationships

Variables	f-square
AF -> EV	0.033
AIRC -> OA	0.085
AIRC x EV -> OA	0.005
AM -> EV	0.008
DE -> EV	0.168
EV -> OA	0.204
EV -> WR	0.618
WR -> OA	0.181

Table 7.
Predictive relevance (Q^2) of endogenous constructs

Variables	Q^2predict	RMSE	MAE
EV	0.422	0.765	0.536
OA	0.488	0.722	0.540
WR	0.436	0.758	0.585

contrast, indirect effects involving Analytics Maturity (AM) via EV are not statistically significant. The sequential mediation results further show that EV → WR → OA is significant ($\beta = 0.216$, $p < 0.001$), indicating that employee voice enhances agility through improved workforce stability. Moreover, both Algorithmic Fairness ($\beta = 0.049$, $p < 0.05$) and Digital Ethics ($\beta = 0.092$, $p < 0.001$) exert significant sequential indirect effects on organizational agility through EV and WR. No significant sequential mediation is observed for Analytics Maturity. Overall, the results demonstrate that fair and ethical AI-HRM practices enhance organizational agility primarily by encouraging employee voice and strengthening workforce retention, while analytics maturity alone is insufficient to activate these behavioral mechanisms.

Table 6 shows the effect sizes (f^2) of structural relationships. Employee Voice (EV) significantly impacts Workforce Retention (WR) ($f^2 = 0.618$) and moderately affects Organizational Agility (OA) ($f^2 = 0.204$). Workforce Retention moderately influences Organizational Agility ($f^2 = 0.181$). Digital Ethics (DE) moderately influenced Employee Voice ($f^2 = 0.168$), while Algorithmic Fairness (AF) and Analytics Maturity (AM) had minor effects on EV. The AI-Readiness Culture × Employee Voice interaction effect on OA was minimal ($f^2 = 0.005$). Table 7 shows all endogenous constructs have positive Q^2predict values, confirming predictive relevance. Q^2 values for Employee Voice (0.422), Organizational Agility (0.488), and Workforce Retention (0.436) indicated moderate to strong predictive power. RMSE and MAE values validated prediction accuracy. Table 8 shows SRMR values for saturated (0.055) and estimated models (0.098) were within acceptable PLS-SEM limits. Additional fit indices (d_ULS, d_G, Chi-square, and NFI) met expectations for complex models, supporting model robustness.

Theoretical and practical implications

Theoretical contributions: This study offers both theoretical and practical contributions to the field of AI-HRM by connecting several theories including Organizational Justice Theory, Psychological Contract Theory, and Dynamic Capabilities Theory within a holistic framework that explains how AI enabled HRM practices influence retention and agility. Its contribution to the literature lies in its empirical confirmation of mediation of psychological contract fulfillment, employee voice and workforce retention—factors which have not been examined to any great extent in AI-HRM contexts with regards to emerging economies. Additionally, including AI-readiness culture as a moderating variable is also an original contribution to the field of study by demonstrating how organizational preparedness will influence the effect of AI interventions. Finally, the research extends cross-cultural HRM literature by analysing between-group variations in AI-HRM adoption across Southeast Asia and highlighting the influence of national institutional environments.

Practical Implications: The results provide implications for HR professionals, technology communities and policymakers in Southeast Asia. Firms seeking to deploy AI in HRM will have to pay attention to algorithmic fairness, promote digital ethics and integrate employee voice mechanisms into their systems for better trust, engagement, and retention. Culture of AI readiness—characterized by leadership commitment, digital literacy and willingness to change—need to be nurtured for reaping the benefits of AI adoption. The findings imply that HR analytics AI-maturity may help driving workforce agility when innovative use is accompanied by moral procedures. National variabilities shall be the

Table 8.
Model fit indices of the structural model

Variables	Saturated model	Estimated model
SRMR	0.055	0.098
d_ULS	2.649	8.238
d_G	1.147	1.262
Chi-square	1485.902	1579.560
NFI	0.811	0.799

reason for dedicated narratives, augmenting pressure on regulatory authorities to custom AI governance frameworks in relation to specific local sociocultural specifics.

Limitations

This study acknowledges several limitations. First of all, as the study was conducted in a cross-sectional design this does not allow any causality inference, and thus even less conclusions based on mediation analysis can be drawn by this method since the sequencing of variables is unknown. Prospective research is necessary to establish these indirect relationships. Furthermore, the common source bias and the use of self-reported data could impose common method bias risk despite steps taken to alleviate it. Additionally, the sample population of participants is limited to only four Southeast Asia countries which may not reflect such results for other regions. Furthermore, SmartPLS can be a useful combined hermeneutic for model testing but does not always capture streams or other non-linear effects (Hair et al., 2017). Finally, the study employed perceptual performance measurements as opposed to objective ones that should be taken into account when planning further investigations.

CONCLUSION

The contributions of this study are to empirically develop a multi-level model that connects AI-enabled HRM practices to workforce retention and organizational agility via the mediation effects of employee voice. By integrating algorithmic fairness, analytics maturity and digital ethics, the model offers a comprehensive perspective on ethical AI adoption in HRM. Findings appear to suggest the critical need for human-centered strategies for implementing AI systems that promote fairness, transparency and inclusivity. The past significance of AI-readiness culture and cross-national distinctions highlights a call for context-specific, culturally grounded and strategically embedded AI-HRM systems. Looking ahead, Southeast Asian organisations and governments must work hand in hand to build an ethical, inclusive, and agile talent ecosystem which will enable them to navigate the future of work in an AI-driven age. The findings confirm the model by corroborating the significance of algorithmic fairness, analytics maturity, digital ethics and employee voice for improving organizational outcomes. The retention of employees and fulfillment of psychological contract are core intermediaries, whereas the culture of AI-readiness has a conditional moderating effect. The cross-national comparisons also underscore the necessity of contextual sensitivity in developing and implementing.

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