



Building Employee Agility in the AI-Enabled Workplace: Digital Leadership, AI Literacy, Digital HRM Practices, and the Moderating Role of Digital Mindset

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ABSTRACT. *This study examines the role of Digital Leadership (DL), AI Literacy (AIL) and Digital Human Resource Management (DHRM) practices in enhancing Employee Agility (EA) in AI-enabled workplaces and the moderating role of Digital Mindset (DM). Drawing on the Dynamic Capabilities (DC) viewpoint, the study conceptualises EA as an adaptable capability, which is a result of the interaction of leadership, individual technological competence, organisational systems, and employees' cognitive orientation towards digital change. A quantitative, cross-sectional approach was used with data from 360 employees in Tangerang-Banten, Indonesia, who were exposed to digital technology and AI applications in their job. Data were analysed using AMOS, Covariance-Based Structural Equation Modelling (CB-SEM). The results showed that AIL and DHRM practices had significant positive effects on EA, whereas DL had no significant direct effect. The relationship between DL and EA was significantly moderated by DM, however, the interaction was negative. In contrast, DM did not significantly moderate the relationship between DHRM practices and EA. The model accounts for 85.8% of the variance in EA. Our findings suggest that agility in AI-enabled workplaces may be more dependent on employees' AI-related capabilities and digitally supportive HR systems than on digital leadership alone. In addition, our findings suggest that DM may change, rather than uniformly increase, the value of digital organisational resources.*

Keywords: *Employee Agility; Digital Leadership; AI Literacy; Digital HRM Practices; Digital Mindset; Dynamic Capabilities; AI-Enabled Workplace*

1. Introduction

Organisations are going digital and this is changing not just how work is done, but also what workers learn, understand and adapt to. Artificial intelligence (AI), data-driven decision-making tools, digital collaboration platforms, automated workflows, and digitally-enabled human resource operations are increasingly woven into the fabric of organisational life (Qutainah et al., 2025). The adoption of technology does not, in and of itself, generate an adaptive workforce. Ultimately, the impact of digital transformation hinges on whether individuals are equipped to recognise new challenges to develop talents and reconfigure traditional routines to translate technological opportunities into successful work behaviour (Tigre et al., 2025). Therefore, the human dimension of digital transformation has grown more crucial in addition to the technological investment itself. Employees need the right technological capabilities to perform effectively in increasingly AI-enabled contexts, while leadership needs to provide direction and meaning in the midst of digital transition (Benlian & Pinski, 2025; Sacavém et al., 2025).

This shifting work environment has revived research interest in Employee Agility (EA), roughly referring to employees' ability to respond successfully to changing job

requirements with proactive, adaptive, and resilient behaviour (Mahmoud et al., 2025; Ramzuni et al., 2026). Organisational responsiveness is ultimately delivered by individuals who have to understand change and adapt new knowledge to continue work in conditions of uncertainty, so employee agility is crucial. EA has been recognised as a significant micro-foundation of organisational agility in a recent bibliometric study of 319 publications and the research growth in this field has been significant (Ramzuni et al., 2026). However, the same review concludes that the literature remains fragmented, especially in relation to the integration of leadership, digital HRM practices, and individual level mechanisms. Research from Southeast Asian settings also remains comparatively limited (Ramzuni et al., 2026).

A major antecedent of agility is digital leadership (DL) (Yıldırım et al., 2025). And as organisations shift from one-off technology implementations to continual digital transformations, leaders are expected to do more than promote the use of new technologies. They need to set out a clear digital orientation and support to stimulate innovation and help people make sense of the implications of technology change for their work. Recent empirical research confirms the usefulness of DL for outcomes connected to agility. Based on data collected from 307 employees, Yıldırım et al. (2025) discovered that DL was favourably related to employees' agility performance, and creative process involvement helped explain this link. Recent findings based on Dynamic Capabilities (DC) Theory also indicate that Digital Leadership is favourably related to agility and organisational flexibility (Uzunbacak & Karagöz, 2026). The findings imply that leadership can establish key circumstances for adaptive behaviour of employees. However, the degree of employee's response to the same digitally-oriented leadership practices may vary, which brings the question of whether the efficacy of DL is contingent upon the perception and cognitive approach of the employees themselves to digital transformation.

AI Literacy (AIL) is another employee-level asset. AIL, however, is distinct from basic digital literacy, in that it includes understanding AI, using AI-enabled technologies responsibly, and being able to evaluate their outputs and limitations, and also make well-informed judgement about their use (Babashahi et al., 2024). As AI becomes available outside of technical occupations and progressively support managerial, professional and administrative employment, these competencies are becoming important to a larger share

of the workforce. Benlian & Pinski (2025) indicate that organisations need to systematically build AI-related abilities more and more, instead of seeing them as expert technical talents. Moreover, empirical research shows that employees with higher AIL likely to have better work outcomes. For example, Naveed et al. (2026) found that AIL has a positive relationship with work performance. Lee & Jeon (2025) indicated that organisational AI resource support and individual characteristics contribute to the development of AI Literacy, which in turn facilitates work performance.

AIL is important to EA, which is the ability of people to react to technology-driven change. Employees who have a grasp of how AI works, what its capabilities and limits are, and how to use it effectively will probably encounter less cognitive and practical obstacles when new AI-powered work practices are implemented. They might be more open to learning new methods of working and adjusting their routines as technology changes the job requirements and solutions. While research directly linking AIL especially with EA is lacking, existing research on general digital literacy provides a key empirical bridge. Chong et al. (2024) show that there is a significant relationship between digital capacity and EA in the models of employee performance. Therefore, the transition from broad digital competence to the more modern concept of AIL presents a chance to investigate if AI-specific skill might have a direct impact on EA at the current time of work.

On the organisational level, Digital Human Resource Management (DHRM) Practices offer another critical foundation for employee adaption. DHRM combines digital technologies into processes and management procedures. A systematic review and bibliometric analysis of 532 publications revealed that DHRM has evolved rapidly, especially in the areas of digital infrastructures, data-driven HR decision-making, digital interfaces, and strategic alignment of HR functions with company transformation (Sakib et al., 2025). Similarly, studies on agile HRM indicate that HR approaches, include continuous learning, employee involvement, empowerment, flexible work arrangements, teamwork, and capability development can help establish an agile workforce (Moh'd et al., 2024). Recent findings on Digital HRM also reveals that digital HR systems have the potential to enhance HR effectiveness and organisational responsiveness, although the advantages rely on the organisational settings under which they are implemented (Mahmoud et al., 2025). Similarly, current research suggests that DHRM practices

management are linked to employees' digital competence, while the organisational context influences the experience of these practices (Zervas & Triantari, 2025).

But the presence of digitally enabled leadership or HR tools doesn't guarantee that employees will translate them into agile behaviour. A more and more relevant explanation is Digital Mindset (DM), an emerging individual-level term that encapsulates employees' cognitive interpretation and orientation toward digital transformation. Goldmann et al. (2025) conceptualise DM as a digital cognitive orientation that shapes the way humans perceive information and technology to convert these perceptions into intentions and behaviours. Importantly, the study stated that DM research is still relatively new and has previously suffered from low conceptual clarity and hence is a promising construct to understand employee responses to digital transformation.

The relevance of DM is especially connected because organisational resources can lead to diverse behavioural consequences depending on how employees interpret and engage with them. A digitally orientated leader may provide vision and opportunities for experimenting, but these signals may affect agility more strongly when employees have a mentality that enables them to recognise and exploit digital opportunities. This boundary-condition reasoning is supported by emerging evidence. For example Saroge & Fitrianingrum (2025) discovered that DM was able to increase the association between Digital Leadership and employee performance. Similarly, Zhao et al. (2025) revealed that employees' digital growth mindset significantly impacted digital agility and engagement in digital transformation, adding to the growing body of evidence suggesting an employee's cognitive orientation toward digital technology is relevant to adaptive behaviour.

Similar case can be made for DHRM Practices. Organisations may invest in digital such as learning platforms, online performance systems, HR analytics, digital employee services and other technology-enabled HR activities. These may be used by employees as administrative systems rather than as possibilities for learning and adaptation. Employees that have a better DM are more likely to see the value of digital resources and use digitally enabled HR practices to build capabilities. Thus, DM can measure the level of the translation of DHRM practices to EA. A rising body of literature on DHRM and digital competence has emerged, however the function of DM as a boundary condition between DHRM and EA remains mainly unexplored. This gap is

particularly noteworthy because current DHRM research increasingly demands for increased attention to the interplay of technical systems with employee-level human variables rather than regarding HR digitalisation as a solely technological process (Sakib et al., 2025).

The main drawback of the developing research is thus not just the lack of evidence that DL, AI-related competences or DHRM matter. Rather, these subjects have developed mostly along independent research lines. Leadership studies usually focus on the extent to which digital leaders shape employee or organisational results (Do & Duong, 2026), AI literature focuses more and more on employees' AI-specific competencies (Babashahi et al., 2024; Quttainah et al., 2025), and DHRM research focuses on technology-enabled people-management systems (Tyagi et al., 2025). Within EA study, specifically, Ramzuni et al. (2026) point to this fragmentation, especially the poor integration of leadership, HR-driven explanations, and digital capabilities. What remains less evident is why identical digital leadership or HR cultures yield differing levels of adaptability among employees. One rationale relates to the introduction of DM as a cognitive boundary condition is digital resources may be more effective when employees have the mental orientation to interpret and engage to leverage those resources.

The research is based on a DC approach which gives a profound basis for describing EA as an individual-level ability to identify changes. The behaviour change allows mobilising knowledge and reconfiguring work processes in dynamic situations. More recently, agility is also increasingly positioned within this logic, indicating the capacity to sense, respond and reconfigure in face of environmental and technological change (Ramzuni et al., 2026; Uzunbacak & Karagöz, 2026). Accordingly, the present study considers DL, DHRM practices as enabling organisational resources, AIL as employee technological capability, and DM as an individual cognitive boundary condition that could affect the extent to which the selected organisational resources are translated into EA.

Fragmentation of literature is also evident in the bibliometric network constructed for the study. The VOSviewer network visualisation, which was based on 300 records published in 2024-2026 and retrieved from Google Scholar using the Publish or Perish tool, demonstrates that DL, constructs relevant to agility, artificial intelligence, digital literacy, and concepts relevant to HRM are distributed among different thematic clusters

rather than being concentrated within a dense and integrated research network. DL falls into a different thematic cluster than agility, while AI, digital literacy, and HRM-related topics are connected across the network but not centred on a common employee agility framework. The visualisation thus gives further evidence that the constructs underlying the present model have been studied in scholarly work mostly in distinct combinations. This pattern, evaluated within the still-developing literature on DM.

In conclusion, the current research studies the direct impact of DL, AIL, and DHRM practices on EA and also examines DM as a moderator of the DL and EA, then DHRM practices and EA relationships. The study makes three contributions to the literature. First, it combines leadership, individual, and HR-system-level explanations of EA into a single empirical framework for deeper integration in the agility literature. Second, rather than assuming that organisational digital resources have similar effects on all employees, it introduces DM as a theoretically meaningful boundary condition that may explain when DL and DHRM Practices become more effective in developing EA. Thirdly, the study offers a more complex account of human adaptation in an AI-enabled workplace by distinguishing between the employee's ability to work with AI and their more general cognitive orientation toward digital transformation by including both AIL and DM. The model also hints from a managerial perspective that investments in digital leadership and HR technology could have more adaptive value if organisations simultaneously increase the technological capabilities and cognitive preparation of employees for digital change.

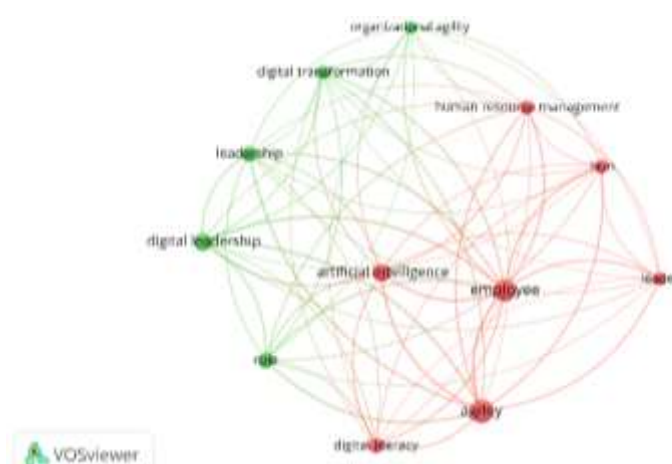


Figure 1 Network visualization of recent research related to Digital Leadership, Employee Agility, AI-related literacy, and HRM (2024–2026)

2. Review of Literature and Development of Hypotheses

2.1 Theoretical Background: Dynamic Capabilities (DC) Perspective

In the present study, the DC approach is mainly used to describe the evolution of Employee Agility (EA) in increasingly digital work situations. Recent studies have moved away from the perspective that agility is a stable personnel attribute and increasingly sees it as an adaptable talent that allows individuals and organisations to perceive changes, adjust to emerging demands and rearrange existing ways of functioning. Ramzuni et al. (2026) evaluate 319 papers on EA and illustrate how modern agility research increasingly incorporates a DC approach. From this perspective, agility is not a resource on its own. Rather, it is the combination of competencies and organisational mechanisms that enables employees to react successfully to changing conditions.

This theoretical perspective is especially essential when considering digital transformation. However, availability of technical resources does not lead to adaptive workforce. Organisations also need leaders who understand and can translate technological change. They nurture the employees who have the skills and knowledge to work with new technology through organisational mechanisms that allow those skills and knowledge to be developed and used. DC Theory has also been used in recent empirical studies to clarify the significance of digital leadership and digital transformation in agility and adaptive results. For example, in a model expressly founded in DC Theory, Uzunbacak & Karagöz (2026) find a positive association between DL and EA. Evidence of this strengthens the belief that digital resources are useful only to the extent that they help employees to recognise change and to adapt their working habits accordingly.

The present study takes into account DL, AIL, and DHRM practices as independent but interrelated resources working at different levels within this logic. DL is a leadership capacity where leaders create direction, facilitate learning, and lead employees through digital change (Do & Duong, 2026). AIL is an individual-level technology ability that allows employees to understand, analyse, and accurately use AI to their work (Benlian & Pinski, 2025; Liu et al., 2025). DHRM Practices is an organizational-level system that integrates digital technology with HR activities such as recruitment, learning and development, performance management, employee communication, and talent management (Sakib et al., 2025). Together these resources

provide assistance in diverse forms to employees' ability to respond to changing job requirements and so provide a viable explanation for the development of EA.

However, the existence of these resources does not indicate that employees will respond to them in the same way. DC depend not only on the availability of resources, but also on perceptions, interpretations and mobilisation of resources by persons in changing situations. This is where the Digital Mindset (DM) is of theoretical relevance. The DM is the cognitive orientation a human has toward digital technology that affects how employees view digital possibilities, understand technological development, and transform these perceptions into actions (Goldmann et al., 2025). Hence, employees with a stronger digital mindset would be better equipped to translate leadership support and digitally enabled HR procedures into agile behaviour. Therefore, DM is theorised as a boundary condition at the individual level in this study that might enhance the benefits of DL and DHRM Practices on EA.

This approach also tackles a key weakness of the current literature on EA. Ramzuni et al. (2026) point out that explanations of agility in terms of leadership, HR, and digital capabilities stay separated and argue for further integration across these streams. The present study tackles this gap by integrating the concept of leadership capability, AI-related individual capability, digitally enabled HR systems, and employees' cognitive orientation toward digital transformation in a unified framework. Thus, from a DC perspective, EA is conceptualised as an individual adaptive capability that is supported by (1) leadership, (2) technological competence, (3) organisational systems. The strength of relationships may be contingent on the employee's DM.

2.2. Employee Agility

Employee agility is the ability of an employee to respond well to changing job requirements while being proactive, flexible and resilient (Ramzuni et al., 2026). Although conceptualizations vary, recent research on employee-agility is progressively converging around three behavioral dimensions, which is proactivity, adaptation, and resilience. As Ramzuni et al. (2026) point out, these three aspects are increasingly employed in contemporary employee-agility studies and reflect the move from seeing agility as reactive flexibility toward seeing it as a broader adaptive capability.

Thus, employee agility is fundamentally different from the general performance of employees. A high performer may be able to accomplish the current activities well, but

not be able to adjust when the tasks involve technologies or the organization's expectations change. An agile employee, in contrast, capable of learning, adapting and acting proactively when the usual routines are disrupted (Ramzuni et al., 2026; Yuniarsih et al., 2026). This divide is particularly salient in digitally intensive workplaces where individuals are often exposed to new technology in the work design and constant skill requirements. Consequently, employee agility can also be seen as a micro-foundation for overall company agility. It is the individuals that decide and act. The organization's response to changes in its surroundings. This means that corporate efforts to become more agile may be wasted if workers are unable or unwilling to change established behaviors. Recent assessments therefore suggest a more explicit integration of leadership, HRM, digital competence, and employee learning into explanations of employee agility (Alviani et al., 2024; Ramzuni et al., 2026; Sakib et al., 2025). This gives a platform for exploring DL, AIL, and DHRM practices as distinct antecedents of EA.

2.3. Digital Leadership and Employee Agility

Digital leadership extends beyond the use of digital tools or conventional leadership practices. It is about the ability of leaders to make sense of technological developments to create a digital direction with purpose, such stimulate experimentation, enable learning and align people to the corporate digital transformation (Mohamed & Fayad, 2025; Quttainah et al., 2025; Tigre et al., 2025). These recent literatures have stressed that effective digital leadership requires a combination of technological expertise, strategic vision and a human-based competency to assist employees through technological change. According to Sacavém et al. (2025), the leadership is critical for the organizational digital transformation as the leaders need to combine the technical capabilities with the strategies and changes in organizational practices.

This type of leadership is critical for Employee Agility. Technological change often necessitates workers to revise established routines, acquire new skills and work on a partial basis of information (Guerrero & Menter, 2024). Leaders who articulate a clear digital goal but also encourage experimentation can eliminate ambiguity and create situations where people are more ready and able to modify their behavior. To summarize, digital leaders may also model learning from failure and normalizing continual change, both of which are congruent with the proactive and adaptable components of EA. There is increasing scientific data to support this association. Yıldırım et al. (2025) analyzing

data on 307 employees revealed that digital leadership was positively associated with agility performance, giving an additional explanatory mechanism via creative process involvement. In line with DC Theory, recent research also indicates a positive association between perceived digital leadership and perceived agility, suggesting that digitally capable leaders enable adaptive organizational responses by facilitating the reconfiguration of routines and capabilities.

These results align with recent requests for a more explicit inclusion of leadership in EA research. While a considerable amount of work has been done in leadership within organizational behavior, Ramzuni et al. (2026) conclude that leadership has been relatively less incorporated into the employee agility literature, especially in conjunction with digital competence and HRM mechanisms. Thus, Digital Leadership might be an important contextual resource that helps employees to build the confidence direction and flexibility they need to respond to changing digital work environments.

H1: Digital leadership has a statistically significant positive influence on employee agility.

2.4. AI Literacy and Employee Agility

With the growing incorporation of AI into regular organizational activity, AI literacy has evolved as a more specific sort of technological competency. It is beyond the ability to handle digital applications. Benlian & Pinski (2025) define AI literacy as a multidimensional workforce capability that includes conceptual to practical, along with the ethical abilities. These competencies enable employees to make informed choices regarding AI in the workflows and critically assess its ramifications. From this perspective, AI-literate employees know not just how to utilize AI but also when to use AI, where its limitations are, and how to assess its outputs.

Recent measurement study also shows that AI literacy has substantial behavioral repercussions. Liu et al. (2025) established a generative AI literacy measure that includes (1) technical competency, (2) prompt optimization, (3) content evaluation, (4) inventive application, and (5) ethical awareness. Their empirical results found a positive relationship between generative AI literacy and work performance. Similarly, Naveed et al. (2026) also discovered a positive association between AI literacy and work performance, implying that the ability to comprehend and utilize AI has become an increasingly valuable human resource.

The proposed relationship with Employee Agility follows a related but theoretically distinct rationale. An employee who is familiar with emerging AI technologies can experiment with new ways of working more confidently. Enable them to analyze alternative solutions more quickly and integrate AI-generated knowledge into changing work requirements. AI Literacy can thereby lower the cognitive and practical barriers to technological transformation. AI-literate employees will be more likely to see AI as a resource and incorporate it into their existing skill set, rather than reacting to it as an external disruption. Although limited direct evidence exists for the link between AI literacy and employee agility particularly, a crucial opportunity for the present study, research on more general digital literacy provides an empirical bridge. Chong et al. (2024) used broader digital literacy in an employee-agility model among HR practitioners and revealed that technology proficiency leads to positive job outcomes due to employee adaptation mechanisms. Their analysis suggests that technology-related employee competence and employee agility are elements of an empirically meaningful chain of adaptation. The current study builds on this relationship from general digital literacy to the relatively new construct of AI literacy in AI-enabled work environments. This change supports the notion that people with higher AI Literacy should be more prepared to engage in continuous learning. Nurture them to adapt existing practices and discover new technology opportunities to respond proactively to job redesign. These traits are quite near to the dimensions of Employee Agility.

H2: AI literacy has a statistically significant positive influence on employee agility.

2.5. DHRM Practices and Employee Agility

DHRM Practices refers to the use of digital technologies to enable and transform human resource activities such as (1) recruitment, (2) onboarding, (3) learning & development, (4) performance management, (5) talent management, (6) employee communication, (7) workforce analytics and other people management processes (Mahmoud et al., 2025). This field has recently experienced tremendous growth. Sakib et al. (2025) performed a systematic review and bibliometric analysis of 532 documents and demonstrated that the research on DHRM is increasingly directed toward data-driven HR from decision-making to alignment with the corporate strategy. Gareem (2026) defines the digital transformation of HR as the assimilation of digital technologies, AI, and

automation into general HR tasks, helping HR to become more data-driven and responsive.

This logic is further supported by research on agile HR. In a systematic mapping of 86 studies, Moh'd et al. (2024) differentiate between agile for HR and HR for Agile. The latter is defined as the conscious development of organizational and workforce agility through HR functions and other HR mechanisms. They conclude that HRM can play a proactive role in building the environment that enable a agile workforce, rather than being simply administrative support for existing personnel. Recent empirical evidence also indicates that DHRM solutions can improve organizational procedures and responsiveness. For example, Mahmoud et al., (2025) demonstrated that the use of DHRM systems considerably improved HR efficiency and stressed the significance of organizational agility in influencing the effectiveness of using such technologies. Although the consequence of the digital HR systems and agility was organizational rather than individual agility, the results support the wider notion that digital HR systems and agility are closely related organizational mechanisms rather than completely separate organizational initiatives.

DHRM Practices can provide a work environment at the employee level where task such as learning, feedback, resource access, and capability development happen with a faster rate. Employees embedded in such systems, therefore, should have more opportunities to adapt their abilities and behaviors as work requirements change. Thus, it is hypothesized that DHRM Practices is expected to have a positive influence on EA.

H3: DHRM has a statistically significant positive influence on employee agility.

2.6. The Moderating Role of Digital Mindset

More recently, digital mindset (DM) has been identified as a key individual-level aspect in explaining how employees respond to digital transformation. It is not only about the capacity to use digital technologies. Instead, it manifests itself in the way people perceive, understand and pursue opportunities provided by digitalisation (Goldmann et al., 2025). According to Goldmann et al. (2025), DM is a cognitive filter that shapes individuals' intents and behaviours in digitally evolving surroundings. Employees with a better Digital Mindset are therefore not just aware of technology change but also more likely to recognise its potential. They will also comprehend its significance to their work and actively make use of digital chances (Souto-Otero et al., 2023). It is worth noting that

a DM is a relatively new notion and current research shows the need for further conceptual and empirical development.

This perspective makes DM particularly essential as border condition in the evolution of EA. Organisational resources may not always translate into similar behavioural responses from employees. One employee may see the same digital effort, leadership style or HR technology as an opportunity, while the other may see it as an additional load or disruption. Employees with a better DM are more likely to be curious about technological change. They will find chances for development and integrate digital solutions into their present work habits. This approach closely coincides with the proactive and adaptive activities that characterize Employee Agility. In line with this rationale, Zhao et al. (2025) have found that employees' digital growth mindset positively affected digital agility and their participation in digital transformation, showing that employees' cognitive orientation toward digital technology plays a substantial role in adaptive behaviour.

The first moderating relationship is DL and EA. DL can explain a digital vision, promote innovation, foster learning, and guide staff through technical change. However, all employees might not convert such leadership behaviours into EA equally. Employees with a strong DM should be better able to grasp the digital direction provided by a leader, identify the opportunities that may be derived from technology projects and translate leadership support into proactive and adaptive action. Conversely, employees with a poorer DM may grasp the leader's direction but are unable to properly translate this into behavioural change. Some emerging empirical evidence exists to support this contingency argument. Saroge & Fitrianingrum (2025) discovered that DM moderated the link between DL and employee performance, meaning that employees with a stronger DM understood and implemented innovations provided by digitally orientated leaders better. Although their study was about employee performance rather than EA, it is an important empirical precedent for presenting DM as a border condition of Digital Leadership.

From a DC perspective, this encounter may be viewed as a combination of an enabling leadership resource and a staff level cognitive orientation. DL offers guidance and possibilities for adaptation, and DM affects how employees perceive and act on those

opportunities. Hence, the impact of DL on EA is likely to be more significant when individuals have a higher level of Digital Mindset.

DM may also moderate the connection between DHRM practices and EA. DHRM offers digitally-enabled tools to employees such as (1) online learning, (2) digital performance management, (3) employee platforms, (4) HR analytics, and (5) technology-supported communication (Espina-romero et al., 2026; Sakib et al., 2025). However, having these technologies available does not guarantee that employees would use them as a resource for learning and adaptation. Employees might only be utilising digital HR systems to satisfy administrative needs, and not to maximise their wider growth potential. Recent DHRM research supports the larger principle that the effect of Digital HRM is context-dependent on where employees experience and use these practices. For example, Zervas & Triantari (2025) demonstrate that the relationship between DHRM practices and employees' digital competence is contingent upon organisational conditions, supporting the view that digital HR practices should not be seen as universally effective technological interventions.

But employees with a strong DM are more likely to see digitally connected HR processes as chances to learn. They will develop their capacities to get feedback and experiment with new ways of working. In this way, DM may be decisive in whether DHRM systems will continue to be purely administrative tools or resources that employees themselves actively use to adapt to evolving work requirements. This rationale is congruent with the perspective of DM as a cognitive filter to identify and leverage opportunities that arise from digitalisation (Goldmann et al., 2025). Thus, when DM is high, employees should be better able to convert the learning and growth possibilities supplied by DHRM practices into adaptable and resilient behaviours.

Unlike the DL relationship, little direct empirical data exists on DM as moderator between DHRM practices and EA. This lack of a relationship is a valuable research opportunity. This interaction builds on the current DHRM research by proposing an employee-level cognitive condition to explain why some employees experience more positive adaptation outcomes from the same digitally enabled HR practices than others. Thus, the positive impact of DHRM practices on EA is likely to be more pronounced when individuals have a greater level of Digital Mindset.

H4: DM has a statistically significant positive moderating effect on the relationship between DL and EA.

H5: DM has a statistically significant positive moderating effect on the relationship between DHRM and EA.

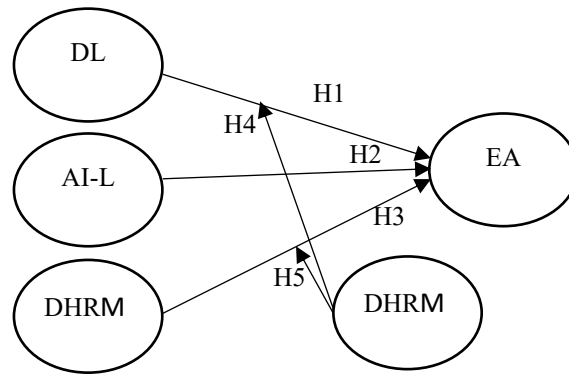


Figure 2 Research Model

3. Research Method

This study employed a quantitative causal-associative research design with hypothesis testing to examine the direct effects of DL, AIL, and DHRM Practices on EA, as well as the moderating role of DM. Researcher interference was minimal, as no manipulation was made to employees' working conditions. Respondents gave their perceptions on the basis of their actual experiences in the workplace. This condition allows the claimed links to be tested under genuinely existing organisational situations.

The target population comprises people working with digital technology and with adequate exposure to digitally enabled organisational and HR activities in Tangerang-Banten. Respondents are also expected to have familiarity with, or interaction with, AI applications for work-related goals. The unit of analysis is the individual employee. The sufficiency of the sample size was examined in terms of the statistical power and model complexity. A sensitivity power analysis with $\alpha = .05$ and power = .80 suggested that 360 respondents could detect an incremental effect size of around ($f^2 = .022$) or larger, using five predictors in the structural model (including two interaction terms). Hence, the sample was deemed appropriate for assessing the postulated direct and moderating relationships using CB-Structural Equation Modelling (SEM).

The study used a cross-sectional time horizon which implies that data were obtained from respondents at one moment in time. Primary data were collected by a

standardised adopted questionnaire from prior study. A non-probability purposive sampling strategy was employed as the participants need to meet certain criteria that are directly related to the research model. DM was measured using seven items adapted from Goldmann et al. (2025) and operationalised as an observable composite moderator in the structural model. For the moderation analysis, composite scores were calculated and the interaction terms were designed by multiplying DL by DM and DHRM by DM.

Table 1 Conceptual Definition and Operational Definition

Variable	Conceptual Definition	Operational Definition	Dimensions	Items	Scale	Reference
Digital Leadership (X1)	The ability of executives to set a direction, enable the use of digital technology, foster innovation, and match digital projects with company goals.	Employees' perceptions of their immediate leader's promotion of digital resources, communication of digital direction, encouragement for experimentation, and alignment of digital activities to organisational goals.	Unidimensional	12	5-point Likert	Khan et al. (2026) Abbu et al., (2025)
AI Literacy (X2)	The capacity of an individual to recognise and understand AI, to use AI appropriately, to assess AI applications and outcomes critically, and to reflect on ethical consequences.	Employees' perceived ability to identify, use, evaluate, and ethically engage with AI applications.	Unidimensional	12	5-point Likert	Wang et al., (2022)
Digital HRM Practices (X3)	Incorporating digital technology, automation, digital learning, communication and data into the HR procedures of organisations.	Employees' perceptions of effectiveness of digitally connected HR processes in their organization.	Unidimensional	5	5-point Likert	Espinero et al. (2026)
Digital Mindset (Z)	DM refers to an individual's underlying cognitive orientation toward digitalisation, which influences the way digital information and opportunities are seen, evaluated, and transformed into intents and behaviour.	DM is operationalised as the employees' self-reported cognitive orientation toward digital transformation. Expressed in their digital consciousness of digital knowledge and ability to recognise and exploit the business value of digitalisation.	Unidimensional	7	5-point Likert	Goldmann et al. (2025)
Employee Agility (Y)	The ability of people to adapt and respond to changing job requirements in a proactive, adaptive and resilient manner.	Employees' perception of their proactive behaviour, the ability to adjust to shifting job demands and resilience while dealing with difficult or unexpected working conditions.	Unidimensional	12	5-point Likert	Elhadidy & Gao (2024)

Data were analyzed using AMOS software, applying the Covariance Based Structural Equation Modeling (CB-SEM). The analysis is delivered in two primary steps. Confirmatory Factor Analysis (CFA) is applied to analyze the measurement model, including construct reliability, validity, and overall fit of the model. Model adequacy is assessed by frequently accepted goodness-of-fit measures such as CFI, TLI, RMSEA and RMR. Next, the structural model is tested for the direct effect of DL, AI literacy, and DHRM practices on EA.

4. Analysis

Data were collected from 360 respondents in June–August 2026. The respondents' characteristics are given in Table 2. The next stage was to evaluate convergent validity by factor loadings, standardized factor loadings above 0.5 were considered acceptable (Sekaran & Bougie, 2016). Table 3 shows that all indicators met the required loading criterion. DL, AIL, DHRM, and EA are represented as latent constructs, whereas DM is operationalised as an observable composite moderator for the formation of the interaction terms. Additionally, the construct reliability was tested based on the criterion that the Average Variance Extracted (AVE) should be greater than 0.5 and the construct reliability should be greater than 0.7 (Sekaran & Bougie, 2016). Finally, the measurement model demonstrated acceptable convergent validity and construct reliability, allowing the analysis to proceed to the structural model.

Table 2 Respondent Category and Description

Category	Description	Total	Percentage
Gender	Male	176	48,9%
	Female	184	51,1%
AI Usage Frequency	Less than once/week	0	0%
	1–4 times/week	0	0%
	Daily	23	6,4%
	Several times/day	337	93.6%

Table 3 Loading Factor

Variable	Loading Factor	Variable	Loading Factor	Variable	Loading Factor	Variable	Loading Factor
DL1	0,714	AIL1	0,778	DHRM1	0,712	EA1	0,697
DL2	0,708	AIL2	0,774	DHRM2	0,684	EA2	0,691
DL3	0,797	AIL3	0,738	DHRM3	0,738	EA3	0,755
DL4	0,752	AIL4	0,772	DHRM4	0,725	EA4	0,731
DL5	0,811	AIL5	0,706	DHRM5	0,726	EA5	0,731
DL6	0,805	AIL6	0,608			EA6	0,763
DL7	0,882	AIL7	0,697			EA7	0,741
DL8	0,870	AIL8	0,670			EA8	0,733
DL9	0,843	AIL9	0,690			EA9	0,713
DL10	0,895	AIL10	0,702			EA10	0,731
DL11	0,844	AIL11	0,671			EA11	0,735
DL12	0,846	AIL12	0,644			EA12	0,700

Table 4 Reliability Assessment

Variable	Total Loading Factor	AVE	C.R.	Results
DL	9,767	0,72	0,97	Valid & Reliable
AIL	8,450	0,81	0,98	Valid & Reliable
DHRM	3,585	0,98	0,97	Valid & Reliable
EA	8,721	0,98	0,98	Valid & Reliable

Given potential departures from multivariate normality, the Bollen–Stine bootstrap was employed to assess the robustness of the overall model fit (Collier, 2020). The Bollen-Stine Bootstrap value was 0.333, which indicates that the designed model corresponds or alligns to the obtained data. Then, the goodness of fit (GOF) of the model was tested using fit indices in the SEM analysis. Overall model fit was evaluated using multiple indices representing different aspects of model fit. The model shows high construct connectedness and proves its effectiveness through several criteria.

Table 5 GOF Model

Fit Measure	Value	Remarks
RMR ($\leq 0,05$)	0,016	Accepted
TLI ($\geq 0,90$)	0,913	
CFI ($\geq 0,90$)	0,918	
IFI ($\geq 0,90$)	0,919	
RMSEA ($< 0,08$)	0,053	

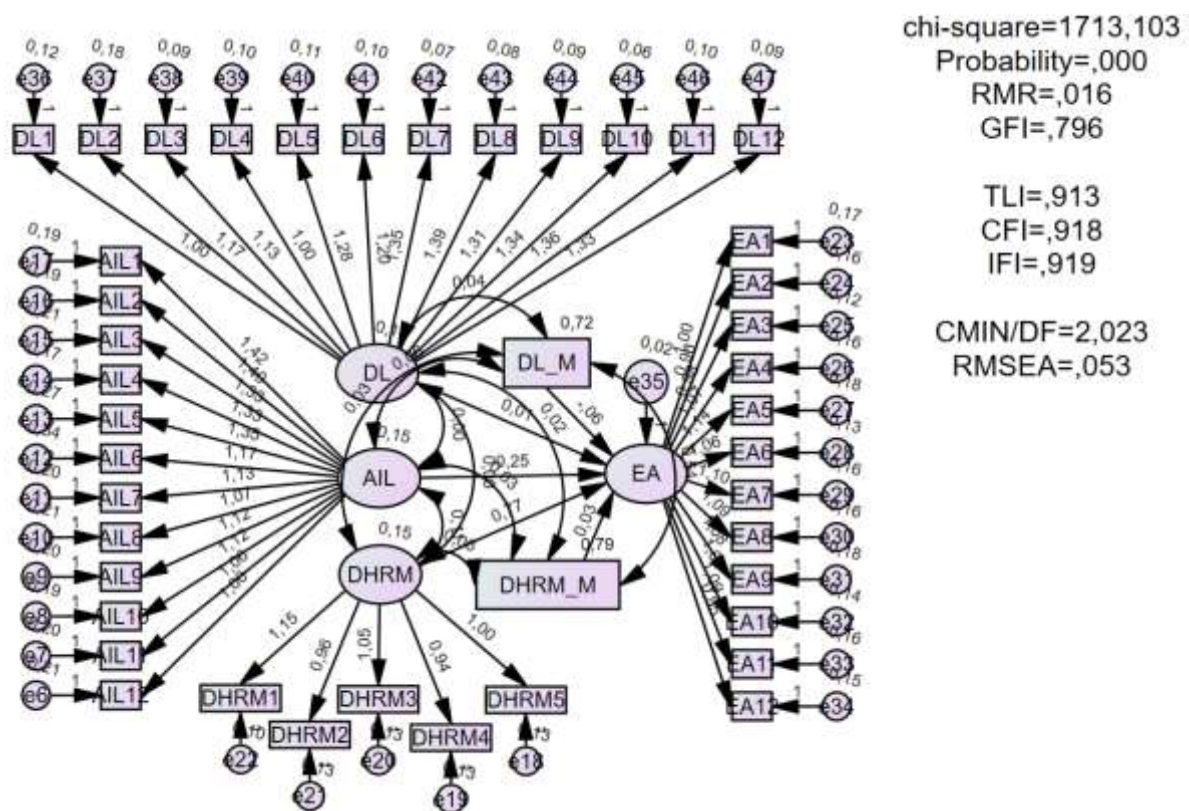


Figure 3 SEM Structural Model

The squared multiple correlation (R^2) of Employee Agility was 0.858 implying that the predictors of the structural model accounted for 85.8% of the variance in Employee Agility. The remaining 14.2% was explained by factors not included in the proposed model and residual variance. This finding suggests that the structural model has a substantial explanatory power for EA. Hypothesis testing was subsequently conducted based on the specified structural relationships. The p-value was utilised to examine the significance of the association between the independent and dependent variables. The outcomes of the hypothesis testing are as follows.

Table 6 Hypothesis Measurement

H	Path	Estimate	S.E.	C.R.	P	Remarks
H1	DL $\rightarrow$ EA	0,015	0,034	0,440	0,660	Not Supported
H2	AIL $\rightarrow$ EA	0,246	0,069	3,541	0,000	Supported
H3	DHRM $\rightarrow$ EA	0,772	0,089	8,709	0,000	Supported
H4	DL $\times$ DM $\rightarrow$ EA	-0,062	0,023	-2,708	0,007	Not Supported
H5	DHRM $\times$ DM $\rightarrow$ EA	0,033	0,021	1,549	0,121	Not Supported

5. Results

The first hypothesis was positively but not significantly associated with EA (Estimate = 0.015; $p = .660$). The probability value was far larger than the .05 level of significance. H1 was not supported, which indicates that DL did not have a significant direct effect on EA in the present sample, controlling for the other factors in the structural model. The second hypothesis investigated the impact of AIL on EA. AIL had a significant positive effect on EA (Estimate= 0.246; $p < .001$). The positive connection implies that higher levels of AIL were connected with higher levels of EA. The C.R. value was above the normal value of 1.96 and the probability value was below .05 which demonstrated that there was statistical evidence to support the hypothesised relationship. Thus, H2 was supported, confirming that AIL had a significant positive influence on EA.

The third hypothesis was that DHRM practices positively influenced EA. The structural estimations found a positive and statistically significant association between DHRM practices and EA (Estimate = 0.772; $p < .001$). The C.R. value of 8.709 and $p < .001$ provided strong statistical evidence for the proposed relationship. Thus, H3 was supported, indicating that stronger perceived DHRM practices were associated with higher EA. The conclusion shows that the more application of DHRM practices perceived by employees the better the Employee Agility, by managing other interactions in the structural model.

Hypothesis four stated that DM significantly moderates the connection between DL and EA positively. The interaction term of DL and DM was statistically significant (Estimate = -0.062; $p = .007$). The study demonstrates a statistically significant moderating impact, albeit the coefficient was negative, not positive as hypothesised. As such, H4 was not supported in the predicted direction. Specifically, the study finds that DM is a significant moderator of the association between DL and EA with a negative interaction.

Hypothesis five found that DM will positively moderate the association between DHRM practices and EA. The interaction between DHRM practices and DM was positively but not statistically significant (Estimate = 0.033; $p = .121$). The coefficient was highly in the expected direction demonstrating positive moderation but the p -value was not less than the .05 level of significance. Thus, there was no statistical evidence to support that viewpoint, as DM did not significantly moderate the DHRM–EA, H5 was not supported.

6. Discussion and Conclusion

The results of this study provide a more complex picture of how EA is created in an AI-enabled workplace. Of the five hypotheses, two were supported and three were not supported in the form hypothesised. This pattern does not mean that the proposed model is wrong, but rather indicates a crucial difference between digital resources that are proximal to employees' adaptive behaviour and those that are more indirect or conditional. The findings revealed that both AIL and DHRM practices had considerable contribution to EA whereas DL did not indicate any significant direct effect. More crucially, DM did not consistently improve the proposed connection. DL-DM was significant but negative, whereas DHRM-DM was non-significant too. To summarise, these findings show that EA may be less a matter of the straightforward accumulation of digital resources and more a matter of how different digital capabilities, organisational systems, and cognitive orientations work in substitution of one another in the workplace.

The first major divergence from predictions is the non-significant connection between DL and EA. Previous research have generally confirmed that DL is an essential enabler for agility. For instance, Yıldırım et al. (2025) observed a positive association between digital leadership and agility performance, whilst Uzunbacak & Karagöz (2026) reported a favourable relationship between perceived DL and organisational agility. The

conclusion obtained does not mean however that DL is useless. Rather, evidence shows that its effect might not be a straight route to agility at the individual employee level. In fact, Yildirim et al. (2025) themselves showed that creative process engagement was a mechanism that linked digital leadership with agility-related outcomes. Thus, leadership may need to be translated via employee experiences and behaviours before it leads to adaptive outcomes. In addition, past research have often concentrated on agility performance or organisational agility, rather than on EA explicitly, which makes the level of analysis a crucial distinction.

Another way of explaining this is that DL may be increasingly a setting that enables, rather than a sufficient capability. In digitally equipped organisations, employees could already expect their leaders to communicate digitally, support the use of technology and encourage adaption. In such a case DL may not be enough to distinguish agile people from the less agile. More important would be whether employees have the capacity to take advantage of digital opportunities, and whether organisational mechanisms allow them to do so. One hypothesis consistent with the present model is that AIL and DHRM practices remained relevant when DL was not. It is also an essential contribution to DC theory. Leadership may contribute to the creation of conditions for adaptation but true microfoundations of agility may be closer to employees' talents and the organisational routines via which those competencies are engaged. Similarly, recent bibliometric evidence suggests that research streams on leadership, HRM, and digital competence in EA are still only partly integrated, indicating that processes linking these domains need additional examination (Ramzuni et al., 2026).

In contrast, the strong positive effect of AIL on EA supports the thesis that the capacity to understand and work successfully with AI has become more and more relevant to employees' adaptability. Employees with AI skills are more likely to be better prepared to investigate alternative solutions produced by AI and master new digital procedures to modify their ways of working when technology requirements change. Consequently, AIL should not be perceived solely as technical knowledge but as an adaptable resource that potentially decreases uncertainty when employees face new technologies and work demands in an increasingly AI-mediated workplace. The research adds to recent findings linking AIL to employee outcomes. For instance, a positive association was discovered between AIL and work performance among academicians by Naveed et al. (2026). The

current study adds to this explanation by demonstrating that AIL is equally involved to EA, an outcome that mirrors employees' ability to respond proactively and adaptively to changing work situations. This is especially the case, as (Ramzuni et al., 2026) have noted that digital competence is an emerging field that has not been effectively integrated in employee-agility research.

The positive influence of DHRM practices on EA further supports the necessity of organisational systems in producing an agile workforce. Digital HR practices provide employees with quicker access to performance. Such procedures could reduce the gap between an embryonic demand for work and an employee's ability to meet it. This finding is in line with the broader idea of HR for agile where HR systems are not only administrative tools but part of the organization infrastructure facilitating worker agility (Moh'd et al., 2024). Recent evidence also shows that DHRM practices are related to employees' perceived digital competence, and digital HR outcomes are dependent on the organisational environment in which the practices function (Zervas & Triantari, 2025). Garem (2026) also indicates that HR digital capabilities can develop in digitally transformed HR workplaces. Taken together, these findings reinforce the idea that DHRM should be seen not just as the digitisation of existing HR procedures, but as an organisational mechanism that can facilitate ongoing adaptation.

Most paradoxical was the discovery that DM moderated the connection between DL and EA. The interaction was statistically significant, but had a negative coefficient and not a positive coefficient. Therefore, H4 was not supported as hypothesised. This finding is interesting from a theoretical perspective because it undermines the common-sense idea that a strong digital mentality should always enhance the benefits of digital leadership. Goldmann et al. (2025) define DM as a cognitive orientation that individuals have in perceiving and responding to digital transformation and demonstrate that it is connected with innovative and entrepreneurial behaviour. Viewed from this perspective, those employees with a strong DM may already be cognitively prepared to spot digital opportunities, experiment with technology and change their behaviour without being told to do so by their superiors.

Hence, one possible interpretation is a substitution effect. DL can be particularly effective when employees are (1) seeking guidance, (2) boost of confidence or assistance in understanding digital change. But as the DM of employees gets more mature, they may

not need leadership to such orientation. Employees who are highly digitally minded may be increasingly self-directed in their exploration of technology and response to change, meaning that greater digital leadership brings progressively less adaptive value. Employees who already exhibit high levels of digital confidence and initiative might not need intense leadership direction in some situations. This view varies from the research of Saroge & Fitrianingrum (2025) which revealed that DM strengthens the influence of DL on employee performance. The opposing conclusion is valuable as their result was employee performance whereas the present study considers EA. In conclusion, DM could act differently on the basis of the expected outcome, e.g., function within current needs or be able to adapt to new needs autonomously.

This conclusion opens up a more general theoretical question, such as do valuable organisational resources need to be complementary? The present evidence is that they may not. A digitally capable leader and a digitally minded employee can both help adaptation from a DC perspective, but their effects may be partly substitutable. Thus, individuals with a low DM may respond more to strong DL because it offers the guidance they have not yet internalised, while employees with a high DM may require more autonomy rather than more digital guidance. Future research needs to specifically compare the DL–EA relationship at low, moderate, and high levels of DM in an effort to identify how the negative interaction plays out.

H5 showed a different pattern, the interaction between DHRM practices and DM was positive but statistically non-significant. This means that DM did not significantly improve the contribution of DHRM practices to EA. One argument is that well-implemented DHRM systems offer employees resources and adaptive opportunities irrespective of their initial DM. Digital learning platforms, HR information systems, digital performance management, and employee-service technology can help standardise access to information and learning opportunities across the workforce. Thus, the benefits of DHRM may be built into organisational routines to a point where they are not dependent on people possessing extremely high levels of DM. This result supports the more general notion that digital HR practices may have an impact on digital competence, but their impact may be conditional on other factors than individual cognition, such as organisational culture and the wider organisational context (Zervas & Triantari, 2025).

Another possibility is that individuals already working in digitally enabled work contexts may be less variable in the basic acceptance of digital HR systems. With digital technologies becoming a part of everyday work, DM may influence the extent to which employees will embrace digital transformation, but not necessarily whether DHRM resources can support their agility. This finding suggests further research. Future research could examine whether (1) digital maturity, (2) job autonomy, (3) psychological safety, (4) learning climate, (5) organisational culture, or (6) the perceived usefulness of digital HR systems serve as stronger boundary conditions of the DHRM–EA relationship.

Therefore, the findings add to the DC Theory with a suggestion of a differentiated architecture of EA. The findings do not necessarily work through simple additive or complementary effects. Alternatively, competences at different levels may augment, displace or lessen the marginal contribution of each other. This viewpoint may provide a potential rationale for the dispersed nature of EA research across the leadership, HR, psychological, and digital-capability streams outlined by Ramzuni et al. (2026). This paper connects those streams, while also showing that integrating them leads to more intricate relationships than simply beneficial outcomes.

The findings signal the managers that organisations risk framing digital transformation as a leadership communication challenge only. It's still necessary to develop digitally orientated leaders, but leadership may not be enough to develop agile people. Organisations can improve their adaptive value by investing in the AIL of employees and DHRM solutions that facilitate easy access such as learning, information, feedback, and HR resources. The negative DL and DM interaction further points to the necessity for more differentiated leadership methods. Employees with a lower DM may need more direction and digital scaffolding, whereas those with a stronger DM may gain more from autonomy and experimentation. Thus, digital leadership may be most effective when it is tailored to the digital preparedness of the employee and not universally applied to the workforce.

There are some limits, which provide up potential for further investigation. The cross-sectional methodology can't capture the evolution of DM, AIL, and EA over time. Single-report data might not describe the actual adaptive behaviour. In future research, longitudinal or multi-source designs could be used to explore pathways via which DL may indirectly influence EA. Similarly, the mediating role of digital competence and

continuous learning might be further investigated in the DHRM–EA relationship. The negative moderation of DM was unanticipated and warrants special attention by replication across industries, levels of digital maturity and national settings. Qualitative research can also assist explain why highly digitally-minded employees may respond differently to digital leadership with insights that interaction coefficients alone cannot disclose.

This study indicates that the development of EA in an AI-enabled workplace may be less about the existence of DL and more about whether employees are able to work smartly with emerging technologies and whether organisational systems allow them to respond quickly to change. The direct influence of DL was not substantiated, AIL and DHRM Practices were major antecedents of Employee Agility. More provocatively, DM was not a universally reinforcing condition, as it significantly changed the DL–EA relationship in the opposite direction to that predicted, and did not significantly moderate the DHRM–EA. These results question the idea that “more digital” at all levels will necessarily yield more agility. Instead, we contend that EA could emerge from a carefully balanced configuration of competence, infrastructure, leadership, and most importantly individual mindset. A promising objective for the next generation of research on EA in more AI-enabled organisations is to understand when these resources complement or substitute each other.

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