**JURNAL LOCUS: Penelitian & Pengabdian**
**Volume 5 No. 6 June 2026**
E-ISSN 2829-7334| P-ISSN 2829-5439
Hompage: https://locus.rivierapublishing.id/index.php/jl

# When Digital HRM Meets Human Readiness: Explaining of Innovative Work Performance Through AI Readiness and Psychological Safety

**Vellen Wibowo**
STMIK Pontianak, Indonesia
Email: vellen.wibowo@stmikpontianak.ac.id

**Keywords:**
Digital HRM Capability; Digital Psychological Safety Climate; AI Readiness; Innovative Work Performance; Higher Education

**Abstract**

The pace of digital transformation in higher education also promotes universities to incorporate digital Human Resource Management (HRM) systems, such as AI-aided recruitment, digital performance management, and online learning platforms. But technological adoption is not enough to induce employees to create more innovation and better performance. This research investigated AI readiness as a strategic human capital capability that provides the organizational framework through which digital infrastructure and psychological climate are linked to innovative work outcomes among university lecturers. Based on the Resource-Based View (RBV) and Dynamic Capability Theory, the research assesses the associations between Digital HRM Capability, Digital Psychological Safety Climate, AI Readiness, and Innovative Work Performance. Data was obtained through a cross-sectional survey of Indonesian lecturers, using a quantitative explanatory design, and analyzed through Structural Equation Modeling (SEM). The findings suggest that the positive relationships between the two factors of Digital HRM Capability and Digital Psychological Safety Climate in predicting AI Readiness will greatly boost Innovative Work Performance. In addition, AI Readiness mediates antecedent effects on Innovative Work Performance. These results suggest that successful university digital transformation is not merely about the deployment of technological platforms, but also the preparedness of staff to utilize AI and an environment that is psychologically supportive of digital experimentation.

## INTRODUCTION

In higher education institutions, the domain of human resource management (HRM) has undergone a profound transformation due to the rapid technological advancement's characteristic of the digital era. The adoption of digital HRM systems including AI-assisted recruitment, digital performance evaluation platforms, learning management systems (LMS), data-driven academic workload monitoring, and algorithm-based assessment tools has become prevalent within universities. It is unequivocal that these technologies have the potential to enhance the efficiency, transparency, and strategic nature of academic staff management. Consequently, it is essential for lecturers not only to adapt to these novel digital workflows but also to cultivate new cognitive, technological, and adaptive competencies to ensure the retention and enhancement of their professional responsibilities (Bondarouk & Ruël, 2013; Bondarouk, Parry, & Furtmueller, 2017).

However, empirical research presents evidence suggesting that digital transformation does not necessarily correlate with heightened employee productivity or innovation. A significant number of digital HRM initiatives have fallen short of achieving their intended outcomes due to factors such as insufficient human readiness, psychological resistance, and misalignment between technological capabilities and organizational needs (Burton, 2025; Ramadhani et al., 2024; Shahid et al., 2025). In knowledge-intensive organizations, such as universities, where lecturers play a pivotal role in fostering innovation, teaching quality, and research productivity, this situation underscores a critical disparity between the adoption of technology and the effective utilization of human capital (Felin et al., 2012).

From a theoretical perspective, the Resource-Based View (RBV) posits that sustainable competitive advantage derives from the development of resources that are valuable, rare, inimitable, and non-substitutable. In this framework, digital technologies alone do not confer a sustainable advantage, particularly when they are widely replicated across institutions. Instead, competitive advantage is rooted in the competencies of human capital; the ability to leverage these competencies effectively determines an organization's capacity to utilize such technologies (Jöhnk, Weißert, & Wyrtki, 2021; Venkatesh, Thong, & Xu, 2012).

Within the context of digital transformation, AI readiness—defined as the degree to which individuals are cognitively, emotionally, and behaviorally prepared to engage with AI-enabled systems—represents a strategic micro-foundation for translating digital HRM investments into tangible performance outcomes. Nonetheless, the successful cultivation of AI readiness is not inherently self-reinforcing. Organizational climate variables, specifically the Digital Psychological Safety Climate, are significantly related to lecturers' abilities to experiment with digital tool adoption, voice concerns, learn from failures, and embrace new behavioral attitudes. A psychologically safe digital environment empowers instructors to interact with AI systems without fear of negative evaluation or job insecurity, thereby fostering exploration, learning, and creativity (WANG, 2025; Wu et al., 2024). In contrast, the absence of such a climate may lead to increased anxiety, resistance, and underperformance in digital HRM initiatives.

Previous studies in HRM and organizational behavior have empirically examined the impact of job satisfaction, organizational commitment, and motivation on employee performance (Jiang et al., 2012; Anderson et al., 2014). However, relatively little attention has been devoted to AI readiness as a strategic capability and as a mediating factor in the relationship between Digital HRM Capability and Innovative Work Performance (IWP). Innovative Work Performance refers to individual behaviors directed toward the generation, promotion, and implementation of novel ideas, processes, and digital solutions in academic work (De Jong & Den Hartog, 2010). While Messmann & Mulder (2012) developed a dynamic measure of IWP in educational settings, the specific role of AI readiness in translating digital HRM practices into IWP remains underexplored. Furthermore, there has been limited investigation of this relationship within the context of higher education, which exhibits distinct characteristics in terms of autonomy, academic identification, and expectations of innovation compared to corporate environments (Raisch & Krakowski, 2021).

Consequently, this research aims to bridge this gap by proposing and empirically investigating an integrative Strategic HRM framework that connects Digital HRM Capability, Digital Psychological Safety Climate, AI Readiness, and Innovative Work Performance among university lecturers. By conceptualizing AI readiness as an intermediary micro-foundation capability, this research aspires to enrich the strategic HRM literature and elucidate the conditions under which digital HRM practices may foster innovative practices within academic institutions. The findings are anticipated to provide valuable insights for university administrators and policymakers in formulating digital HRM strategies that effectively leverage cutting-edge technology while nurturing human resource capabilities, readiness, and innovation capacity in the digital age.

## RESEARCH METHOD

### Research Design

This study used a quantitative explanatory research design with a cross-sectional survey approach. This explanatory design is applicable because the purpose is to examine the causal relationships between latent constructs relating to digital HRM, AI readiness, digital psychological safety, and innovative work performance in lecturers. For this study, we used a cross-sectional design, because institutional digital HR practices were relatively stable within the observed period and to assess perceptions of lecturers across institutions of higher education at a single point in time. This design is consistent with previous empirical work in digital HRM and innovation behavior, particularly in higher education settings. This study builds on ability–motivation–opportunity (AMO) theory and socio-technical systems theory as it introduces digital HRM capability as an organizational resource that influences psychological climate and individual AI readiness impacting innovative work performance.

### Population and Sample

The population of this study was lecturers within a variety of Indonesian higher education institutions, including public and private university educators who have adopted digital HR systems. These could be the e-performance appraisal systems, the digital learning management systems for staff development, or the HR solutions that incorporate artificial intelligence (AI) as HR machinery or HR systems. Lecturers were chosen as the subject of the empirical study as they are at a special place among higher education institutions. As well as functioning as educators and researchers, lecturers are knowledge workers who constantly produce and transmit knowledge. Meanwhile, they are active users of institutional technologies and frequently play an innovation role that adapts and shapes ongoing technological change in their organizations. Lecturers in this regard are a suitable population for investigating the impact of digital HRM and AI-supported systems on work-related outcomes. The sample will be aimed at 250 to 400 participants. This measurement range is considered to be enough for Structural Equation Modeling (SEM) analysis. Methodologically, this number corresponds to the generic SEM number of five to ten respondents for each estimated parameter in the model. Moreover, it is generally recommended that a sample in this range is used to guarantee stability and power in the model, especially when the research model also includes mediation of the variables. This research uses a stratified purposive sampling process to choose the respondents. Stratification is performed that will be inclusive of all institutional contexts. More specifically, the population is split according to two important criteria: the type of higher education institution (public vs private universities), and the level of digital HR implementation of the institution (basic digitalization or advanced AI-enhanced HR systems). It is within these strata that purposive sampling methods are employed to guarantee that the sample of respondents are relevant for the research’s objectives. Only lecturers who worked at their institutions for a minimum of one year are enrolled, since this time frame will be a way of ensuring that the lecturers will have a good experience of the institutional systems and practices. Furthermore, respondents should have been accustomed to or at least have used digital HR platforms adopted by any institutions they surveyed. Employing this sampling methodology, the study seeks to ensure that the data collected accurately reflects a diverse pool of lecturers across different institutional environments while maintaining relevance to the ongoing study on digital HRM practices and the outcomes of AI in higher education.

**Measurement of Variables**

All constructs are measured on a five-point Likert scale, 1 = strongly disagree, 5 = strongly agree. Measurement items have been adapted from existing literature and contextualized to Indonesian higher education. Expert validation and pilot testing of the instrument are planned before full implementation.

**Table 1.** Measurement of Variables

| Variable | Role in Model | Conceptual Definition | Dimensions / Indicators | Key References |
|---|---|---|---|---|
| Digital HRM Capability (DHRC) | Independent Variable | The organization's ability to design, integrate, and utilize digital and AI-enabled HR systems to enhance employee capability, motivation, and opportunity in performing work. | 1. Digital performance evaluation clarity<br>2. Availability of AI-based training programs<br>3. Accessibility of digital feedback mechanisms<br>4. Integration of HR digital systems across functions | Vrontis et al. (2022) |
| Digital Psychological Safety Climate (DPSC) | Mediating Variable | Shared perceptions among lecturers that the work environment supports experimentation, learning, and risk-taking in digital and AI-based work contexts without fear of negative consequences. | 1. Institutional support for digital experimentation<br>2. Tolerance for technological errors and learning failures<br>3. Leadership encouragement for AI utilization | Newman et al. (2017); Frazier et al. (2017) |
| AI Readiness (AIR) | Mediating Variable | An individual's preparedness to adopt, use, and adapt to AI technologies, encompassing competence, confidence, learning orientation, and positive attitudes toward AI. | 1. AI competence 2. AI self-efficacy 3. Learning agility 4. Positive AI orientation | Venkatesh et al. (2012); Jarrahi (2018); Pillai et al. (2020) |
| Innovative Work Performance (IWP) | Dependent Variable | Individual behaviors directed toward the generation, promotion, and implementation of novel ideas, processes, and digital solutions in academic work. | 1. Idea generation 2. Process innovation<br>3. Technology-based service improvement<br>4. Adaptability to digital systems | De Jong & Den Hartog (2010); Messmann & Mulder (2012) |

Source: Adapted from the respective references as listed in the Key References column. Measurement items were contextualized to the Indonesian higher education setting

## RESULTS AND DISCUSSION

**Table 2.** Descriptive Statistics Result

| Variable | Indicator | Mean | SD | Median | Min | Max |
|---|---|---|---|---|---|---|
| Digital HRM Capability | | **4.35** | **0,51** | **4,00** | **3,00** | **5,00** |
| 1 | DHRC1 | 4,50 | 0,50 | 4,50 | 4,00 | 5,00 |
| 2 | DHRC2 | 4,30 | 0,46 | 4,00 | 4,00 | 5,00 |
| 3 | DHRC3 | 4,16 | 0,52 | 4,00 | 3,00 | 5,00 |
| 4 | DHRC4 | 4,43 | 0,50 | 4,00 | 4,00 | 5,00 |
| Digital Psychological Safety Climate | | **4.17** | **0,57** | **4,00** | **3,00** | **5,00** |
| 1 | DPSC1 | 4,20 | 0,54 | 4,00 | 3,00 | 5,00 |
| 2 | DPSC2 | 3,82 | 0,43 | 4,00 | 3,00 | 5,00 |
| 3 | DPSC3 | 4,50 | 0,50 | 4,50 | 4,00 | 5,00 |
| AI Readiness | | **4.25** | **0,54** | **4,00** | **3,00** | **5,00** |
| 1 | AIR1 | 3,90 | 0,48 | 4,00 | 3,00 | 5,00 |
| 2 | AIR2 | 4,39 | 0,56 | 4,00 | 3,00 | 5,00 |
| 3 | AIR3 | 4,46 | 0,50 | 4,00 | 4,00 | 5,00 |
| 4 | AIR4 | 4,23 | 0,42 | 4,00 | 4,00 | 5,00 |
| Innovative Work Performance | | **4.40** | **0,51** | **4,00** | **3,00** | **5,00** |
| 1 | IWP1 | 4,43 | 0,50 | 4,00 | 4,00 | 5,00 |
| 2 | IWP2 | 4,43 | 0,50 | 4,00 | 4,00 | 5,00 |
| 3 | IWP3 | 4,50 | 0,50 | 4,50 | 4,00 | 5,00 |
| 4 | IWP4 | 4,25 | 0,51 | 4,00 | 3,00 | 5,00 |

Source: Primary data processed, 2025

According to the findings in Table 2, every research measurement variable has very high mean value (approximately more than 4.00) on a 5.00 scale. Result: From digital human resource management ability to innovative work effort, respondents report very favourable attitude towards all aspects analyzed in this research. Innovative Work Performance obtained the highest average of 4.40, determined primarily by indicator IWP3 with a mean level of 4.50. This high score signifies that the environment that is examined in this study has successfully stimulated lecturers' innovative behaviors effectively. On the other side, the Digital HRM Capability follows with an average score of 4.35. Meanwhile, the indicator DHRC1 (mean value 4.50) emerges as the most dominant item in the same variable, which confirms that the organization's digital capability in HR management is already highly developed and well recognized by lecturers.

Additionally, the AI Readiness variable shows an average score of 4.25, with indicator AIR3 (mean value of 4.46) emerging as its strongest element. This illustrates that respondents show a strong level of both mental and technical readiness to adopt artificial intelligence technologies. In contrast, Digital Psychological Safety Climate records an average value of 4.17. Although this score is still considered high, indicator DPSC2 has the lowest mean among all indicators, at 3.82. This finding provides an important note for organizations. While lecturers generally feel psychologically safe within the digital ecosystem, there is still room for improvement in certain aspects of the psychological safety climate so that they can feel fully free from social risk when experimenting with new technologies. The consistency of the relatively small standard deviation (SD) values across all variables—ranging from 0.51 to 0.57—indicates that respondents' answers tend to be homogeneous, suggesting that there is no extreme diversity of opinions among them.

**Table 3.** Validity and Reliability Result

| Variable | Indicator | Loading Factor | Cronbach's Alpha | CR | AVE |
|---|---|---|---|---|---|
| **Digital HRM Capability** | | | **0,866** | **0,909** | **0,715** |
| 1 | DHRC1 | 0,916 | | | |
| 2 | DHRC2 | 0,797 | | | |
| 3 | DHRC3 | 0,771 | | | |
| 4 | DHRC4 | 0,889 | | | |
| **Digital Psychological Safety Climate** | | | **0,732** | **0,844** | **0,644** |
| 1 | DPSC1 | 0,785 | | | |
| 2 | DPSC2 | 0,735 | | | |
| 3 | DPSC3 | 0,881 | | | |
| **AI Readiness** | | | **0,822** | **0,882** | **0,653** |
| 1 | AIR1 | 0,733 | | | |
| 2 | AIR2 | 0,867 | | | |
| 3 | AIR3 | 0,842 | | | |
| 4 | AIR4 | 0,782 | | | |
| **Innovative Work Performance** | | | **0,884** | **0,921** | **0,746** |
| 1 | IWP1 | 0,924 | | | |
| 2 | IWP2 | 0,873 | | | |
| 3 | IWP3 | 0,911 | | | |
| 4 | IWP4 | 0,732 | | | |

Source: SEM analysis using SmartPLS, 2025

Table 3 shows that all variables in the current study meet the test of very good convergent validity because the Average Variance Extracted (AVE) of each of the variables exceeds the minimum limit of 0.50. The highest AVE value of 0.746 is obtained for the Innovative Work Performance, followed by Digital HRM Capability (0.715), AI Readiness (0.653), and Digital Psychological Safety Climate (0.644). Further, all the indicators have loading factor values well above the desired threshold value of 0.70. The indicator IWP1 (0.924) and DHRC1 (0.916) also indicate the highest loading values. These results show that each questionnaire question item accurately reflects and measures the intended latent variables in the research model.

Regarding the internal consistency, the data from the reliability test confirms the reliability and stability of the instruments applied in this study. This is indicated by the Cronbach's Alpha and Composite Reliability (CR) values, which collectively exceed the recommended cut-off of 0.70. In particular, the Innovative Work Performance variable shows the highest level of reliability, with Composite Reliability (CR) = 0.921 and Cronbach's Alpha = 0.884. Other variables also have very high reliability scores, including Digital HRM Capability (CR: 0.909), AI Readiness (CR: 0.882), and Digital Psychological Safety Climate

(CR: 0.844). Accordingly, all the obtained data in this research show a high level of reliability, ensuring that subsequent analyses can be termed statistically robust and dependable.

**Table 4.** Discriminant Validity (Cross Loading)

| | AI Readiness | DHRC | DPSC | Innovative Work Performance |
|---|---|---|---|---|
| AIR1 | **0,733** | 0,546 | 0,599 | 0,566 |
| AIR2 | **0,888** | 0,867 | 0,712 | 0,883 |
| AIR3 | **0,842** | 0,660 | 0,821 | 0,835 |
| AIR4 | **0,782** | 0,596 | 0,626 | 0,701 |
| DHRC1 | 0,801 | **0,916** | 0,770 | 0,907 |
| DHRC2 | 0,651 | **0,797** | 0,593 | 0,669 |
| DHRC3 | 0,667 | **0,771** | 0,459 | 0,626 |
| DHRC4 | 0,736 | **0,889** | 0,592 | 0,802 |
| DPSC1 | 0,675 | 0,427 | **0,785** | 0,599 |
| DPSC2 | 0,461 | 0,358 | **0,735** | 0,480 |
| DPSC3 | 0,849 | 0,831 | **0,911** | 0,881 |
| IWP1 | 0,843 | 0,901 | 0,760 | **0,924** |
| IWP2 | 0,799 | 0,813 | 0,703 | **0,873** |
| IWP3 | 0,849 | 0,831 | 0,881 | **0,911** |
| IWP4 | 0,732 | 0,515 | 0,641 | **0,756** |

Source: SmartPLS 4 output, 2025

The findings of the Discriminant Validity test calculated in Table 4 based on cross-loading values show that each indicator of the present research exhibits stronger correlation with its latent variable than it does with other variables. As an example, DHRC1 shows a loading value of 0.916 on the Digital HRM Capability variable, which is significantly stronger and is significantly greater than with AI Readiness (0.801), Digital Psychological Safety Climate (0.770), or Innovative Work Performance (0.907). A consistent pattern is also observed across other variables. For example, IWP1 hits the Innovative Work Performance scale with a strength of 0.924, which means the indicator correlates most strongly with its target construct. These results indicate that overall, each construct in the model is conceptually different and empirically different from the others. That is, the constructs have little to no overlap, which proves that the model is fit for further hypothesis testing on the basis of the required discriminant validity.

**Table 5.** Hypothesis Testing Direct and Indirect Effect

| Hypothesis | | Original sample (O) | T statistics (\|O/STDEV\|) | P values | Conclusion |
|---|---|---|---|---|---|
| 1 | Digital HRM Capability positively influences AI Readiness | 0,473 | 17,839 | 0,000 | Accepted |
| 2 | Digital Psychological Safety Climate positively influences AI Readiness | 0,518 | 18,883 | 0,000 | Accepted |

| | | | | | |
|---|---|---|---|---|---|
| 3 | AI Readiness positively influences Innovative Work Performance | 0,420 | 9,601 | 0,000 | Accepted |
| 4 | AI Readiness mediates the relationship between Digital HRM Capability and Innovative Work Performance | 0,199 | 9,893 | 0,008 | Accepted |
| 5 | AI Readiness mediates the relationship between Digital Psychological Safety Climate and Innovative Work Performance | 0,217 | 7,591 | 0,008 | Accepted |

Source: SEM bootstrapping results, 2025

**Direct Effects**.

1. Hypothesis 1: The Influence of Digital HRM Capability on AI Readiness. The test results show that Digital HRM Capability positively and significantly influences AI Readiness with an Original Sample value of 0.473. This is confirmed by a very high T-statistics value of 17.839 (greater than the threshold = 1.96) and P-value = 0.000. Our results suggest that greater digital human resource management power of an organization correlates to greater lecturers' readiness to adopt and use artificial intelligence technologies on their job.
2. Hypothesis 2: Digital Psychological Safety Climate impacts AI readiness. From the data analysis, it is found out that Digital Psychological Safety Climate has a significant (path coefficient= 0.518) and positive effect on AI Readiness. Here the hypothesis is wholly validated: T-statistics = 18.883; P-value = 0.000. The findings demonstrate that having a work environment that fosters psychological safety within a digital economy is important for lecturers to embrace new technologies with the assurance of avoiding failure or judgment.
3. Hypothesis 3: The Influence of AI Readiness on Innovative Work Performance. AI readiness is also positively related to Innovative Work Performance, Original Sample 0.420. This relationship is significant statistically, with the computed threshold being 9.601 and the p-value equal to 0.000. These finding, therefore, show us an empirical observation that when lecturers are competent and confident to cope with AI technology, to a degree, they are more innovative in their actions in the fulfilment of organizational tasks. (4.2) indirect effects (Mediation Effects).
4. Hypothesis 4: The Mediating effect of AI Readiness of Digital HRM Capability on Innovative Work Performance of New Innovative HR in HCM. The indirect effect analysis yielded results: AI Readiness significantly mediates the relationship between Digital HRM Capability and Innovative Work Performance with original sample value of 0.199. The data indicate that this hypothesis is accepted as T-statistics value is 9.893 which equals P-value of 0.008. So, this indicates that HRM capabilities through digital means not only have a direct influence on innovative work performance, they also promote innovative work performance because of the very first effect of the enhanced technological readiness lecturers have to introduce AI technologies into their work.

5. Hypothesis 5: The mediating role of AI Readiness between the digital psychological safety climate and the innovation work performance. The final hypothesis is also agreed with, in that AI Readiness mediates the effect between Digital Psychological Safety Climate and Innovative Work Performance (0.217). This is consistent with a T-statistics of 7.591 and P-value of 0.008. The results show that creating a digital psychological safety climate first develops lecturers' AI readiness, and subsequently enhances their overall innovative work performance.

**Table 6.** R-Square Test

| | R-square | R-square adjusted |
|---|---|---|
| AI Readiness | 0,846 | 0,845 |
| Innovative Work Performance | 0,935 | 0,935 |

Source: PLS-SEM analysis, 2025

According to Table 6 (R-Square Test) data, the research model has a very high explanatory power for the dependent variables. The R-square value of AI Readiness was 0.846, which means that 84.6% of the variation in lecturers' readiness to adopt artificial intelligence can be accounted for by the variables Digital HRM Capability and Digital Psychological Safety Climate. More importantly, the R-square value for Innovative Work Performance is 0.935, which means the model can explain 93.5% of the variation in lecturers' innovative work performance. These are extremely high values in terms of social science research, indicating that the variables in this model are significantly influential and relevant determinants of the general performance outcome of innovation in organizations.

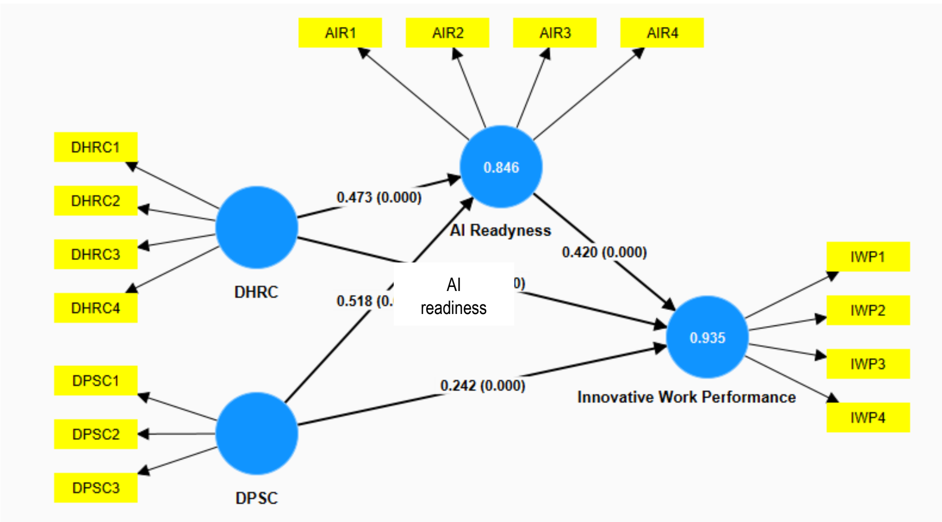


**Figure 1.** Bootstrapping Model
Source: SmartPLS 4 bootstrapping output, 2025

**Table 7. Q-Square Test**

| | SSO | SSE | Q² (=1-SSE/SSO) |
|---|---|---|---|
| AI Readiness | 1248,000 | 570,333 | 0,543 |
| Digital HRM Capability | 1248,000 | 1248,000 | |

| | SSO | SSE | Q² (=1-SSE/SSO) |
|---|---|---|---|
| Digital Psychological Safety Climate | 936,000 | 936,000 | |
| Innovative Work Performance | 1248,000 | 383,824 | 0,692 |

Source: Predictive relevance calculation (Stone-Geisser $Q^2$), 2025

The $Q^2$ test is performed to check the predictive power of independent variables of the model as against the dependent variables in an out-of-sample condition. The key criterion is to have the $Q^2 > 0$ for the model to be predictive. Further validation of the predictive validity of the model comes from findings of the Q-Square in Table 7. The AI Readiness variable generates a $Q^2$ score at 0.543, whereas the Innovative Work Performance variable returns a higher $Q^2$ at 0.692. With respect to the model evaluation criterion that $Q^2$ must be greater than zero ($Q^2 > 0$) to demonstrate predictive relevance, these outcomes clearly indicate that this research model had very high predictive accuracy. In short, it can predict future dependent variables' outcomes based on the independent variables included in the model in a highly significant, powerful manner.

The results of this study provide empirical support for the relationships among Digital HRM Capability, Digital Psychological Safety Climate, AI Readiness, and Innovative Work Performance. Overall, the findings indicate that digital transformation in higher education is not merely a technological shift but a complex process that involves organizational capabilities, psychological conditions, and individual readiness to engage with emerging technologies.

Hypothesis One proposed that Digital HRM Capability has a positive effect on AI Readiness, and the results show that this relationship is very strong. This finding highlights the importance of digital HR systems in preparing lecturers to work with technologies such as artificial intelligence. Digital HRM practices, including online training platforms, digital performance management systems, and AI-supported talent development programs, create an integrated infrastructure that supports continuous learning and skill development. In higher education institutions, these systems allow lecturers to access AI-related training, participate in digital upskilling programs, and gradually increase their confidence in using intelligent technologies.

From the perspective of Dynamic Capability Theory, Digital HRM Capability functions as an organizational mechanism that allows lecturers to sense technological opportunities and develop the competencies needed to respond to them. Therefore, strong digital HR systems not only modernize administrative processes but also play a strategic role in developing the workforce capabilities required for the AI-driven future of academia.

The second hypothesis examined the influence of Digital Psychological Safety Climate on AI Readiness and revealed a positive and significant relationship. This finding emphasizes the importance of psychological conditions in shaping lecturers' responses to technological change. In knowledge-intensive environments such as universities, the introduction of AI technologies can sometimes generate anxiety, including fears related to performance evaluation or concerns about professional relevance. When they perceive the digital workplace as a safe environment for experimentation, they become more willing to explore unfamiliar technologies.

A psychologically safe climate communicates that mistakes made while experimenting with digital tools are part of the learning process rather than signs of incompetence. As a result, lecturers become more open to using AI-powered teaching tools, research analytics platforms, and automated systems. This finding reinforces the idea that digital transformation cannot be achieved solely through technological investment; it also requires a supportive psychological environment that encourages learning, exploration, and adaptation.

Hypothesis Three proposed that AI Readiness positively influences Innovative Work Performance, and the empirical results strongly support this relationship. These findings suggest that the ability to effectively interact with AI technologies leads to higher levels of innovation in work processes. Lecturers who possess strong AI readiness are more likely to integrate intelligent tools into multiple aspects of academic work, including teaching design, data analysis, research collaboration, and knowledge dissemination.

For example, AI-based data analysis tools can accelerate research activities, while AI-supported learning platforms can provide more personalized learning experiences for students. Such applications encourage lecturers to experiment with new teaching methods and research approaches, thereby increasing their creative output. In this sense, AI readiness functions as a micro-level capability that converts technological potential into actual innovative behavior.

Beyond these direct relationships, the mediation analysis provides deeper insight into how organizational factors influence innovation. The fourth hypothesis revealed that AI Readiness mediates the relationship between Digital HRM Capability and Innovative Work Performance. This result suggests that digital HR systems enhance innovation primarily by strengthening lecturers' technological readiness rather than influencing innovative behavior directly.

Digital HR initiatives such as AI training programs, digital mentoring platforms, and competency analytics systems enable lecturers to develop both the knowledge and confidence needed to apply AI tools in their work. Once this readiness is established, lecturers are better able to transform digital resources into innovative practices in teaching and research. This finding aligns with strategic HRM perspectives, which emphasize that HR systems influence organizational performance indirectly through the development of human capital capabilities.

Similarly, the fifth hypothesis confirmed that AI Readiness mediates the relationship between Digital Psychological Safety Climate and Innovative Work Performance. This finding suggests that psychological safety alone does not automatically lead to innovation. Instead, psychological safety creates the conditions that encourage lecturers to build readiness toward new technologies, which ultimately drives innovative performance.

When lecturers feel safe experimenting with digital tools, they are more likely to explore AI applications, participate in digital training programs, and share technological knowledge with colleagues. Over time, this process strengthens their AI readiness, which subsequently enhances their innovative contributions within the institution. In this way, psychological safety acts as a catalyst for capability development, while AI readiness becomes the mechanism through which innovation is realized.

Taken together, these findings reveal a clear pathway of digital transformation within higher education institutions. Digital HRM Capability provides the structural foundation for developing digital competencies, Digital Psychological Safety Climate creates a supportive environment for experimentation, AI Readiness represents the individual capability that enables effective technology utilization, and Innovative Work Performance emerges as the final behavioral outcome.

Another important insight from this study lies in the high explanatory power of the research model. The large R-square values for AI Readiness and Innovative Work Performance indicate that digital capability, psychological climate, and individual readiness together explain a substantial portion of the factors that drive innovation in academic settings. This suggests that universities seeking to enhance innovation should focus not only on adopting new technologies but also on implementing human-centered digital transformation strategies.

Such strategies include strengthening digital HR systems, fostering psychologically safe digital environments, and systematically developing AI readiness among academic staff. Ultimately, the findings highlight that innovation in the age of artificial intelligence is fundamentally human-centered. While organizations may invest heavily in advanced technologies, true innovation emerges from individuals who learn how to use those technologies creatively and effectively. By reinforcing digital HR capabilities, nurturing psychological safety, and building AI readiness, higher education institutions can create an ecosystem in which technological advancement and human innovation mutually reinforce one another.

## CONCLUSION

The study provides valuable insights into the relationships between Digital HRM Capability, Digital Psychological Safety Climate, AI Readiness, and Innovative Work Performance. However, several areas remain open for further investigation. Future research could extend this model to other knowledge-intensive industries such as technology, healthcare, or financial services. Examining the model in different organizational contexts would help determine whether the relationships identified in this study are consistent across sectors or shaped by industry-specific conditions. Future studies may also explore additional variables that could further explain how digital HR systems influence employee outcomes. Factors such as digital leadership, organizational learning culture, knowledge sharing, or digital resilience may function as moderating or mediating variables in the development of AI readiness and innovation. Since this study applied a cross-sectional design, future research could also employ longitudinal approaches to observe how AI readiness and innovative work performance evolve over time as organizations increasingly adopt AI technologies. In addition, mixed-method approaches that combine quantitative analysis with qualitative methods such as interviews or case studies could provide richer insights into how employees experience digital transformation and AI adoption in their daily work. Thus, this study demonstrates that digital transformation in higher education can lead to innovative work performance, but not through technological infrastructure alone. The findings identify Digital HRM Capability and Digital Psychological Safety Climate as key factors that significantly enhance lecturers' AI Readiness, which in turn drives higher Innovative Work Performance. AI Readiness serves as a critical mediating mechanism, meaning that organizational capabilities and psychological support primarily influence innovation by strengthening employees' competence, confidence, and motivation to work with AI technologies. Consequently, universities should adopt a human-centered approach: invest in integrated digital HR platforms, cultivate a psychologically safe environment that encourages experimentation and tolerates mistakes, and systematically develop AI readiness through training programs, literacy workshops, and collaborative projects. Without ready and willing lecturers, even the most advanced digital infrastructure will fail to generate meaningful innovation. Thus, successful digital transformation requires a balanced strategy that aligns organizational systems, psychological climate, and individual technological capabilities.

## REFERENCES


Anderson, N., Potočnik, K., & Zhou, J. (2014). Innovation and creativity in organizations: A state-of-the-science review, prospective commentary, and guiding framework. *Journal of Management, 40*(5), 1297–1333.

Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., & Venkatraman, N. (2013). Digital business strategy: Toward a next generation of insights. *MIS Quarterly, 37*(2), 471–482.

Bondarouk, T., & Ruël, H. (2013). The strategic value of e-HRM: Results from an exploratory study in a governmental organization. *International Journal of Human Resource Management*.

Bondarouk, T., Parry, E., & Furtmueller, E. (2017). Electronic HRM: Four decades of research on adoption and consequences. *International Journal of Human Resource Management*.

Burton, S. L. (2025). Navigating Digital Transformation: Integrating Technological, Organizational, and Environmental Factors. In *Digital Competence in Agile and Hierarchical Organizations* (pp. 170–187). Routledge.

De Jong, J. P., & Den Hartog, D. N. (2010). Measuring innovative work behaviour. *Creativity and Innovation Management, 19*(1), 23–36.

Felin, T., Foss, N. J., Heimeriks, K. H., & Madsen, T. L. (2012). Microfoundations of routines and capabilities: Individuals, processes, and structure. *Journal of Management Studies, 49*(8), 1351–1374.

Frazier, M. L., Fainshmidt, S., Klinger, R. L., Pezeshkan, A., & Vracheva, V. (2017). Psychological safety: A meta-analytic review and extension. *Personnel Psychology, 70*(1), 113–165.

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human–AI symbiosis in organizational decision making. *Business Horizons, 61*(4), 577–586.

Jiang, K., Lepak, D., Hu, J., & Baer, J. (2012). How does human resource management influence organizational outcomes? A meta-analytic investigation of mediating mechanisms. *Academy of Management Journal, 55*(6), 1264–1294.

Jöhnk, J., Weißert, M., & Wyrtki, K. (2021). Ready or not, AI comes—An interview study of organizational AI readiness factors. *Business & Information Systems Engineering, 63*(1), 5–20.

Messmann, G., & Mulder, R. H. (2012). Development of a measurement instrument for innovative work behaviour as a dynamic and context-bound construct. *Human Resource Development International, 15*(1), 43–59.

Newman, A., Donohue, R., & Eva, N. (2017). Psychological safety: A systematic review of the literature. *Human Resource Management Review, 27*(3), 521–535.

Pillai, R., Sivathanu, B., & Dwivedi, Y. K. (2020). Adoption of artificial intelligence (AI) for talent acquisition in organizations. *International Journal of Information Management*.

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review, 46*(1), 192–210.

Ramadhani, W., Khuzaini, K., & Shaddiq, S. (2024). Resistance to change: Human resources issues in the implementation of Industry 4.0 technology. *Proceeding: Islamic University of Kalimantan*.

Selwyn, N. (2019). *Should robots replace teachers? AI and the future of education*. Polity Press.

Shahid, S., Kaur, K., Mohyuddin, S. M., Prikshat, V., & Patel, P. (2025). Revolutionizing

HRM: a review of human-robot collaboration in HRM functions and the imperative of change readiness. *Business Process Management Journal*, *31*(7), 2892–2928.

Strohmeier, S. (2020). Digital human resource management: A conceptual clarification. *German Journal of Human Resource Management*, *34*(3), 345–365.

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*(1), 157–482.

Vrontis, D., Christofi, M., Pereira, V., Tarba, S., Makrides, A., & Trichina, E. (2022). Artificial intelligence, robotics, advanced technologies and human resource management: A systematic review. *International Journal of Human Resource Management*.

WANG, T. (2025). *The impact of AI usage on employee work outcomes: The mediating roles of personal control and job insecurity and the moderating role of AI trust*.

Wu, T.-J., Liang, Y., & Wang, Y. (2024). The buffering role of workplace mindfulness: How job insecurity of human-artificial intelligence collaboration impacts employees' work–life-related outcomes. *Journal of Business and Psychology*, *39*(6), 1395–1411.