

When does digital readiness matter more for AI integration? A nonlinear marginal-effects analysis

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Abstract. This study examines the nonlinear association between digital management readiness and functional artificial intelligence (AI) integration, with particular attention to changes in marginal associations across the readiness continuum and heterogeneity among enterprise-size classes. Digital readiness is operationalized through the multidimensional Digital Management Readiness Index (DMRI), encompassing digital infrastructure, digital management, human capital, and data and security capabilities. Functional AI Integration Index (FAII) captures the extent of AI use across enterprise functions. The empirical analysis applies generalized additive models and marginal-effects estimation to identify nonlinearities without imposing predefined readiness thresholds. The results demonstrate a nonlinear relationship between DMRI and FAII. The nonlinear specification explains 88.1% of the variation in functional AI integration, compared with 78.7% under the linear model. The marginal association increases from 7.477 at the 5th percentile of DMRI to 72.079 at the 95th percentile,

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indicating an approximately 9.6-fold increase across the observed readiness continuum. No evidence of saturation is identified within the examined range. Enterprise-size analysis further indicates that differences among small, medium-sized, and large enterprises are largely associated with their unequal positioning along the readiness continuum. Size-specific nonlinear functions provide no material improvement over a common readiness trajectory. The findings establish digital readiness as a continuous capability configuration whose relevance for AI integration intensifies as digital capabilities accumulate. The study contributes a nonlinear, capability-position perspective to the literature on enterprise AI integration and suggests that readiness-based segmentation can complement conventional firm-size criteria in digitalization and AI-support policies.

Keywords: artificial intelligence integration, digital management readiness, digital capabilities, nonlinear relationship, marginal effects; enterprise size, digital transformation, Digital Management Readiness Index.

JEL Classification: O33, M15, C14.

1. INTRODUCTION

Artificial intelligence (AI) has become an increasingly important component of enterprise digital transformation, extending its influence across production, marketing, customer relations, data analytics, cybersecurity, administrative processes, and managerial decision-making. The growing functional diversification of AI applications has intensified scholarly interest in the organizational conditions that enable enterprises to move from technological adoption to systematic AI integration. Recent research increasingly associates this process with the broader digital capabilities of organizations, including digital platforms, analytical and integration capabilities, human capital, managerial competencies, and established ICT systems (Alaskar, 2025; Aljehani et al., 2026; Amjad & Shang, 2026; Murad et al., 2026; Meidute-Kavaliauskiene et al., 2026).

The growing organizational relevance of AI is also reflected in its expanding application across consumer-facing and managerial activities. Dias et al. (2023) show that firms increasingly recognize the business relevance and benefits of AI, while Prieto-Gutierrez et al. (2023) document the rapid expansion of AI-related research across the social sciences. At the same time, the diffusion of AI forms part of a broader technological transition associated with Industry 4.0 and the emerging Industry 5.0 paradigm (Michulek & Gajanova, 2023).

The increasing dependence of AI integration on the broader digital environment has brought digital readiness to the forefront of contemporary research. From an organizational perspective, digital readiness reflects the capacity of enterprises to mobilize technological, managerial, human, and data-related resources in support of digitally enabled activities. Its relevance becomes particularly pronounced in the context of AI, where effective integration frequently requires interaction among several complementary digital capabilities. The existing literature consequently provides substantial evidence linking digital development, organizational capabilities, and related enabling conditions to the adoption and integration of AI.

At the same time, the literature offers different interpretations of the role played by accumulated digital capabilities. One stream of research emphasizes their enabling and reinforcing properties, suggesting that stronger digital foundations increase the capacity of organizations to exploit advanced technologies. Another stream draws attention to persistent implementation barriers and the organizational, institutional, and governance conditions that may restrict the conversion of technological capacity into effective AI use.

Evidence of unequal AI integration across institutional contexts (Adeniranye et al., 2026), implementation barriers separating AI innovation from operational adoption (Olaye & Seixas, 2023), and structural discrepancies between AI capabilities and their incorporation into decision processes (Dadelo, 2026) demonstrates that higher technological capacity does not necessarily correspond to proportionally greater AI integration.

This divergence points to an important question concerning the functional form of the relationship between digital readiness and AI integration. Much of the existing empirical evidence evaluates whether digital capabilities, competencies, infrastructure, or organizational conditions are associated with AI-related outcomes. Such evidence is valuable for establishing the general relevance of digital readiness; however, the predominance of average relationships leaves the variation of this association across different readiness levels comparatively underexplored. A statistically significant average association does not establish that an equivalent improvement in digital readiness has the same relevance for enterprises located at different points of the readiness distribution.

This issue is particularly important because digital readiness represents a continuum of accumulated organizational capabilities. The association with AI integration may remain approximately constant across this continuum, strengthen over particular readiness ranges, weaken as enterprises advance digitally, or follow a more complex nonlinear trajectory. Each configuration implies a different interpretation of how digital capabilities are related to enterprise AI integration. Consequently, establishing a positive average relationship alone provides limited information about the readiness levels at which additional digital capacity is associated with the greatest differences in functional AI integration.

Enterprise size introduces a further dimension to this problem. Small, medium-sized, and large enterprises differ in their resources, organizational structures, technological capacities, and patterns of digitalization. Size-related disparities are therefore commonly interpreted as evidence of heterogeneous technological adoption and transformation. Yet enterprise size may also be associated with systematically different positions along the digital-readiness distribution. Under a nonlinear relationship, observed differences across enterprise-size classes may consequently capture genuine size-specific characteristics, differences in readiness positions, or a combination of both.

Despite substantial progress in identifying the technological, organizational, managerial, and human conditions associated with AI integration, the shape of the digital readiness–AI integration relationship remains insufficiently understood. Thus, it remains unclear whether a linear specification adequately represents the association between multidimensional digital readiness and functional AI integration. Besides, limited evidence exists on how the marginal strength of this association changes across the observed readiness continuum. Third, the extent to which enterprise-size heterogeneity reflects distinct readiness–AI relationships or differential positioning along a common readiness trajectory has yet to be established systematically.

The present study addresses these gaps through a nonlinear marginal-effects analysis of the relationship between digital management readiness and functional AI integration. Digital readiness is operationalized through the Digital Management Readiness Index (DMRI), which captures complementary dimensions of digital infrastructure, digital management, digital human capital, and data and security capabilities. Functional AI integration reflects the extent of AI use across enterprise activities. This framework permits an examination of the shape of the readiness–AI association, the variation of its marginal strength across the DMRI continuum, and its heterogeneity across enterprise-size classes.

The paper is organized as follows: Section 2 reviews the theoretical and empirical landscape concerning digital readiness, nonlinearities in AI integration, and enterprise-size heterogeneity. Section 3 presents the data, variable construction, DMRI methodology, and empirical strategy. Section 4 reports the empirical results, including tests of functional form, marginal-effects estimates across the readiness continuum, and

enterprise-size analyses. Section 5 discusses the findings and their theoretical and practical implications. Section 6 concludes the study, outlines its limitations, and identifies directions for further research.

2. LITERATURE REVIEW

2.1. Digital management readiness as a foundation for AI integration

The rapid diffusion of artificial intelligence across business functions has shifted scholarly attention from the question of whether firms adopt digital technologies to the more complex issue of whether organizations possess the capabilities required to integrate AI effectively into established managerial and operational processes. AI integration differs from the isolated acquisition of a digital tool because its effective use requires complementary technological, organizational, human, and managerial resources. Consequently, the emerging literature increasingly treats AI implementation as part of a broader digital transformation trajectory in which pre-existing digital capabilities determine an organization's ability to absorb, configure, and exploit increasingly advanced technologies.

This perspective is consistent with the broader digital transformation literature, which conceptualizes technological change as a cumulative organizational capability-building process rather than a discrete investment decision. The past studies indicate that digital transformation is not limited to technological acquisition but extends to the redesign of organizational processes and the involvement of employees in digitally enabled change. Hernik et al. (2025), for example, demonstrate the importance of employee engagement and organizational support for the acceptance of digital transformation within business process management. Recent evidence demonstrates that the relationship between digital transformation and organizational outcomes is frequently transmitted through intermediate capabilities. Aljehani et al. (2026), for example, show that the effects of digital transformation in SMEs operate through AI and big-data analytical capability and process-integration capability. Their findings are particularly important because they indicate that digitalization alone does not automatically produce superior organizational outcomes; instead, firms require the ability to translate digital resources into analytical and integrated business processes. Moreover, the authors find differences between small and medium-large firms in the combinations of capabilities associated with governance performance, suggesting that the organizational context in which digital resources accumulate matters for their subsequent exploitation.

A similar capability-based interpretation emerges from Alaskar (2025), who examines the integration of AI and business analytics and demonstrates that integration capabilities and digital platforms constitute important mechanisms through which AI-enabled analytics contribute to data-driven and technological innovation. Drawing on the dynamic capability view and organizational information processing theory, the study moves beyond a technology-availability explanation and emphasizes the organizational mechanisms that allow firms to combine AI, analytics, data, and digital platforms. This distinction is central to the concept of digital management readiness. A firm may have access to AI technologies but still be unable to deploy them effectively if its internal systems, data architecture, managerial processes, or integration capabilities are insufficiently developed.

Digital capabilities therefore represent an important complementary asset in AI-enabled transformation. Murad et al. (2026), drawing explicitly on dynamic capability theory, identify digital capabilities as an organizational condition that strengthens the contribution of knowledge integration to sustainable entrepreneurial outcomes in AI-driven transformation. Their operationalization of digital capabilities includes digital literacy, technological problem solving, skills development, and the ability to apply digital technologies to strategic and innovative activities. This formulation supports a

multidimensional understanding of readiness in which technological infrastructure constitutes only one component of a broader capacity to use digital technologies productively.

Human and managerial capabilities are equally important. Amjad and Shang (2026) demonstrate that the organizational consequences of AI strategy depend partly on digital leadership. Their study of organizations implementing AI initiatives finds that stronger digital leadership enhances the relationship between AI strategy and employees' perceived usefulness of AI tools, thereby strengthening downstream creative outcomes. Although the study focuses on employee creativity rather than AI adoption intensity, it reinforces the proposition that AI integration is embedded in a managerial environment: strategic intent must be supported by leaders capable of guiding technological adoption, developing employee acceptance, and aligning AI use with organizational goals. It should be noted that, Khalil and Alsenaidi (2024), for example, identify a set of digital competencies required for effective AI integration and emphasize continuous capability development and supporting infrastructure. Lu and Said (2025) similarly approach AI integration through the development of digital human capital, while Karakose et al. (2023) connect digital leadership to broader technology-integration processes. These studies broaden the interpretation of readiness beyond hardware and software and support the inclusion of human capital and managerial competence among the prerequisites for more advanced AI use.

However, the role of human capabilities appears more complex than a simple “more capability–more integration” relationship. Jiang and Meng (2025), using a three-wave study, find that digital mindset and AI sensemaking significantly predict AI integration, whereas digital teaching competence and trust in AI do not exhibit similarly consistent direct effects. This result is theoretically relevant for the present study because it suggests that individual dimensions of digital readiness may not translate mechanically into AI integration. Their usefulness may depend on how other organizational resources, perceptions, and complementary capabilities are configured.

Institutional and structural conditions also shape AI integration. Adeniranye et al. (2026) demonstrate substantial variation in AI integration across institutions and link this variation to differences in resources, geographic position, institutional history, networks, infrastructure, policy frameworks, and other structural conditions. Organizational type alone does not fully explain differences once these underlying characteristics are taken into account. Although the empirical setting is higher education, the result carries a broader implication for organizational AI research: observed differences between categories of organizations may reflect differences in their accumulated resource and capability positions rather than fundamentally distinct adoption mechanisms.

At the macro level, Meidute-Kavaliauskiene et al. (2026) likewise emphasize the interdependence of ICT integration, AI-related human capital, innovation capacity, digital trade intensity, and broader digital transformation. Their analysis of European countries demonstrates that digital and AI development should not be treated as isolated domains but as interconnected components of technological capacity. Such evidence is relevant for enterprise-level analysis because firms operate within digital ecosystems where access to ICT, skilled labour, data infrastructure, and advanced technological capabilities develops cumulatively and unevenly.

The broader digital ecosystem also continues to evolve through the emergence of new technology-enabled financial infrastructures and services. Research on digital currencies and FinTech similarly demonstrates how technological innovation expands the architecture of digitally mediated economic activity (Baltgailis et al., 2023).

The functional character of AI adoption further increases the importance of underlying digital readiness. AI is increasingly embedded in accounting, analytics, production, customer management, digital workplaces, security, and other business processes rather than being adopted as a single general-purpose organizational technology. Sampaio and Silva (2025), for instance, document the growing convergence of

digitalization, automation, AI, robotic process automation, blockchain, and intelligent decision support within accounting systems. This functional diversification is consistent with evidence from specific areas of enterprise digitalisation. E-commerce has become an important component of digital transformation and competitive positioning among SMEs (Kiselicki et al., 2022), while digital marketing strategies increasingly shape entrepreneurial and market-oriented business practices (AL-Shourah, 2024). The technological frontier of these processes continues to expand. Faruk et al. (2026), examining metaverse adoption among marketing professionals, show that the uptake of emerging digital technologies depends on perceived usefulness and ease of use as well as broader organizational and industry conditions, further illustrating that technology adoption is embedded in a wider configuration of enabling factors. Their bibliometric assessment shows that AI integration is becoming intertwined with the broader digital transformation of functional business systems rather than evolving independently of them. Comparable patterns are visible in studies of AI-enabled analytics and process integration (Aljehani et al., 2026), AI–business analytics integration (Alaskar, 2025), digital supply-chain and manufacturing applications (Alheet, 2026), and organizational AI employees (Wang & Zhang, 2026).

AI integration could itself reshape organizational processes after adoption. Wang and Zhang (2026) show that the integration of AI digital employees affects organizational adaptability through cross-boundary knowledge sharing and collective psychological safety. Their results further identify an accelerating marginal relationship between psychological safety and organizational adaptability, illustrating that relationships inside AI-intensive organizational systems need not be linear. Although this nonlinear relationship concerns an organizational mediator rather than digital readiness directly, it provides additional evidence that AI-related organizational effects may change in magnitude at different levels of enabling conditions.

Evidence from individual business applications likewise indicates that the organizational value of advanced digital technologies depends on how they are incorporated into existing decision and operational processes. Kolková and Ključnikov (2022), for instance, compare AI-based, statistical, hybrid, and practice-based forecasting approaches across SMEs and large enterprises, illustrating both the growing practical relevance of AI-enabled analytical tools and the importance of organizational context in their application.

The results of analyses showed that the advanced AI integration is unlikely to be independent of the digital capabilities accumulated by an organization. Technological infrastructure, data-management systems, digital business applications, integration capabilities, human digital skills, cybersecurity practices, managerial capabilities, and digital leadership together create the organizational environment in which AI could be embedded into business functions. Accordingly, digital readiness is better conceptualized as a multidimensional organizational state than as the possession of any single technology.

Most existing studies ask whether digital capabilities, digital transformation, leadership, infrastructure, or organizational readiness positively influence AI-related outcomes. Thus, they predominantly estimate average direct, indirect, or moderating effects. This analytical logic implicitly treats an additional unit of digital capability as having a broadly comparable value regardless of whether an organization is at a low, intermediate, or advanced level of readiness. The literature therefore provides evidence that digital readiness matters, but considerably less evidence regarding when along the readiness continuum it matters most.

At very low levels of digital readiness, improvements in individual capabilities may be insufficient because complementary infrastructure, skills, managerial systems, or data resources are still missing. Once a critical bundle of capabilities has been accumulated, additional readiness may enable firms to integrate AI across multiple business functions more rapidly. Conversely, among highly digitally mature firms, much of the feasible AI integration may already have occurred, causing additional improvements in readiness to generate progressively smaller marginal gains. Under either mechanism, the readiness–AI relationship would be nonlinear, and an average linear coefficient would conceal substantively important variation across the readiness distribution.

The available literature therefore motivates a shift from the conventional question of whether digital readiness facilitates AI adoption to a more precise question concerning the functional form of this relationship. Before examining where readiness produces its largest marginal contribution, it is first necessary to determine whether the association itself can reasonably be represented as linear across the observed readiness continuum.

RQ1. Is the association between digital management readiness and functional AI integration linear across the observed readiness continuum?

2.2. Beyond linearity: changing marginal effects of digital readiness

Establishing digital readiness as a prerequisite for AI integration does not necessarily imply that its contribution remains constant across all stages of digital development. Organizations at different positions on the readiness continuum face different technological constraints, implementation challenges, and opportunities for exploiting AI. Consequently, the same incremental improvement in digital readiness may have markedly different implications for AI integration depending on the organization's initial readiness level. This raises an issue that remains insufficiently addressed in the existing literature: not simply whether digital readiness matters, but whether its marginal importance changes as readiness accumulates.

Olaye and Seixas (2023), examining barriers to the translation and adoption of digital healthcare and AI technologies into clinical practice, identify a persistent gap between technological innovation and actual implementation. Their findings illustrate that the availability of advanced technologies is insufficient when organizational and implementation conditions required for their assimilation remain underdeveloped. The implication extends beyond healthcare: at low levels of readiness, improvements in isolated technological resources may generate limited organizational returns because other prerequisites continue to act as binding constraints.

A similar distinction between technological capability and its effective incorporation into organizational decision processes is developed by Dadelo (2026). By introducing the Decision Integration Deficit Index, the study explicitly distinguishes the predictive capacity of AI-driven digital health systems from their integration into actual decision-making structures. This distinction is conceptually relevant to functional AI integration because organizations can possess increasingly sophisticated digital and analytical capabilities without converting them proportionately into operational AI use. The existence of such an integration deficit implies that the transition from technological capacity to organizational application may depend on the maturity of the surrounding digital and decision architecture.

Jallali et al. (2026) conceptualize AI integration together with engagement and digital resilience within a multidimensional framework, indicating that successful AI use is embedded in a wider configuration of digital conditions rather than determined by technological availability alone. Likewise, Hoang (2025) emphasizes the role of e-leadership development in AI integration, while Küçükuncular and Ertugan (2025) connect sustainable AI integration with digital education, ethical integration, and empowerment. Although these studies originate from educational settings, their common implication is organizationally relevant: the effective integration of AI requires combinations of digital, human, managerial, and adaptive capacities whose importance may change as the surrounding digital environment develops.

Thus, the results of analysis allow to outline that at the lower end of the readiness continuum, organizations may still lack a minimum configuration of mutually supportive capabilities. Improvements in connectivity or cloud use, for example, may have limited implications for AI integration if firms simultaneously lack enterprise systems, analytical routines, ICT specialists, training, or adequate data-security practices. Under such conditions, readiness components function less as substitutes than as complements: weakness in one dimension can constrain the productive use of improvements in another.

The findings suggest a constraint-dominated lower segment of the readiness continuum. When multiple digital prerequisites remain below operationally useful levels, an incremental improvement in aggregate readiness may produce only a modest increase in functional AI integration. The relevant mechanism is not the absence of value in digitalization but the inability of individual improvements to generate their full potential while complementary constraints remain binding. In marginal terms, the readiness–AI slope may therefore be relatively weak at very low readiness levels.

As digital capabilities accumulate, however, this configuration may change. Once organizations possess a sufficiently broad digital foundation, individual improvements can reinforce rather than merely compensate for other capabilities. Data can circulate through integrated systems, digitally skilled employees can work with more sophisticated applications, security mechanisms can support data-intensive operations, and existing digital management technologies can provide organizational interfaces through which AI applications are deployed. The removal of successive bottlenecks may therefore increase the marginal association between readiness and functional AI integration.

Studies examining combinations of AI with other advanced digital technologies illustrate how such reinforcement can occur. Alnaser and Elmousalami (2025) analyze the benefits and challenges associated with AI-based digital-twin integration in construction, whereas Oleniacz et al. (2026) examine pathways involving LiDAR, IoT, and AI integration in digital-twin environments. These technologically focused studies concern specific applications rather than enterprise-level readiness, but they illustrate a broader pattern: advanced AI use increasingly emerges from combinations of mutually connected digital technologies rather than from isolated adoption.

The same logic can be observed in studies of digitally integrated economic processes. Wang et al. (2026) examine digital–real integration and identify AI as one of the mechanisms connecting digital transformation with energy productivity. Hou et al. (2026) similarly investigate digital–real integration in the context of urban green transition and explicitly consider the role of AI alongside innovation. Shankar and Sagar (2026), in turn, examine AI and blockchain as interconnected digital pathways supporting low-emission tourism and carbon-market integration. Despite substantial differences in their units of analysis, these studies demonstrate that AI increasingly operates as part of broader digital configurations.

This evidence is compatible with an activation or acceleration segment in which improvements in readiness become more strongly associated with AI integration. Once key digital prerequisites are jointly available, additional readiness can potentially be exploited across several organizational functions simultaneously. In this range, moving from one level of readiness to the next may produce a larger change in AI integration than an equivalent readiness increase among firms that remain constrained by missing foundational capabilities.

However, increasing marginal effects need not persist indefinitely. At advanced levels of digital readiness, the constraints on further AI integration may progressively shift away from basic digital capacity. Once core infrastructure, digital management systems, human capabilities, and data-security practices are well established, additional improvements in the same readiness dimensions may generate progressively smaller opportunities for extending AI use. Further integration may instead depend on factors that are not fully captured by general digital readiness, including regulation, ethical requirements, task suitability, organizational redesign, strategic priorities, and the economic viability of particular AI applications.

Several studies in the amalesed literature point toward such a transition in the nature of constraints. Seringa et al. (2026) emphasize ethical requirements associated with integrating digital biomarkers into AI systems, while Shehadeh et al. (2026) combine explainable AI with other emerging technologies, illustrating how advanced technological environments raise additional requirements concerning explainability and integration. At more mature stages, therefore, the principal constraint may no longer be whether an

organization possesses basic digital capacity but whether increasingly sophisticated AI applications can be appropriately governed and embedded.

Fathy et al. (2025) provide a further illustration of this transition by approaching cloud- and AI-driven solutions through strategic integration rather than technological adoption in isolation. Their framework highlights that advanced digital applications must ultimately be aligned with strategic objectives and organizational contexts. Similarly, emerging AI applications across smart agriculture (Narayan et al., 2025), infrastructure management (Alourani et al., 2026), and other digitally intensive environments demonstrate that as technological foundations become more advanced, integration increasingly involves coordination among multiple technologies and organizational processes rather than merely expanding access to individual digital tools.

These considerations suggest a third, maturity or saturation segment. Firms positioned at the upper end of the digital-readiness distribution may already possess most of the digital prerequisites required for feasible AI applications. Consequently, additional improvements in readiness may continue to support AI integration but produce smaller marginal changes than those observed during the transition from intermediate to advanced readiness. In this range, the readiness–AI curve would begin to flatten as other technological, organizational, strategic, and institutional constraints become relatively more important.

Taken together, the literature therefore allows three theoretically plausible mechanisms to be distinguished along the readiness continuum: constraint, activation, and saturation. These mechanisms provide a rationale for expecting the marginal association between digital management readiness and AI integration to vary rather than remain constant. Importantly, however, the available evidence does not establish that these mechanisms necessarily generate a particular functional form in enterprise-level data.

One possible configuration is an S-shaped trajectory in which the association is initially weak, strengthens across intermediate readiness levels, and subsequently flattens. Yet alternative patterns are equally plausible. Firms with very low readiness may obtain particularly large gains from basic digital improvements, producing initially strong but subsequently diminishing marginal effects. Alternatively, complementarities among digital capabilities may cause the marginal association to increase throughout most of the observed range. The existing literature therefore provides stronger grounds for expecting non-constancy than for imposing any specific nonlinear shape *ex ante*.

A threshold approach presupposes that the relationship changes at identifiable cut-off points and divides organizations into discrete regimes. A continuous nonlinear approach instead permits the slope of the readiness–AI relationship to evolve throughout the observed readiness distribution. For a multidimensional construct such as digital management readiness, the latter is theoretically attractive because organizational capabilities generally accumulate gradually rather than appearing simultaneously once an externally specified threshold is crossed.

The methodological implication is that a single linear coefficient may conceal substantively different relationships across the readiness continuum. Consider two firms whose DMRI values differ by the same amount. If one moves within a constraint-dominated range and the other within an activation range, the same increase in measured readiness may be associated with very different changes in functional AI integration. Similarly, an equivalent DMRI improvement among already highly ready firms may have a smaller association with additional AI integration if the relevant digital prerequisites have largely been satisfied.

This issue is not adequately resolved by dividing firms *ex ante* into arbitrary low-, medium-, and high-readiness categories. Such categorization imposes discontinuities on an inherently continuous construct and may conceal precisely the changes in slope that are of substantive interest. Estimating the relationship flexibly and deriving marginal effects across the observed DMRI distribution instead makes it possible to

determine where the readiness–AI association strengthens, where it reaches its greatest magnitude, and where it subsequently weakens.

Despite the rapidly expanding literature on AI integration represented in the selected studies (from digital healthcare and education to manufacturing, infrastructure, tourism, trade, and digitally integrated economic systems) the predominant question remains whether particular technological or organizational conditions facilitate AI integration. Much less is known about how the marginal contribution of an organization's broader digital readiness changes as that readiness itself accumulates. This represents a substantive gap because an average positive association does not reveal the readiness levels at which additional digital capability is most strongly associated with expansion in functional AI use.

Accordingly, after establishing whether the readiness–AI relationship departs from linearity, the central analytical task is to trace its slope continuously across the observed readiness distribution. This shifts attention from the conventional question of whether digital readiness matters to the more consequential question of when it matters more.

RQ2. How does the marginal association between digital management readiness and functional AI integration change across the readiness continuum?

2.3. Enterprise size and heterogeneity in the readiness–AI integration relationship

Enterprise size is frequently invoked as an important source of heterogeneity in digital transformation because organizations of different sizes differ systematically in their access to technological, financial, human, and managerial resources. Larger firms generally operate more complex organizational structures and broader portfolios of business processes, creating both greater opportunities and greater organizational demands for advanced digital technologies. Smaller firms, by contrast, often face more restrictive resource environments but may possess simpler structures and shorter decision-making chains. These differences make enterprise size a plausible determinant of both digital readiness and the capacity to translate readiness into functional AI integration.

More broadly, research on enterprise heterogeneity suggests that firm characteristics and the surrounding socioeconomic context can shape organizational behaviour in ways that cannot always be reduced to firm size alone. Čera et al. (2020), examining SMEs in the Czech Republic and Slovakia, show that the relevance of firm characteristics may vary across organizational outcomes and national settings. Similarly, Kolnhofer-Derecskei et al. (2024) emphasize the role of firm and contextual characteristics in SME behaviour, while Kot et al. (2016) demonstrate that entrepreneurial characteristics and perceptions may differ substantially across national contexts. At the regional level, Lewandowska et al. (2021) further connect entrepreneurship and innovativeness with the socioeconomic conditions of regional development. Together, these studies reinforce the need to distinguish organizational categories from the broader capability and contextual conditions in which enterprises operate.

However, treating firm size as an independent explanation for differences in AI integration may obscure an important conceptual distinction. Enterprise size can influence where a firm is located on the digital-readiness continuum, while the mechanism through which readiness enables AI integration may remain broadly similar across size classes. If small, medium-sized, and large enterprises systematically occupy different portions of the readiness distribution, observed differences in AI integration could be interpreted as size effects even when they primarily reflect differences in accumulated digital capabilities.

This issue becomes increasingly relevant as AI moves from experimental applications toward integration into specific organizational functions. Sampaio and Silva (2025), examining digital transformation in accounting, show that automation and AI integration are embedded within a broader transformation of accounting processes involving increasingly sophisticated digital technologies. Their

analysis highlights that AI adoption develops alongside the digitalization and automation of established organizational functions rather than independently of them. Thus, the capacity to integrate AI into accounting or related administrative processes depends partly on the digital environment already surrounding these activities.

Alheet (2026) examines AI-driven metaverse integration in manufacturing and positions digital supply-chain resilience as an important mechanism within this technological transformation. The study illustrates that advanced AI applications increasingly depend on pre-existing digitally connected operational environments. Similarly, Le et al. (2025) conceptualize smart warehousing through the joint integration of warehouse-management systems, AI, IoT, and digital-twin technologies, illustrating how AI becomes one component of a broader digital architecture rather than a stand-alone organizational technology.

Gebreab et al. (2024) integrate generative AI into digital-twin development through 3D modelling and data integration, while Tang et al. (2023) examine the integration of mixed reality, AI object recognition, and digital twins in an Industry 4.0 environment. Kia et al. (2025) and Sadri (2025) likewise study AI integration within digital-twin systems in industrial and building-management contexts. Although these studies are primarily technological rather than organizational, they reveal a common feature of advanced AI deployment: sophisticated AI applications tend to operate within ecosystems of already interconnected digital technologies.

This observation has direct implications for enterprise-size comparisons. Larger enterprises may appear to integrate AI more extensively not necessarily because size itself changes the fundamental readiness–AI mechanism, but because they are more likely to possess multiple complementary digital systems simultaneously. In contrast, smaller enterprises may remain concentrated in readiness ranges where one or more components of the required digital architecture are still absent. Consequently, comparing mean AI-integration levels across enterprise-size groups cannot by itself distinguish a genuine size-specific mechanism from a difference in the groups' positions along the digital-readiness continuum.

The distinction between organizational category and underlying capacity is supported by evidence from other institutional settings. Siddiqui et al. (2026), for example, explicitly approach readiness for digital records and telediagnostics as a step toward subsequent AI. This sequence is important because it conceptualizes advanced AI integration as conditional on prior digital capacity rather than simply on organizational willingness to adopt AI. Similarly, Giansanti et al. (2025) investigate AI integration across different professional roles within an existing digital workflow, whereas Kammerer-Jacquet et al. (2026) examine the practical integration of AI into routine digital pathology workflows. Across these contexts, variation in AI integration is closely connected to the digital structures and workflows already in place.

It should be noted that Singh and Kumar (2026) explicitly connect digital literacy, ChatGPT adoption, and broader AI integration, highlighting the relationship between existing digital competencies and the use of emerging AI tools. Cordero et al. (2026), examining changes in perceived needs for AI integration, similarly demonstrate that integration requirements vary with existing digital experience and capability development. These studies do not address enterprise size directly, but they reinforce the broader proposition that observable group differences in AI integration may originate from differences in underlying readiness rather than from group membership *per se*.

This distinction becomes even more important when the readiness–AI relationship is nonlinear. Suppose, for example, that small enterprises are disproportionately concentrated in the lower part of the readiness distribution, medium-sized enterprises around its middle, and large enterprises toward its upper end. If the marginal association between readiness and AI integration varies along this continuum, each size class will mechanically exhibit a different average readiness–AI slope even when all enterprises follow the same underlying nonlinear trajectory.

Under such circumstances, separate linear models estimated for small, medium-sized, and large enterprises could generate apparently different coefficients. Yet these coefficients would not necessarily demonstrate that enterprise size moderates the readiness–AI relationship. They could instead arise because each size group estimates a local approximation to a different segment of the same nonlinear function. A relatively weak coefficient among small firms might correspond to a constraint-dominated lower-readiness segment; a stronger coefficient among medium-sized firms could capture an acceleration segment; and another weaker coefficient among large enterprises could reflect a high-readiness saturation range. What appears to be between-group heterogeneity could therefore be, at least partly, within-continuum heterogeneity.

Nevertheless, the available literature provides limited evidence capable of separating enterprise-size effects from readiness-position effects. Existing research documents substantial variation in AI integration across organizational contexts and identifies numerous technological, human, and structural prerequisites, but it rarely asks whether predefined organizational groups continue to exhibit different trajectories after their positions on a common readiness continuum are explicitly considered. Consequently, observed heterogeneity may be over-attributed to organizational categories when part of it reflects differences in accumulated digital readiness.

Addressing this gap requires treating enterprise size and digital readiness not as competing explanations but as analytically separable dimensions. Enterprise size may determine access to resources and therefore influence the distribution of readiness, while readiness may determine the range in which additional digital capabilities produce the greatest marginal contribution to AI integration. If size-specific curves converge within common readiness ranges, this would support the interpretation of a largely shared readiness trajectory. If substantial differences remain at comparable readiness levels, the evidence would instead point toward genuinely distinct size-dependent mechanisms.

This reasoning leads to the third research question:

RQ3. Do enterprise-size classes exhibit distinct readiness–AI relationships, or do they primarily occupy different segments of a common readiness trajectory?

3. METHODOLOGY

3.1. Data and variable construction

The empirical analysis was based on enterprise statistics by country, enterprise size, and year. The sample covered 27 European countries, including Ukraine, for 2023 and 2025. Enterprises were divided into three size classes: small (10–49 employees), medium-sized (50–249 employees), and large (250 or more employees). The balanced analytical sample comprised 162 observations. The data were obtained from Eurostat (2026) and the State Statistics Service of Ukraine (2026).

The geographical scope was selected because European enterprises were undergoing a common policy-driven digital transformation while remaining heterogeneous in their levels of digital readiness and AI adoption. Since 2023, the Digital Decade Policy Programme 2030 has provided a common framework for this transformation, including targets for more than 90% of SMEs to reach at least a basic level of digital intensity and for at least 75% of enterprises to use cloud computing, big data, or artificial intelligence by 2030. At the same time, progress toward these targets has differed across countries and enterprise-size classes. The subsequent period was characterised by further diffusion of AI and other advanced digital technologies, although the European Commission continued to report differences in their uptake and barriers to advanced digitalisation among SMEs. This combination of a common digital-policy framework, increasing adoption of AI, and cross-country and enterprise-size variation provides an empirical setting for

examining whether the association between digital readiness and functional AI integration changes across the readiness continuum. Ukraine was included as an EU candidate country, undergoing digital transformation and increasing integration into the European digital environment. At the same time, the study does not assume complete homogeneity across countries. Cross-country differences in digital infrastructure, skills, enterprise digitalisation, and institutional conditions are treated as part of the empirical variation within the common European digital-transformation context. The purpose of the analysis is therefore not to estimate country-specific trajectories, but to examine whether the association between digital management readiness and functional AI integration follows a common nonlinear pattern across heterogeneous country–enterprise-size observations. Accordingly, Ukraine is included as an analytically comparable observation within the broader European digital-readiness continuum rather than treated as a separate country case. For the EU countries, the indicators were obtained from Eurostat's ICT Usage and E-commerce in Enterprises statistics, while the corresponding indicators for Ukraine were obtained from the State Statistics Service of Ukraine.

Digital management readiness was measured using the Digital Management Readiness Index (DMRI), constructed from nine indicators: enterprise resource planning (ERP), customer relationship management (CRM), business intelligence (BI), e-commerce, cloud technologies, digital communication tools, ICT specialists, ICT training, and ICT security. These indicators correspond to areas covered by Eurostat's enterprise ICT statistics and collectively represent technological, informational, human capital, and security-related components of enterprise digital readiness. Eurostat's survey framework explicitly covers e-commerce, cloud computing, data analytics and business software, ICT specialists and training, ICT security, and other forms of enterprise digitalisation. The inclusion of ERP, CRM, and BI captures the enterprise's capacity to organise, integrate, and analyse information used in management processes. ERP integrates information across functional business areas, CRM structures customer-related information, while BI provides analytical outputs from internal and external data for decision-making and strategic planning. These functions make them relevant indicators of the information and management infrastructure within which AI applications can be integrated. E-commerce and digital communication tools represent the digitalisation of interactions with markets and external stakeholders, while cloud computing captures access to scalable digital infrastructure and computing resources. ICT specialists and ICT training represent internal human and organisational capabilities required to implement and operate digital technologies. ICT security captures the capacity to maintain the integrity, availability, and confidentiality of the information systems on which digitally integrated business processes depend. The inclusion of technological adoption, ICT capabilities, skills, and security is also consistent with the broader OECD approach to measuring business digitalisation, which distinguishes information-management tools, e-commerce, cloud computing, ICT skills, and digital security as components of business digital uptake. The indicators were normalized to the $[0, 1]$ interval and aggregated using weights obtained by the entropy-weight method. A common weighting structure was applied to all observations.

The dependent variable, Functional AI Integration Index (FAII), was constructed from Eurostat indicators describing the purposes for which enterprises use AI. Functional AI integration was measured using seven areas of enterprise activity: marketing, production, logistics, ICT security, administration and management, finance, and research and development. The Functional AI Integration Index (FAII) was calculated as:

$$FAII_i = \frac{1}{7} \sum_{f=1}^7 AI_{if}, \quad (1)$$

where AI_{if} denotes the AI integration indicator for observation i and functional area f .

Equal weighting was applied because the seven indicators represent parallel functional domains of AI application rather than components for which differential importance was assumed.

Table 1

Descriptive statistics of the data

Construct	Variable	Mean	SD	Min	Median	Max
Digital management readiness	ERP	60.275	24.231	4.700	63.875	97.190
	CRM	41.012	20.645	1.900	39.295	85.930
	BI	37.349	25.682	2.320	32.855	95.720
	E-commerce	33.917	14.544	1.500	33.445	67.360
	Cloud technologies	61.954	23.819	1.500	66.010	99.060
	Digital communication tools	93.267	13.999	23.900	97.965	100.000
	ICT specialists	46.123	26.763	7.910	42.720	89.720
	ICT training	29.669	22.249	2.200	22.730	76.540
	ICT security	93.251	9.733	40.200	96.775	100.000
Functional AI integration	AI for marketing	8.162	7.279	0.620	5.645	35.760
	AI for production	6.110	7.332	0.110	2.785	32.260
	AI for logistics	4.017	4.089	0.070	2.390	18.930
	AI for ICT security	9.360	10.308	0.120	5.375	54.580
	AI for administration and management	8.511	8.806	0.140	5.345	46.810
	AI for finance	6.319	6.411	0.000	4.025	37.010
	AI for R&D	5.514	5.803	0.200	3.410	32.840

Source: authors' calculations based on Eurostat (2026) and the State Statistics Service of Ukraine (2026).

3.2. Methods

As a preliminary analysis, descriptive statistics for DMRI and FAII were calculated by enterprise size and year. Their bivariate association was examined using Pearson's r and Spearman's ρ , calculated for the full sample and separately by enterprise size and year. These statistics were used to describe the data and were not used to determine the functional form of the DMRI–FAII relationship.

The first research question was addressed by comparing a restricted linear specification with a generalized additive model (GAM) that allowed the relationship between DMRI and FAII to vary nonlinearly. The common model structure was:

$$FAII_{ist} = \alpha + s(DMRI_{ist}) + \gamma_s + \delta_t + \varepsilon_{ist} \quad (2)$$

where $FAII_{ist}$ denotes functional AI integration for country i , enterprise-size class s , and year t ; $DMRI_{ist}$ is digital management readiness; $s(\cdot)$ is the estimated function of DMRI; γ_s represents enterprise-size effects; δ_t represents year effects; and ε_{ist} is the residual term.

For the linear benchmark, $s(DMRI)$ was restricted to a linear form. For the nonlinear specification, the relationship was represented by a spline function:

$$s(x) = \sum_{k=1}^K \beta_k B_k(x) \quad (3)$$

where $B_k(x)$ denotes the k -th spline basis function and β_k is the corresponding coefficient. Eight spline basis functions were used in the nonlinear specification.

The GAM was estimated using penalized least squares:

$$\hat{\beta} = \arg \min_{\beta} \left[\sum_{i=1}^n (y_i - \hat{y}_i)^2 + \lambda \beta' S \beta \right] \quad (4)$$

where S is the penalty matrix and λ controls smoothness. The smoothing parameter was selected by grid search.

The linear and nonlinear specifications contained the same enterprise-size and year controls and were estimated using the same 162 observations. Their fit was compared using the Akaike Information Criterion (AIC), corrected AIC (AICc), generalized cross-validation criterion (GCV), scale estimate, R^2 , and effective degrees of freedom (EDoF).

AIC and AICc were calculated as:

$$AIC = -2\ln(\hat{L}) + 2k \quad (5)$$

$$AICc = AIC + \frac{2k(k+1)}{n-k-1} \quad (6)$$

where $\hat{L}$ is the maximised likelihood, k represents model complexity, and n is the sample size.

Lower AIC, AICc, and GCV values indicate a preferable balance between model fit and complexity. The comparison between the restricted linear model and the nonlinear GAM therefore provided the empirical basis for answering RQ1.

The second research question concerned variation in the magnitude of the readiness–AI association. After selecting the functional form in RQ1, the estimated GAM was differentiated with respect to DMRI. The marginal association at readiness level x was defined as:

$$ME(x) = \frac{\partial E(FAII|DMRI=x)}{\partial x} \quad (7)$$

The derivative was estimated numerically using a central finite difference:

$$\widehat{ME}(x) = \frac{\hat{\mu}(x+h) - \hat{\mu}(x-h)}{2h}, h = 0.001 \quad (8)$$

where $\hat{\mu}(x)$ denotes the average adjusted predicted FAII at DMRI level x .

For each evaluated DMRI value, DMRI was set to x for all observations while the observed enterprise-size and year categories were retained. The resulting predictions were averaged across the sample:

$$\hat{\mu}(x) = \frac{1}{n} \sum_{i=1}^n \hat{E}[FAII_i | DMRI_i = x, Size_i, Year_i] \quad (9)$$

Marginal effects were evaluated at 150 equally spaced points between the 5th and 95th percentiles of the observed DMRI distribution. Restricting the analysis to Q05–Q95 limited inference in sparsely represented tails of the readiness distribution. Uncertainty in the marginal-effect estimates was evaluated using a country-cluster bootstrap. The country was used as the resampling unit because each country contributed six observations corresponding to three enterprise-size classes and two years. In each bootstrap replication, 27 countries were sampled with replacement and all six observations belonging to a selected country were retained.

For $B = 500$ bootstrap replications, the GAM was re-estimated, and the marginal-effect function was recalculated. Pointwise 95% confidence intervals were obtained as:

$$CI_{95\%}(x) = [Q_{0.025}\{\widehat{ME}^{*(b)}(x)\}, Q_{0.975}\{\widehat{ME}^{*(b)}(x)\}], \quad (10)$$

where $b = 1, \dots, 500$.

The smoothing parameter selected for the original model was held fixed across bootstrap replications. The bootstrap therefore quantified sampling uncertainty conditional on the selected smoothing structure. The estimated marginal-effect curve was used to determine whether the DMRI–FAII association remained constant, increased, decreased, or changed direction across the observed readiness continuum. The confidence interval was additionally examined to determine whether an internal point existed at which the marginal association changed from including zero to remaining above zero. The boundary of the evaluated Q05–Q95 range itself was not treated as a threshold.

To summarize changes in the slope of the estimated marginal-effect function, a continuous piecewise-linear approximation was additionally applied:

$$ME(x) = \alpha + \beta_1 x + \beta_2 (x - T_1)_+ + \beta_3 (x - T_2)_+ + u(x) \quad (11)$$

where $(x - T)_+ = \max(0, x - T)$

The slopes of the resulting three portions were:

$$S_1 = \beta_1, S_2 = \beta_1 + \beta_2, S_3 = \beta_1 + \beta_2 + \beta_3 \quad (12)$$

One-, two-, and three-segment approximations were compared using residual sum of squares and

$$BIC^* = n_g \ln \left(\frac{RSS}{n_g} \right) + k \ln(n_g) \quad (13)$$

where n_g is the number of points on the marginal-effect grid.

This criterion was used only as a descriptive approximation criterion because the grid points were derived from the same GAM and cannot be regarded as independent observations. Consequently, T_1 and T_2 were interpreted as descriptive boundaries separating portions of the estimated marginal-response trajectory.

The third research question examined the role of enterprise size. This question requires distinguishing functional-form heterogeneity from differences in DMRI support. The analysis, therefore, consisted of three related steps.

Separate GAMs were first estimated for small, medium-sized, and large enterprises:

$$FAII_{it}^{(g)} = \alpha_g + s_g(DMRI_{it}) + \delta_t + \varepsilon_{it} \quad (14)$$

where $g \in \{S, m, all, Medium, Large\}$.

Because each size-specific subsample contained 54 observations, five spline basis functions were used. Each function was estimated and interpreted only within the observed DMRI range of the corresponding size class.

Size-specific marginal associations were then calculated as:

$$ME_g(x) = \frac{\partial E(FAII \mid DMRI = x, Size = g)}{\partial x} \quad (15)$$

These estimates were used to describe how the slope changed within the observed readiness range of each enterprise-size class. Direct comparison outside overlapping DMRI support was avoided. A formal comparison was then conducted using the full sample of 162 observations. The common-trajectory model was:

$$M_0: FAIL_{ist} = \alpha + s(DMRI_{ist}) + \gamma_s + \delta_t + \varepsilon_{ist} \quad (16)$$

The alternative specification allowed the smooth DMRI function to differ by enterprise size:

$$M_1: FAIL_{ist} = \alpha + \sum_{g=1}^3 I(Size_i = g) s_g(DMRI_{ist}) + \gamma_s + \delta_t + \varepsilon_{ist} \quad (17)$$

Because M_0 and M_1 were estimated using the same observations and dependent variable, their information criteria were directly compared. The comparison statistics were defined as:

$$\Delta AIC = AIC_{M_0} - AIC_{M_1} \quad (18)$$

$$\Delta AICc = AICc_{M_0} - AICc_{M_1} \quad (19)$$

Under these definitions, $\Delta IC > 0$ indicates a lower information criterion for the size-specific model M_1 , whereas $\Delta IC < 0$ indicates a lower information criterion for the common-trajectory model M_0 . The stability of the model comparison was assessed using the same country-cluster bootstrap procedure with 500 replications. Both models were estimated for each bootstrap sample, and the proportions were calculated by formulas 20 and 21.

$$P(\Delta AIC > 0) = \frac{1}{B} \sum_{b=1}^B I(\Delta AIC_b > 0) \quad (20)$$

and

$$P(\Delta AICc > 0) = \frac{1}{B} \sum_{b=1}^B I(\Delta AICc_b > 0) \quad (21)$$

These quantities indicate the proportion of country-cluster bootstrap samples in which the size-specific model had a lower information criterion than the common-trajectory model.

The descriptive boundaries obtained from the marginal-response approximation in RQ2 were used to examine where enterprise-size classes were located along the DMRI continuum. For each size class, the proportions of observations located below T_1 , between T_1 and T_2 , and at or above T_2 were calculated:

$$P_{gj} = \frac{n_{gj}}{n_g} \times 100 \quad (22)$$

where n_{gj} denotes the number of observations from enterprise-size class g located in readiness portion j , and n_g is the total number of observations in that size class.

Materials and Methods should be described with sufficient details to allow others to replicate and build on published results. Please note that publication of your manuscript implicates that you must make all materials, data, computer code, and protocols associated with the publication available to readers. Please disclose at the submission stage any restrictions on the availability of materials or information. New methods and protocols should be described in detail while well-established methods can be briefly described and appropriately cited.

4. EMPIRICAL RESULTS AND DISCUSSION

4.1. The core empirical results

Table 2 presents the descriptive statistics for DMRI and FAII by enterprise size and year. Mean DMRI increased with enterprise size in both observation years. In 2023, the mean values were 0.197 for small enterprises, 0.427 for medium-sized enterprises, and 0.736 for large enterprises. In 2025, the corresponding values were 0.208, 0.447, and 0.778. Within each size class, mean DMRI was higher in 2025 than in 2023.

Table 2

DMRI and FAII by enterprise size and year

size	year	mean	std	median	min	max	mean	std	median	min	max
		DMRI					FAII				
S1	2023	0.1968	0.0815	0.1845	0.0157	0.3697	1.3440	0.7279	1.0400	0.2171	2.8457
	2025	0.2082	0.0799	0.2031	0.0179	0.3758	3.6194	1.9077	3.3371	0.9286	7.1414
S2	2023	0.4272	0.1299	0.4231	0.1248	0.6617	3.6549	1.8608	3.1729	0.9971	7.4829
	2025	0.4472	0.1302	0.4463	0.1130	0.6856	6.5888	3.3210	6.4943	1.7257	13.5957
S3	2023	0.7356	0.1546	0.7552	0.2829	0.9530	8.9398	5.1792	8.6200	1.9429	19.7271
	2025	0.7782	0.1485	0.7981	0.2859	0.9756	16.9896	7.8908	15.7257	2.5143	34.4543

Source: developed by the authors.

FAII followed the same ordering by enterprise size. For small enterprises, mean FAII increased from 1.344 in 2023 to 3.619 in 2025. For medium-sized enterprises, it increased from 3.655 to 6.589, while for large enterprises it increased from 8.940 to 16.990. The standard deviation of FAII also increased across enterprise-size classes, from 0.728–1.908 among small enterprises to 5.179–7.891 among large enterprises.

Across the pooled sample, the Pearson correlation between DMRI and FAII was 0.821, while the Spearman rank correlation was 0.876 (Table 3).

Table 3

Pearson and Spearman correlations between DMRI and FAII

Sample	N	Pearson r	p-value	Spearman ρ	p-value
Panel A. Pooled sample					
Full sample	162	0.821	<0.001	0.876	<0.001
Panel B. By enterprise size					
Small (S1)	54	0.543	<0.001	0.589	<0.001
Medium (S2)	54	0.740	<0.001	0.772	<0.001
Large (S3)	54	0.744	<0.001	0.850	<0.001
Panel C. By year					
2023	81	0.866	<0.001	0.937	<0.001
2025	81	0.886	<0.001	0.920	<0.001

Source: developed by the authors.

Both coefficients were statistically significant ($p < 0.001$). Within enterprise-size classes, Pearson correlations were 0.543 for small, 0.740 for medium-sized, and 0.744 for large enterprises. The corresponding Spearman coefficients were 0.589, 0.772, and 0.850. Positive associations were also observed separately in 2023 (Pearson $r = 0.866$; Spearman $\rho = 0.937$) and 2025 ($r = 0.886$; $\rho = 0.920$). These correlations describe the direction and magnitude of the bivariate association but do not impose or test a particular functional form. The linear and nonlinear specifications were therefore compared to address RQ1.

Table 4 compares the linear specification with the nonlinear GAM. The nonlinear GAM had an AIC of 744.963, compared with 832.317 for the linear specification, a difference of 87.354 AIC units. AICc values were 746.159 and 832.651, respectively, giving a difference of 86.492. GCV decreased from 10.091 to 6.001, and the scale parameter decreased from 3.094 to 2.338. The proportion of explained variation increased from $R^2 = 0.787$ in the linear specification to $R^2 = 0.881$ in the nonlinear GAM.

Table 4

Comparison of linear and nonlinear specifications for the DMRI–FAII relationship

Model	EDoF	AIC	AICc	GCV	Scale	R^2
Linear specification	4.637	832.317	832.651	10.091	3.094	0.787
Nonlinear GAM	8.045	744.963	746.159	6.001	2.338	0.881

Source: developed by the authors.

The estimated GAM relationship is presented in Figure 1.

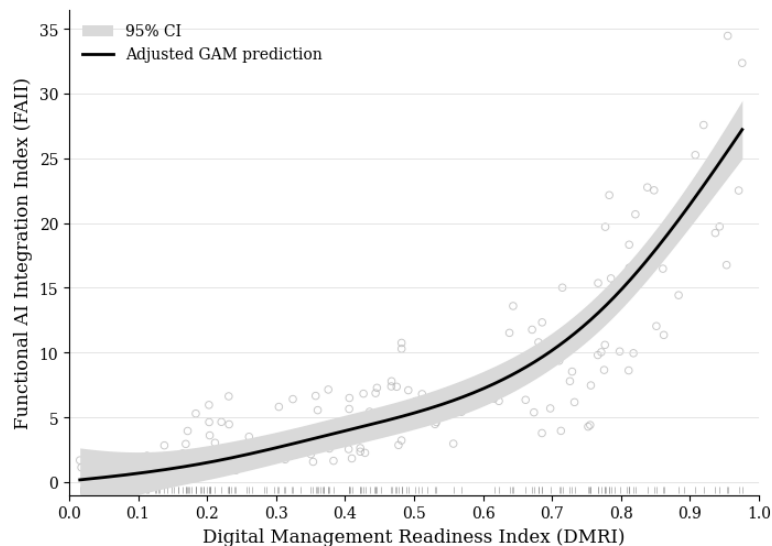


Figure 1. Estimated functional relationship between digital readiness and functional AI integration

Source: developed by the authors.

Predicted FAII increased across the observed DMRI range. The slope of the estimated function was lower at the lower part of the DMRI distribution and increased toward the upper part of the distribution. The estimated function therefore departed from the constant-slope assumption imposed by the linear specification. Accordingly, for RQ1, the model-comparison criteria indicate that the nonlinear specification provides a better fit to the observed DMRI–FAII relationship than the linear specification.

To examine RQ2, the first derivative of the estimated GAM function was evaluated over the Q05–Q95 range of the observed DMRI distribution. Table 5 reports marginal effects at selected points of this range.

Table 5

Marginal association of digital readiness with functional AI integration at selected readiness levels

Readiness level	DMRI	Marginal effect	95% CI
Q05	0.126	7.477	[5.395; 11.661]
Q25	0.229	10.908	[8.212; 13.331]
Median	0.424	13.138	[9.739; 17.629]
Q75	0.711	39.001	[33.095; 47.362]
Q95	0.891	72.079	[49.343; 92.359]

Source: developed by the authors.

At Q05 ($DMRI = 0.126$), the estimated marginal effect was 7.477, with a 95% country-cluster bootstrap confidence interval of [5.395, 11.661]. The estimate increased to 10.908 [8.212, 13.331] at Q25 and to 13.138 [9.739, 17.629] at the median. At Q75 ($DMRI = 0.711$), the estimated marginal effect was 39.001 [33.095, 47.362], and at Q95 ($DMRI = 0.891$) it was 72.079 [49.343, 92.359]. The Q95 marginal effect was 9.64 times the corresponding estimate at Q05.

Figure 2 shows that the marginal effect increased over the evaluated readiness range, particularly in its upper part.

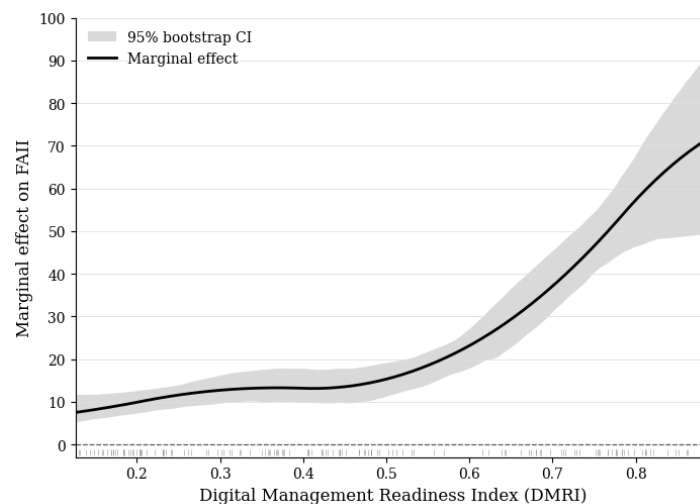


Figure 2. Marginal effect of DMRI on FAII with 95% country-cluster bootstrap CI

Source: developed by the authors.

The lower bound of the pointwise 95% country-cluster bootstrap confidence interval remained above zero throughout the Q05–Q95 range. No point within the evaluated range was identified at which the confidence interval changed from including zero to excluding zero. Thus, the analysis did not identify an internal DMRI threshold separating statistically unsupported and supported associations. Instead, the estimated marginal association was positive throughout the evaluated range and varied in magnitude with DMRI.

A three-segment approximation of the marginal-response curve was subsequently used for descriptive purposes. The estimated boundaries were $DMRI = 0.524$ and $DMRI = 0.660$. The slopes of the marginal-response curve were 17.729 below the first boundary, 103.299 between the two boundaries, and 190.519 above the second boundary. These boundaries summarize changes in the shape of the estimated marginal-response curve and are not treated as statistically identified thresholds. For RQ2, the results therefore indicate that the marginal association between DMRI and FAII increases across the observed readiness continuum rather than remaining constant.

Figure 3 presents GAM trajectories estimated separately for small, medium-sized, and large enterprises.

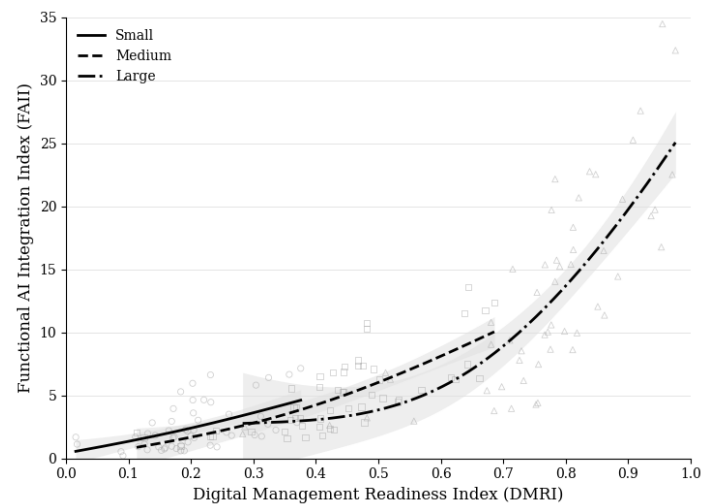


Figure 3. Size-specific readiness–AI trajectories

Source: developed by the authors.

The observed DMRI ranges differed across the three size classes: 0.016–0.376 for small enterprises, 0.113–0.686 for medium-sized enterprises, and 0.283–0.976 for large enterprises. The size-specific curves were therefore estimated and displayed only within the observed support of each group.

Within the Q05–Q95 range for small enterprises, the estimated marginal effect increased from 9.700 at $DMRI = 0.090$ to 13.214 at $DMRI = 0.344$, corresponding to a Q95/Q05 ratio of 1.36. For medium-sized enterprises, the marginal effect increased from 10.364 at $DMRI = 0.214$ to 22.722 at $DMRI = 0.650$, giving a ratio of 2.19. For large enterprises, it increased from 8.448 at $DMRI = 0.461$ to 71.769 at $DMRI = 0.954$, corresponding to a ratio of 8.50. In each size class, the largest estimated marginal effect within the Q05–Q95 range occurred at its upper boundary.

Because the three size classes occupied different DMRI ranges, the separate trajectories were supplemented by a comparison between a common-smooth model (M0) and a model containing size-specific smooths (M1). Table 6 reports the results.

Table 6

Comparison of common and enterprise-size-specific readiness–AI trajectories

Model		EDoF	AIC	AICc	GCV	R^2
M0: Common smooth		8.045	744.963	746.159	6.001	0.881
M1: Size-specific smooths		9.532	749.073	750.687	6.210	0.880
Comparison	Original Δ	Bootstrap median	95% bootstrap interval		$P(\Delta > 0)$	
ΔAIC	−4.109	−3.374	[−8.592; 1.916]		0.068	
$\Delta AICc$	−4.528	−3.750	[−8.962; 1.621]		0.062	
Enterprise-size positioning along the digital-readiness continuum						
Size of enterprises		Lower readiness	Intermediate readiness		Higher readiness	
Small		100	0		0	
Medium		79.6	14.8		5.6	
Large		11.1	1.9		87	

Source: developed by the authors.

M0 had an AIC of 744.963 and an AICc of 746.159, compared with 749.073 and 750.687 for M1. GCV values were 6.001 and 6.210, respectively, while R^2 was 0.881 for M0 and 0.880 for M1. Defining the model-comparison statistic as the information criterion for M0 minus that for M1 produced $\Delta AIC = -4.109$ and

$\Delta AICc = -4.528$. Negative values favour M0. In the 500 country-cluster bootstrap replications, median ΔAIC was -3.374 , with a 95% bootstrap interval of $[-8.592, 1.916]$, and median $\Delta AICc$ was -3.750 $[-8.962, 1.621]$. Positive differences, corresponding to a lower information criterion for the size-specific model, occurred in 6.8% of replications for AIC and 6.2% for AICc.

The distribution of observations across the descriptive portions of the DMRI continuum is presented in Figure 4.

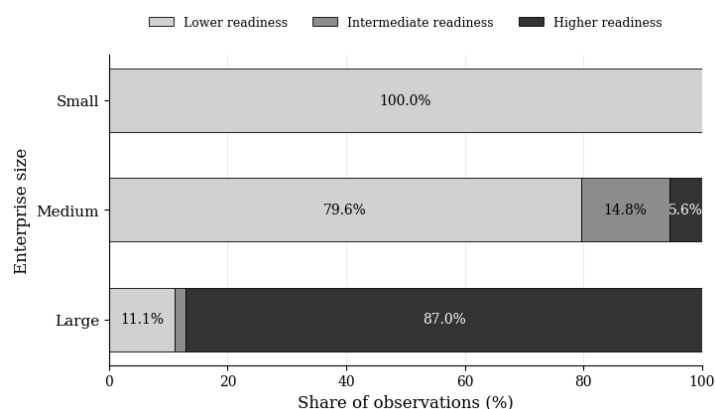


Figure 4. Distribution of enterprise-size classes across descriptive portions of the digital readiness continuum.

Source: developed by the authors.

All small-enterprise observations were located below $DMRI = 0.524$. Among medium-sized enterprises, 79.6% were below 0.524, 14.8% were between 0.524 and 0.660, and 5.6% were at or above 0.660. Among large enterprises, the corresponding proportions were 11.1%, 1.9%, and 87.0%. For RQ3, the size-specific specification did not improve the information criteria relative to the common-smooth specification, and this result was reproduced in most country-cluster bootstrap samples. At the same time, the three enterprise-size classes occupied different portions of the DMRI distribution. The estimated differences across size classes are therefore consistent with differential positioning along a common nonlinear DMRI–FAII trajectory rather than requiring separate size-specific functional forms.

4.2. Discussion

The findings extend the literature on digital readiness and AI integration by demonstrating that the relevance of digital capabilities varies across the readiness continuum. Previous studies have established the importance of technological, organizational, managerial, and human capabilities for AI implementation. Alaskar (2025) emphasizes integration capabilities and digital platforms as foundations for AI-supported innovation, while Aljehani et al. (2026) identify AI-enabled analytics and process integration as important mechanisms of digital transformation. The present study develops this capability-based perspective by showing that accumulated digital capabilities are associated with AI integration with different strength at different levels of readiness.

The observed pattern is consistent with a complementarity mechanism. As digital capabilities accumulate, their joint configuration may create increasingly favourable conditions for embedding AI across enterprise functions. This interpretation corresponds with Fathy et al. (2025), who emphasize the strategic integration of cloud- and AI-driven technologies, and with studies highlighting the interdependence of digital platforms, analytics, data, skills, and organizational processes (Alaskar, 2025; Aljehani et al., 2026).

Digital readiness can therefore be interpreted as a system of mutually reinforcing capabilities whose combined development expands the organizational capacity for functional AI integration.

The findings also refine the constraint–activation–saturation perspective discussed in the literature. Previous research provides theoretical grounds for weaker relationships at low readiness, followed by stronger associations as complementary constraints are removed and potential attenuation at advanced stages. The present evidence is compatible with the constraint and activation mechanisms, while saturation is not apparent within the observed readiness range. This suggests that advanced digital readiness may continue to expand opportunities for AI integration by supporting more complex combinations of data systems, digital platforms, organizational processes, and AI applications.

The continuous character of this relationship also has implications for digital-maturity research. Approaches based on discrete maturity stages can be useful for classification, yet they may conceal gradual changes occurring within the digital-development process. The present findings support a continuous capability perspective in which organizational readiness develops through cumulative technological investment, learning, and adaptation. Consequently, predefined low-, medium-, and high-readiness categories may provide an incomplete representation of heterogeneity in the readiness–AI relationship.

The enterprise-size findings provide a further qualification to previous research. Existing studies frequently associate higher AI adoption among large enterprises with greater financial resources, developed ICT infrastructure, specialized human capital, and stronger implementation capacity. These structural differences remain relevant; however, the present study indicates that part of the observed size heterogeneity can be explained by enterprises' positions along the digital-readiness continuum. Large enterprises are more likely to reach advanced readiness positions, while smaller enterprises tend to remain concentrated at lower levels.

This interpretation is consistent with Adeniranye et al. (2026), who relate differences in AI integration to disparities in digital resources, infrastructure, institutional structures, and other enabling conditions. The present study extends this argument by distinguishing enterprise size from underlying capability position. Size may influence access to the resources required for capability accumulation, while digital readiness captures the organizational state within which functional AI integration develops.

This distinction also has methodological significance. When enterprise-size classes occupy different regions of a nonlinear readiness distribution, separate group-specific estimates may capture different local segments of the same underlying relationship. Apparent size-based heterogeneity may therefore emerge without fundamentally different mechanisms of AI integration across enterprise groups. This issue deserves particular attention in studies using size-specific subsamples or interaction effects to examine heterogeneity in digital transformation.

The study contributes to the literature by integrating nonlinearity, capability accumulation, and enterprise heterogeneity within a common analytical perspective. Digital readiness emerges as a dynamic capability configuration whose relevance for functional AI integration depends on an enterprise's position along the readiness continuum. Enterprise size remains important because it influences the capacity to accumulate these capabilities, while differences in readiness position explain an additional dimension of heterogeneity. This perspective provides a more differentiated understanding of how enterprises progress toward broader functional AI integration and clarifies when digital readiness becomes particularly consequential for AI integration.

5. CONCLUSION

This study examined the nonlinear association between digital management readiness and functional AI integration and assessed whether enterprise-size heterogeneity reflects distinct readiness–AI trajectories

or differences in enterprises' positions along a common readiness continuum. The results provide clear evidence that the relationship is nonlinear. The nonlinear specification explained 88.1% of the variation in FAII, compared with 78.7% for the linear model, while AIC decreased from 832.317 to 744.963, confirming the empirical relevance of modelling digital readiness as a continuous nonlinear process.

The marginal-effects analysis further shows that the importance of digital readiness increases markedly across the observed continuum. The estimated marginal association rises from 7.477 at the 5th percentile of DMRI to 13.138 at the median and 72.079 at the 95th percentile, representing an approximately 9.6-fold increase between the lower and upper parts of the distribution. The association remains positive throughout the evaluated range, with no statistically supported internal threshold or evidence of saturation. These findings indicate that accumulated digital capabilities become increasingly consequential for functional AI integration as enterprises advance digitally.

Enterprise-size differences are substantial but appear to reflect primarily unequal positioning along this nonlinear trajectory. Small enterprises occupy a DMRI range of 0.016–0.376, medium-sized enterprises 0.113–0.686, and large enterprises 0.283–0.976. Moreover, 87.0% of large-enterprise observations are concentrated in the higher-readiness segment, whereas all small-enterprise observations remain in the lower-readiness portion. Allowing separate nonlinear functions for enterprise-size classes does not materially improve model performance, supporting the interpretation of a broadly common readiness–AI trajectory. Thus, enterprise size remains relevant to AI integration, particularly through its association with the level of accumulated digital capabilities.

Policies designed to stimulate enterprise AI integration should incorporate digital readiness alongside conventional firm-size criteria. For enterprises at lower readiness levels, support should prioritize coordinated development of digital infrastructure, management systems, ICT skills, and data-security capabilities. For enterprises that have already achieved stronger digital foundations, measures facilitating deeper functional deployment of AI may generate greater returns. Readiness-based targeting could therefore complement SME-oriented policies and improve the alignment of support instruments with enterprises' actual digital capability configurations.

Several limitations define the scope of the conclusions. The empirical design identifies associations and does not establish causality or the direction of potential feedback between digital readiness and AI integration. The country–year–size structure of the dataset limits the analysis of firm-level organizational mechanisms and heterogeneity within enterprise-size classes. The composite DMRI may also conceal differences in the contribution of individual readiness dimensions. Finally, the absence of saturation applies to the observed DMRI range and cannot exclude a possible turning point beyond the available data.

Future research should therefore extend the analysis using longitudinal firm-level data and designs capable of addressing endogeneity and reciprocal relationships between digital capability accumulation and AI integration. Decomposing DMRI would allow the nonlinear contribution of digital infrastructure, management systems, human capital, and data-security capabilities to be evaluated separately and their complementarities to be identified. Further studies could also examine whether the observed trajectory varies across industries, countries, institutional environments, and specific AI functions. Such extensions would help establish whether the accelerating readiness–AI relationship represents a general feature of enterprise digital transformation or is contingent on particular technological and institutional conditions.

The results indicate that where an enterprise is located on the digital-readiness continuum is critical for understanding its functional AI integration. Digital readiness remains positively associated with AI integration throughout the observed range, while its marginal relevance increases substantially at more advanced levels. This nonlinear capability perspective provides a more precise basis for explaining enterprise heterogeneity and for designing differentiated pathways toward broader AI integration. The pooled design does not aim to identify country-specific digital-readiness trajectories. Although the sample captures

substantial cross-country heterogeneity, including differences between EU Member States and Ukraine, these differences are incorporated into the broader readiness continuum rather than modelled as separate national regimes. Future research with larger country-specific samples could examine whether the nonlinear readiness–AI relationship differs systematically across institutional contexts.

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