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# From Digital Leadership and AI Usage to Relative Firm Performance: The Mediating Role of Business Model Innovation in Iranian Knowledge-Based Firms

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## Abstract

Iranian knowledge-based firms operate under institutional and resource constraints that may limit their ability to translate digital capabilities into performance gains. This study aimed to explain the effect of digital leadership and organizational artificial intelligence (AI) usage intensity on the relative performance of Iranian knowledge-based firms, with an emphasis on the mediating role of business model innovation. Digital leadership was conceptualized as a second-order construct comprising innovative and supportive dimensions. Business model innovation was examined as a mechanism through which managerial and technological effects are transmitted to relative performance. In terms of purpose, this study was applied, and in terms of method, it followed a descriptive-survey design. Cross-sectional data were collected through using a structured questionnaire, and after data screening, 264 valid questionnaires were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings indicated that digital leadership had a positive and significant effect on organizational AI usage intensity, business model innovation, and relative performance. In addition, organizational AI usage intensity had a significant effect on business model innovation but no significant direct effect on relative performance, suggesting that its performance value may be realized primarily through business model innovation. Consistent with this interpretation, the business model innovation showed the strongest direct effect on relative performance and significantly mediated the main relationships. The findings suggested that managers of knowledge-based firms should integrate organizational AI usage with digital leadership and business model innovation, while policymakers should support capability-building initiatives that enable firms to convert AI use into firm-level value and performance gains.

## Keywords

Digital Leadership, Organizational Artificial Intelligence (AI), Business Model Innovation, Firm Relative Performance, Knowledge-based Firms

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## Introduction

In the contemporary knowledge-based economy, the competitiveness of firms depends more than ever on their ability to utilize digital technologies, reconfigure business models, and transform technological capabilities into organizational performance. The emergence of advanced technologies has transformed the traditional business paradigms and has highlighted the necessity of employing novel approaches in leadership and resource management. According to the Upper Echelons Theory (Hambrick & Mason, 1984), the strategic orientations and ultimate performance of an organization are influenced by the characteristics and perceptions of its top managers. In such a context, digital leadership emerges as a pivotal capability that requires not only a deep understanding of technology but also the ability to guide the organization through structural and cultural changes. Relying on the Resource-Based View (Barney, 1991), digital leadership can serve as an intangible, valuable, and rare resource, paving the way for creating sustainable competitive advantages for firms.

However, the impact of digital leadership on firm performance is not merely a linear and direct relationship. The literature indicated that the leadership effectiveness in the digital age depends on mediating mechanisms that translate strategies and managerial capabilities into tangible organizational outcomes. One such mechanism is organizational AI usage intensity. Drawing on the Technology–Organization–Environment (TOE) framework, the adoption and implementation of complex technologies such as artificial intelligence (AI) require leadership support, organizational readiness, and an understanding of environmental pressures (Baker, 2012).

AI can enhance the capabilities, creativity and performance of the organization by optimizing the processes, managing complex data and improving the quality of decision making (Mikalef & Gupta, 2021). However, the success of adoption of this technology depends on the leaders who can communicate a digital vision and reduce organizational resistance (Mollah et al., 2026).

The organizational value of AI does not arise from technological use alone. It depends on whether AI-enabled capabilities are translated into changes in how the firm creates, delivers, and captures value. This need to convert the technological potential into a reconfigured value logic provides the conceptual bridge between organizational AI usage and business model innovation. The Dynamic Capabilities Theory (Teece et al., 1997) focuses on the firm's ability to reconfigure its resources and business models in the face of evolving environments. By identifying the opportunities enabled by technologies such as AI and mobilizing complementary organizational resources, digital leaders can catalyze the business model innovation (Aagaard & Tucci, 2024).

Research indicated that the business model innovation can act as a bridge between technological innovation, the reconfiguration of value creation logic, and the sustainability of organizational performance (Boons & Lüdeke-Freund, 2013; Di Vaio,Palladino, et al., 2020).

Yet, despite the increasing relevance of these concepts, a review of the literature showed a substantial research gap. Most of the prior research has investigated the impact of digital leadership, AI adoption or use, and business model innovation on firm performance in individual or dyadic relationships. For example, a number of studies have investigated the role of leadership in the adoption of technology, but the joint role of organizational AI usage intensity and business model innovation in explaining how digital leadership capabilities are transformed into superior firm performance has been little empirically explored. Understanding this causal chain is essential for bridging the gap between strategic theories and managerial practices in the digital economy. Accordingly, the theoretical contribution of this study lay in developing an integrated process explanation of how digital leadership is translated into firm relative performance. Rather than treating digital leadership, organizational AI usage intensity, and business model innovation as isolated predictors, the proposed model assigns each construct a distinct role within a sequential capability-conversion process. Specifically, the model extends Upper Echelons Theory by positioning organizational AI usage intensity as an intermediate organizational mechanism through which top managers' digital orientations are translated into organizational actions. It also connects the Resource-Based View (Barney, 1991) with Dynamic Capabilities Theory (Teece et al., 1997) by conceptualizing the business model innovation as the reconfiguration process through which valuable leadership and AI-related capabilities are converted into performance outcomes. Finally, drawing on the Technology–Organization–Environment framework, the model conceptualizes AI usage as an organizationally embedded process rather than as a stand-alone technological investment. Taken together, this integrated perspective clarifies the theoretical pathway linking digital leadership, organizational AI usage intensity, business model innovation, and firm relative performance (Baker, 2012; Hambrick & Mason, 1984).

The novelty of this study lay in specifying and empirically testing a unified explanatory mechanism through which digital leadership is translated into firm relative performance via organizational AI usage intensity and business model innovation, rather than in examining these established constructs as isolated predictors. First, the study operationalized digital leadership as a reflective–reflective second-order construct comprising innovative and supportive dimensions, thereby capturing both the strategic–technological and human–organizational foundations of digital transformation within a single model. Second, the study focused on organizational AI usage intensity rather than treating AI merely as an adoption decision or a general technological capability. Third, it simultaneously examined the direct, mediating, and sequential pathways through which digital leadership and organizational AI usage are translated into firm relative performance via business model innovation. This configuration enabled the study to explain not only whether these capabilities are associated with performance, but also the organizational process through which their value is realized. This is especially important for knowledge-based firms, as their competitive advantage is more dependent on specialized knowledge, technological capacity, organizational learning and the ability to convert technology into economic value rather than physical assets.

This issue is particularly salient in Iran, where the innovation system exhibits a marked asymmetry between relatively strong innovation outputs and weaker enabling inputs. According to the Global Innovation Index 2025, Iran ranked 46th in innovation outputs but 109th in innovation inputs, while institutions, business sophistication, and infrastructure were among its comparatively weaker pillars (World Intellectual Property Organization [WIPO], 2025). This asymmetry makes Iranian knowledge-based firms a theoretically informative context rather than merely a setting for data collection. Under such conditions, access to advanced technologies, including AI, may be insufficient on its own. The translation of technological use into innovation and relative performance may depend especially on firm-level mechanisms such as digital leadership, the organizational integration of AI, and business model reconfiguration. The Iranian context therefore provides an opportunity to examine how managerial and organizational capabilities shape the conversion of technological resources into economic values when enabling conditions are uneven. In this context, the TOE framework explains why organizational AI usage is shaped by organizational readiness and environmental conditions, the Resource-Based View conceptualizes digital leadership and AI-related resources as potential sources of strategic value, and Dynamic Capabilities Theory explains how these resources can be reconfigured through business model innovation to generate performance outcomes.

Therefore, the purpose of this study was to develop and test an integrated conceptual model that explains how digital leadership is translated into firm relative performance through organizational AI usage intensity and business model innovation. By jointly examining the managerial, technological, and business-model mechanisms involved in this process, the study sought to provide a more comprehensive explanation of value realization in digitally transforming knowledge-based firms.

Using a Structural Equation Modeling (SEM) approach, this study sought to explain how digital leadership contributes to organizational performance by facilitating the organizational use of AI and the reconfiguration of business models.

## Literature Review

A review of the research literature indicated that the path of organizational evolution and survival in the digital age is closely linked to the fundamental theories of strategic management. The starting point of this scholarly discussion is the Upper Echelons Theory (Hambrick & Mason, 1984), which argues that strategic decisions and organizational outcomes are a reflection of the characteristics, values, and perceptions of top managers. This approach evolved in later decades with the Resource-Based View (Barney, 1991). These perspectives emphasize that the creation of sustainable competitive advantages does not merely depend on possessing valuable and rare resources; rather, it is the organization’s capability to combine, coordinate, and effectively utilize these resources that creates performance differences. However, in today’s highly dynamic and technology-intensive environments, reliance on static resources alone is not sufficient. In response to this limitation, the Dynamic Capabilities Theory (Eisenhardt & Martin, 2000; Teece et al., 1997) was introduced, emphasizing the organizations' capacity to integrate, build, and continuously reconfigure internal and external competencies.

Within the digital transformation literature, data-driven analytics have likewise been conceptualized as a source of dynamic capabilities that strengthen environmental scanning, organizational agility, product and service innovation, digital strategy formulation, and digital value creation (Talafidaryani et al., 2025). Alongside these strategic foundations, the Technology-Organization-Environment framework (Baker, 2012) also provides a comprehensive and detailed basis for explaining how multiple and intertwined organizational, technological, and environmental factors influence the speed and quality of technological innovation adoption. These theoretical foundations have provided a suitable basis for the literature's transition from traditional concepts toward the emerging patterns such as digital leadership and organizational AI usage intensity.

In examining the evolution of the concept of leadership, a transition can be observed from knowledge-oriented approaches to digitally transformative approaches. Previous studies mainly emphasized the role of knowledge-oriented leadership in enhancing the knowledge management practices and innovation performance (Donate & de Pablo, 2015; Mardani et al., 2018). In these studies, leaders were considered as facilitators of knowledge flows and as promoters of organizational learning. With the advent of the digital age, this role has grown and digital leadership has become an important capability to navigate technology and organizational change. Recent studies have shown digital leadership capabilities can promote the performance of technology-oriented firms through digital innovations, and can also be a catalyst for achieving sustainable development outcomes in organizations (Xu et al., 2026). Research on the synergy between digital leadership and AI in human resource management has shown that this combination can significantly improve sustainable effectiveness (Mollah et al., 2026). AI and digital technologies are profoundly transforming the paradigms of decision-making and structures of tasks in organizations. AI, as one of the main drivers of the digital revolution, has drastically transformed business decision-making processes from intuitive modes to analytical and predictive approaches (Kumar & Shrivastava, 2025), and in some cases led to the redefinition and redesign of business support functions (Bauer & Wolff, 2022). Recent evidence further indicated that AI can enhance strategic decision-making and organizational agility in volatile environments, although the realization of these benefits requires ethical governance, organizational alignment, and effective implementation practices (Ghasemi Hamedani & Shaddeli, 2025).

It has been demonstrated that at a broader level, digital transformation plays an important mediating role in organizational strategic renewal. Thus, it significantly improves human resource productivity (Sharafi & Hoseini, 2024). Likewise, these technologies contribute to the transition from traditional knowledge management systems to synergistic approaches in research and development institutions (Tineo-Mendoza & Hernández-Cenzano, 2025). On the other hand, in the Fourth and Fifth Industrial Revolutions, technology communication models for the realization of sustainable supply chains have been introduced as an unavoidable need (Zarei & Naderi, 2024). Empirical studies have revealed that Big Data Analytics and machine learning have significant impacts in the domains of management, healthcare, and agriculture (Pallathadka et al., 2023). Nevertheless, the successful implementation of these technologies is not the same in all organizations. For example, in small and medium-sized enterprises, this transformation requires a multilevel and gradual approach (Garzoni et al., 2020) to reduce implementation risks and strengthen value co-creation in industrial markets and ecosystems like healthcare (Leone et al., 2021). In the past few decades, the literature on business model innovation has been strongly correlated with AI capabilities and sustainable development goals. The theoretical basis of this link can be traced back to the notion of the triple bottom line (Elkington, 1998) that introduced the requirement for simultaneous and balanced attention to economic, social and environmental dimensions into the management literature. This basic approach has been used to conceptualize sustainable business models as drivers of organizational innovation (Boons & Lüdeke-Freund, 2013) and as a key necessity in the age of digital imperatives (Brenner, 2018). The conceptual architecture of these models and their analysis in recent studies showed that sustainability is not just a strategic choice or a limited form of corporate social responsibility, but it has become an important prerequisite for the ecosystemic survival of organizations (Najmaei & Sadeghinejad, 2023; Shakeel et al., 2020). The literature review in this regard indicated that AI plays a driving role in aligning business models with the United Nations Sustainable Development Goals (Di Vaio, Palladino et al., 2020). The relevance of this technology is even more obvious in crisis situations, as during the COVID-19 pandemic, AI has made it possible to rethink and be resilient to models of food and agricultural systems (Di Vaio, Boccia, et al., 2020).

Comparing these two studies showed how a single technology can serve both as a long-term planning tool for achieving sustainable development goals and as a rapid-response mechanism under crisis conditions.

In addition, innovation in business models supported by AI capabilities has created new boundaries in value creation, delivery, and capture; boundaries that were less imaginable in many traditional business models (Aagaard & Tucci, 2024). To guide this path, the use of ontology-based intelligent decision support systems for designing business architecture has been recommended in order to reduce the managers' cognitive errors and provide strategic decision-making with stronger analytical support (Hamrouni et al., 2021). Nevertheless, the literature warned that the implementation of technological tools alone does not guarantee sustainability and superior performance. The formation of a strong organizational culture that supports sustainable AI is a fundamental prerequisite for the success of these projects (Isensee et al., 2021). For example, evidence obtained from Taiwan's manufacturing sector showed that using AI to strengthen green innovation capacity is realized only through integrated strategies and alignment of the organizational structure with sustainability goals (Saiyed et al., 2025).

In summary, although numerous studies have separately examined digital leadership, AI capabilities or applications, business model innovation, and organizational performance, there remains limited empirical understanding of the sequential mechanism of transforming digital leadership into firm relative performance through organizational AI usage intensity and business model innovation. Particularly in the context of Iranian knowledge-based firms, there is limited empirical evidence on how the innovative and supportive dimensions of digital leadership can, through strengthening the organizational AI usage intensity, create the conditions for business model reconfiguration and ultimately lead to superior relative performance. This gap highlights the necessity of empirically testing an integrated model in which digital leadership, AI, and business model innovation are examined not as isolated variables, but as components of a causal chain in explaining the firm relative performance.

## Theoretical Foundations

The theoretical framework integrates four complementary perspectives, each explaining a distinct component of the proposed model. Upper Echelons Theory (Hambrick & Mason, 1984) links top managers' digital orientations to strategic and technological choices, thereby providing the basis for conceptualizing digital leadership. The Resource-Based View (Barney, 1991) frames digital leadership and AI-related organizational resources as potential sources of strategic value, while Dynamic Capabilities Theory (Eisenhardt & Martin, 2000; Teece et al., 1997) explains how these resources can be reconfigured through business model innovation to generate performance outcomes. The Technology–Organization–Environment framework (Baker, 2012) is used as a contextual lens for understanding why organizational AI usage is embedded in organizational readiness, leadership support, and broader implementation conditions, rather than as a separately tested model. Together, these perspectives provide a focused theoretical explanation of the proposed sequence from digital leadership to organizational AI usage intensity, business model innovation, and the firm relative performance.

### The Second Order Conceptualization of Digital Leadership

One of the aspects of this research is the conceptualization of digital leadership as a second order construct including two different but complementary dimensions, namely innovative digital leadership and supportive digital leadership, rather than a unidimensional construct. Innovative digital leadership is the knowledge, strategic insight and mastery of technological trends by the leaders. They have a thorough understanding of information systems architecture, data integration, and the transformative potential of emerging technologies. This dimension provides the necessary technical and knowledge base for digital transformation from the perspective of knowledge management, directing the organization towards the construction of knowledge-based infrastructures and the best management of information (Donate & de Pablo, 2015; Mardani et al., 2018).

Supportive digital leadership is based on the assumption that digital transformation is not only a technology transition but also a cultural and organizational change. This dimension involves the role of managers in creating psychological safety, promoting a culture of learning, reducing resistance to change, and managing well-being in dynamic work environments (Cuesta-Valiño et al., 2026; Xu et al., 2026). Supportive digital leaders foster the environment for incremental and sustainable adoption of emerging technologies within the organizational context, by providing financial resources, emotional support, and strategic alignment among the employees (Isensee et al., 2021).

The combination of these two dimensions creates an organizational environment in which digital leadership can act as a driving force for digital transformation, organizational AI usage, business model innovation, and ultimately, the enhancement of the firm's relative performance.

### The Effect of Digital Leadership on Organizational AI Usage Intensity

Based on the theoretical logic of the study, it is expected that the second-order construct of digital leadership, through its two innovative and supportive dimensions, will be one of the main drivers of organizational AI usage intensity. The use of AI goes beyond the purchase or installation of software and requires changes in core processes, decision-making systems, data infrastructure, and organizational culture. Research suggested that digital leaders play a key role in institutionalizing AI by enabling knowledge flows and building a supportive organizational culture (Mollah et al., 2026). The innovative dimension of digital leadership addresses the strategic vision to harness technologies such as machine learning and Big Data Analytics, while the supportive dimension mitigates implementation barriers through the allocation of human and financial resources and alleviation of concerns about automation (Florea & Croitoru, 2025). This synergy facilitates the integration of AI not as a stand-alone tool but as a strategic resource in organizational decision-making and value creation processes (Kumar & Shrivastava, 2025).

Accordingly, the following hypothesis was proposed:

**H1:** Digital leadership positively influences organizational AI usage intensity.

### The Business Model Innovation as a Dynamic Capability

The business model innovation, as one of the key dynamic capabilities, is responsible for transforming strategic inputs (i.e., digital leadership) and technological inputs (i.e., organizational AI usage intensity) into performance outcomes. From this perspective, the business model innovation is not merely a change in product or process, but the reconfiguration of the logic of value creation, value delivery, and value capture in the organization.

In the Iranian context, where relatively strong innovation outputs coexist with weaker innovation inputs and uneven enabling conditions, Dynamic Capabilities Theory is particularly relevant because it emphasizes the firms' ability to reconfigure internal resources and business models to convert technological potential into organizational value (Teece et al., 1997; WIPO, 2025).

#### Digital Leadership and Business Model Innovation

Digital leadership can be the primary driver of business model innovation because digital leaders are the architects of transformation in the organization's value creation logic. By combining an innovative vision and digital knowledge to identify technological opportunities, along with organizational support to encourage ideation, they steer the organization from traditional models toward innovative models (Garzoni et al., 2020).

Accordingly, the following hypothesis was proposed:

**H2:** Digital leadership positively catalyzes the business model innovation.

#### Organizational AI Usage Intensity and Business Model Innovation

Organizational AI usage intensity can also provide a foundation for business model innovation. As a transformative technology, AI redefines traditional support, production, and decision-making functions, enabling the redesign of organizational boundaries (Bauer & Wolff, 2022). The use of ontology-based intelligent systems and predictive analytics allows organizations to fundamentally redesign the architecture of value creation, value delivery, and value capture (Hamrouni et al., 2021). Systematic literature indicated that AI is one of the main drivers for rethinking and transitioning toward sustainable business models (Di Vaio, Boccia, et al., 2020; Di Vaio, Palladino, et al., 2020).

Accordingly, the following hypothesis was proposed:

**H3:** Organizational AI usage intensity positively facilitates the business model innovation.

#### The Business Model Innovation and the Firm's Relative Performance

On the other hand, the business model innovation can lead to the enhancement of the firm's relative performance. In today's economy, the sustainability of performance depends on the sustainability of the business model (Boons & Lüdeke-Freund, 2013). The business model innovation creates sustainable competitive advantages by aligning economic goals with social and environmental responsibilities in the form of a triple bottom line approach (Elkington, 1998; Shakeel et al., 2020). The evolution of the conceptual architecture of innovative and green business models enables organizations to maintain their economic growth and achieve performance above the industry average, even under crisis conditions (Saiyed et al., 2025).

Accordingly, the following hypothesis was proposed:

**H4:** The business model innovation positively enhances the firm's relative performance.

### Digital Leadership and the Firm's Relative Performance

Beyond its indirect influence through technological and business-model mechanisms, digital leadership may also contribute directly to the firm's relative performance by strengthening strategic alignment, facilitating technology-enabled decision-making, and coordinating organizational resources during digital transformation. From an Upper Echelons perspective, top managers' digital orientations can shape strategic choices and organizational responses to technological change (Hambrick & Mason, 1984). From a resource-based perspective, digital leadership can function as a valuable intangible capability that supports the effective mobilization of technological, human, and knowledge resources (Barney, 1991). Accordingly, the following hypothesis was proposed:

**H5:** Digital leadership positively contributes to the firm's relative performance.

### Organizational AI Usage Intensity and the Firm's Relative Performance

From a theoretical perspective, it is expected that the penetration of AI into the operational and strategic layers of the firm will have a positive effect on the firm's relative performance by improving decision-making, reducing human errors, increasing organizational agility, and enhancing productivity. AI-based systems reduce human errors by processing large volumes of data and increase organizational agility in responding to market fluctuations (Zarei & Naderi, 2024). In unstable industrial environments, the algorithmic capabilities of AI can make supply chains more resilient and improve resource allocation efficiency (Pallathadka et al., 2023). Furthermore, the involvement of AI in interactive platforms enables value co-creation with stakeholders, and through this mechanism, it can improve the firm's financial and competitive performance indicators relative to competitors (Leone et al., 2021).

However, the AI productivity paradox suggests that advances in and increased use of AI do not necessarily produce immediate or directly observable performance gains. Brynjolfsson et al. (2019) argued that the benefits of AI may emerge only after firms undertake complementary investments in organizational redesign, process innovation, new skills, and other intangible capabilities. From this perspective, organizational AI usage intensity may be insufficient on its own to improve the firm's relative performance unless AI-enabled resources are embedded in complementary organizational mechanisms. In the present model, the business model innovation represents such a mechanism because it enables firms to translate AI-supported insights and process capabilities into changes in value creation, value delivery, and value capture. Thus, although AI usage has the potential to enhance decision quality, organizational agility, and resource allocation, the realization of its performance benefits may depend on the firm's capacity to undertake complementary organizational transformation.

Accordingly, although organizational AI usage has the potential to improve the firm performance, the AI productivity paradox suggests that the realization of these benefits may depend on complementary organizational investments and reconfiguration capabilities. This theoretical tension provides the basis for testing the following direct-effect hypothesis:

**H6:** Organizational AI usage intensity positively contributes to the firm's relative performance.

### Mediation of Business Model Innovation

Above arguments suggested that the business model innovation might mediate the effect of both digital leadership and organizational AI usage intensity on the firm's relative performance. Digital leadership can help identify and mobilize opportunities for business model renewal, while organizational AI usage can offer data-driven insights and process capabilities to support changes in value creation, value delivery, and value capture. Indeed, the effect of these managerial and technological inputs on firm performance might be more visible when considering it from the perspective of business model innovation (Aagaard & Tucci, 2024; Bauer & Wolff, 2022; Clauss, 2017). Therefore, the following mediation hypotheses were proposed:

> **H7:** The relationship between digital leadership and the firm's relative performance is mediated by business model innovation.
>
> **H8:** Business model innovation mediates the relationship between organizational AI usage intensity and the firm's relative performance.

### The Sequential Indirect Mechanism

Within the sequential pathway proposed in this study, digital leadership is positioned as the initiating managerial capability because it provides the strategic direction, resource commitment, and organizational support required for the effective organizational use of AI. Once AI is embedded in organizational processes, its data-driven insights, automation potential, and coordination capabilities can reveal opportunities for redesigning how the firm creates, delivers, and captures value. The business model innovation therefore follows the organizational AI usage in this pathway because it represents the reconfiguration mechanism through which AI-enabled possibilities are translated into revised business logic. This ordering is consistent with Dynamic Capabilities Theory, which emphasizes that technological resources create value through their integration and reconfiguration within organizational processes, and with research showing that AI can reshape the components and logic of business models (Aagaard & Tucci, 2024; Teece et al., 1997). Accordingly, the proposed sequence is conceptualized as digital leadership → organizational AI usage intensity → the business model innovation → the firm's relative performance.

Accordingly, the following sequential mediation hypothesis was proposed:

> **H9:** Digital leadership has a positive and significant indirect effect on the firm's relative performance through the sequential path of organizational AI usage intensity and business model innovation.

### The Role of Control Variables in the Model

To more accurately estimate the effects of the main variables, a set of firm-level control variables was incorporated into the conceptual model of the study. These variables included industry sector, firm size, firm age, R&D intensity, and export orientation. The inclusion of these variables in the model is important because part of the performance differences among firms may stem from their structural, institutional, and strategic characteristics, not merely from digital leadership, organizational AI usage, or business model innovation.

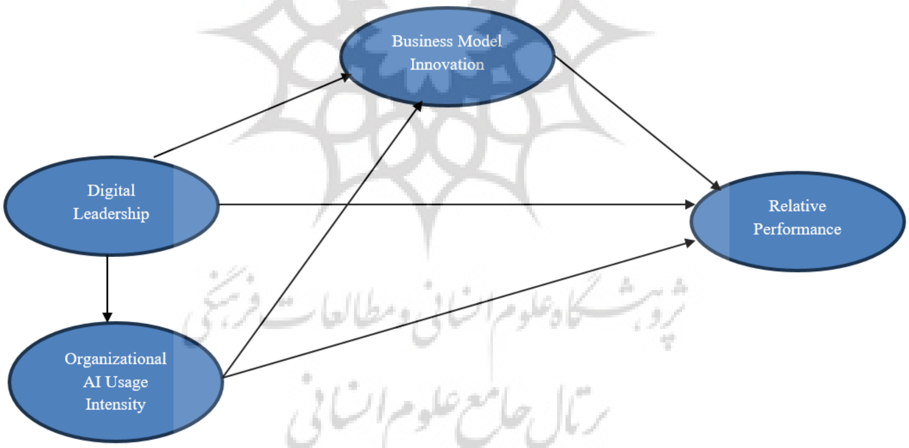
Industry can reflect the structural, technological, and competitive differences across different fields. The firm size was also entered into the model due to its relationship with available resources, capacity for investment in new technologies, and the possibility of allocating specialized human resources. The firm age is important because organizational experience can, on one hand, increase accumulated experience and the ability to manage uncertainty.

The firm's strategic characteristics, including export orientation and R&D intensity, may also influence the firm's willingness and ability to adopt innovation. Firms that have a more prominent presence in international markets and allocate higher budgets to research and development, due to competitive pressure and higher absorptive capacity, are structurally more inclined to adopt innovations and intelligent systems (Tineo-Mendoza & Hernández-Cenzano, 2025).

### Conceptual Model

Based on the theoretical arguments and hypotheses developed above, the proposed conceptual model is presented in Figure 1.

**Figure 1.**
**The Conceptual Model of the Study**




**(Source: The Researcher's Findings)**

## Methodology

In terms of purpose, the present study was applied, and in terms of data collection, it fell within the category of descriptive-survey studies. Given the research objective of testing the hypothesized structural relationships among latent variables, this study was a quantitative and correlational study based on Structural Equation Modeling. The research data were collected cross-sectionally using a structured questionnaire adapted from international scales. The unit of analysis in this study was the firm, and the respondents included senior managers, middle managers, senior experts, and key informants knowledgeable about the firm's strategic, technological, innovation-related, and performance conditions.

### Population, Sampling, and Data Collection Process

The statistical population of the present study consisted of knowledge-based firms active in Iran that held valid knowledge-based certification at the time of data collection. The unit of analysis of the study was the firm, and the unit of response was one of the managers or key individuals of each firm who had sufficient knowledge and information regarding digital strategies, the extent of organizational AI usage, activities related to business model innovation, and the firm performance. Accordingly, the chief executive officer (CEO), founder, board member, chief technology officer (CTO), R&D manager, digital transformation manager, or other qualified managers were considered potential respondents. Given the geographical dispersion of knowledge-based firms, the impossibility of accessing all members of the statistical population, and the necessity of obtaining information from informed individuals within the firms, a non-probability purposive and convenience sampling method was employed.

The data collection process was conducted over a five-month period, and the research questionnaire was sent to 1,098 eligible knowledge-based firms. Of this number, 786 questionnaires, equivalent to 71.58% of the total distributed questionnaires, were not returned despite follow-ups. In total, 312 questionnaires were received, representing an initial response rate of 28.42%. The received questionnaires were reviewed before entering the analysis in terms of completeness of responses, respondent eligibility, presence of invalid response patterns, and overall data quality.

During the data screening stage, 23 questionnaires were excluded from the dataset due to a high volume of missing data or non-response to the main items of the research constructs, 17 questionnaires were excluded due to the observation of invalid response patterns (including straight-line responses or obvious inconsistency among responses), and 8 questionnaires were excluded because the respondent or firm did not meet the necessary criteria. Thus, a total of 48 questionnaires were removed from the received responses, and 264 complete and valid questionnaires entered the statistical analysis process. The final valid response rate of the study was 24.04%, and the retention rate of the returned questionnaires after screening was 84.62%.

To ensure data quality, efforts were made to have the questionnaire completed only by individuals who had sufficient knowledge of digital strategies, the status of intelligent technology usage, business model innovation, and the firm's relative performance. Before the final analysis, the data were also checked for completeness of responses, logical consistency, absence of influential missing data, and information adequacy. Furthermore, given the nature of PLS-SEM, multivariate normality was not a necessary prerequisite for the analysis; nevertheless, the data were examined in terms of response range, unusual patterns, obvious outliers, and overall consistency.

At the organizational level, control variables including the firm size, the firm age, R&D intensity, export orientation, and industry sector were incorporated into the model. The firm size was measured based on the number of employees, the firm age based on the number of years of activity, R&D intensity based on the ratio of R&D expenses to sales, and export orientation based on the share of exports in total sales. The firm's industry of activity was also entered into the model through dummy variables. In the final model, two dummy variables, Ind_Health and Ind_Industrial, were included to control for industry differences, with the *other* group considered the reference group. The inclusion of these variables in the model was aimed at controlling for structural and organizational effects to estimate the main relationships among digital leadership, organizational AI usage intensity, business model innovation, and the firm's relative performance with greater accuracy.

### Data Collection Instrument and Measurement of Variables

The primary tool for data collection was a standardized and structured questionnaire, the items of which were adapted from validated scales and adjusted to the context of Iranian knowledge-based firms. To measure the research variables, five-point and seven-point Likert scales were used. For the constructs of digital leadership, business model innovation, and the firm's relative performance, responses were measured on a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. To measure the organizational AI usage intensity, a seven-point scale was used, indicating the frequency of the firm's use of various AI applications ranging from 1 = never to 7 = almost always.

Digital leadership was considered a second-order latent construct. This construct represents the ability of organizational leaders to create a digital vision, direct technological changes, support employees, and facilitate the digital transformation process. Nine items adapted from the scale developed and validated by Büyükbeşe et al. (2022) were used to measure this variable. This construct consists of two first-order dimensions of *innovative digital leadership* and *supportive digital leadership*. The innovative digital leadership dimension was measured with 6 items, emphasizing the leader's ability to create an innovative vision, understand digital technologies, take the lead in digital transformation, and attract digital talent. The supportive digital leadership dimension was measured with 3 items, reflecting the leader's role in supporting employees, acting as a guide, and paying attention to their well-being and working conditions during digital transformation.

The organizational AI usage intensity refers to the extent to which the firm actually uses AI-based systems and tools in its business processes. This construct was measured with 6 items adapted from the study by Mi et al. (2023) and tailored to the context of knowledge-based firms. The items of this construct cover various applications of AI in displaying the status and flow of business processes, designing or redesigning processes, coordinating and scheduling work processes, automating activities, and providing information about the firm's resources and inventories. Based on the results of measurement model and the nature of the items, this construct was assessed reflectively in the research model.

The business model innovation represents the extent of the firm's significant changes in the way it creates, delivers, and captures value. This construct was measured using 10 items. The items related to this variable were adapted from the operational version of Madhavan et al.'s study (2022) and were theoretically based on the comprehensive business model innovation framework of Clauss (2017). These items cover various dimensions of innovation in the combination of products and services, entering new markets or customer groups, collaborating with new partners and suppliers, changes in the value proposition, information exchange in the value chain, operational processes and routines, pricing methods, revenue generation, and customer retention. This construct was assessed reflectively in the research model.

The firm's relative performance refers to the evaluation of the firm's performance compared with its main competitors. To measure this construct, 5 items adapted from Mikalef and Gupta's study (2021) were used. These items assess the firm's overall success, market share, growth, profitability, and innovation compared with competitors. The use of relative performance indicators was chosen because it focuses the respondents' evaluation on comparing the firm with its main competitors rather than absolute financial values, thereby reducing some of the environmental, industrial, and scale differences among the firms. This construct was also considered reflective in the research model.

### Data Analysis Method

To test the conceptual model and research hypotheses, the PLS-SEM method was used. Data analysis was conducted using SmartPLS 3 software. The choice of this method was considered appropriate given the predictive nature of the model, the presence of a second-order construct, its ability to analyze the measurement and structural models, and its capability to estimate complex relationships among latent and observed variables.

The data analysis process was conducted in two main stages: measurement model evaluation and structural model evaluation. In the first stage, the measurement model of the reflective constructs of the research was evaluated. The main constructs included digital leadership, organizational AI usage intensity, business model innovation, and the firm's relative performance. For these constructs, reliability and validity were examined through outer loadings, Cronbach's alpha, rho_A, composite reliability, and average variance extracted (AVE). To evaluate discriminant validity, the Fornell-Larcker (1981) criterion was used. Control and dummy variables, including the firm size, the firm age, R&D intensity, export orientation, *Ind_Health*, and *Ind_Industrial*, were entered as observed variables into the model and were not reported in the reliability and validity assessment of the latent constructs.

Since digital leadership was modeled in this study as a reflective-reflective second-order construct, a two-stage approach was used to estimate it. In the first stage, the two first-order constructs, *innovative digital leadership* and *supportive digital leadership*, were estimated with their respective items. Then, the latent variable scores of these two dimensions were extracted and entered into the model in the second stage as indicators of the second-order construct of digital leadership.

In the second stage, the structural model was evaluated. In this stage, path coefficients, t-statistics, and p-values were calculated for the direct relationships of the model. To test the significance of the path coefficients and indirect effects, a bootstrapping method with 5,000 subsamples was utilized. In addition to statistical significance, the structural model was evaluated using the standardized root mean square residual (SRMR), while its explanatory power was assessed through the coefficient of determination ($R^2$) and the adjusted coefficient of determination (Adjusted $R^2$) for the endogenous variables, including organizational AI usage intensity, business model innovation, and the firm's relative performance. The effect size ($f^2$) was also examined to assess the relative contribution of each main exogenous construct to the explained variance of its corresponding endogenous construct. The mediating effects were also evaluated by examining the specific indirect effects in the bootstrapping output.

## Findings

In this section, the PLS-SEM approach and SmartPLS 3 software were used to test the research hypotheses and examine the relationships among the variables. Following standard procedures, the model was evaluated in two main steps. In the first step, the measurement model was assessed to ensure the validity and reliability of the research constructs. In the second step, the structural model was evaluated to examine the path coefficients, the explanatory power of the model, and the research hypotheses.

### The Assessment of the Measurement Model

Table 1 presents Cronbach's alpha, rho_A, composite reliability, and average variance extracted for the main constructs of the study. In this table, only the main latent constructs are reported. Control and dummy variables, including the firm size, the firm age, R&D intensity, export orientation, Ind_Health, and Ind_Industrial, were not reported in the assessment of reliability and validity of latent constructs due to their observed or single-item nature.

**Table 1.**
**The Construct Reliability and Validity**

| Construct | Cronbach's Alpha | rho_A | Composite Reliability | Average Variance Extracted (AVE) |
|---|---|---|---|---|
| Business Model Innovation | 0.926 | 0.928 | 0.938 | 0.601 |
| Digital Leadership | 0.835 | 0.845 | 0.924 | 0.858 |
| Organizational AI Usage Intensity | 0.829 | 0.837 | 0.876 | 0.542 |
| Relative Performance | 0.901 | 0.905 | 0.927 | 0.717 |

**(Source: The Researcher's Findings)**

Based on the results presented in Table 1, the main constructs of the study demonstrated an acceptable level of reliability and convergent validity. Cronbach's alpha is 0.926 for business model innovation, 0.835 for digital leadership, 0.829 for organizational AI usage intensity, and 0.901 for relative performance. These values indicated that the main constructs of the model have satisfactory internal consistency.

In addition, rho_A is reported as 0.928 for business model innovation, 0.845 for digital leadership, 0.837 for organizational AI usage intensity, and 0.905 for relative performance. These results further confirmed the appropriate internal reliability of the main constructs.

In terms of composite reliability, the values obtained for the main constructs were also at a desirable level. Composite reliability is 0.938 for business model innovation, 0.924 for digital leadership, 0.876 for organizational AI usage intensity, and 0.927 for relative performance. Therefore, the composite reliability of the main constructs was considered acceptable.

Regarding the convergent validity, the average variance extracted is 0.601 for business model innovation, 0.858 for digital leadership, 0.542 for organizational AI usage intensity, and 0.717 for relative performance. Since all these values are above 0.50, it can be concluded that the main constructs of the study have adequate convergent validity.

After assessing the reliability and convergent validity, the discriminant validity of the main constructs was evaluated using the Fornell–Larcker criterion (1981). Table 2 presents the Fornell–Larcker matrix for the main constructs. In this table, the diagonal values represent the square root of the average variance extracted for each construct, while the off-diagonal values indicate the correlations among the constructs.

**Table 2.**
**The Discriminant Validity: Fornell–Larcker Criterion**

| Construct | Business Model Innovation | Digital Leadership | Organizational AI Usage Intensity | Relative Performance |
|---|---|---|---|---|
| Business Model Innovation | 0.775 | | | |
| Digital Leadership | 0.523 | 0.926 | | |
| Organizational AI Usage Intensity | 0.508 | 0.571 | 0.736 | |
| Relative Performance | 0.611 | 0.454 | 0.407 | 0.847 |

**(Source: The Researcher's Findings)**

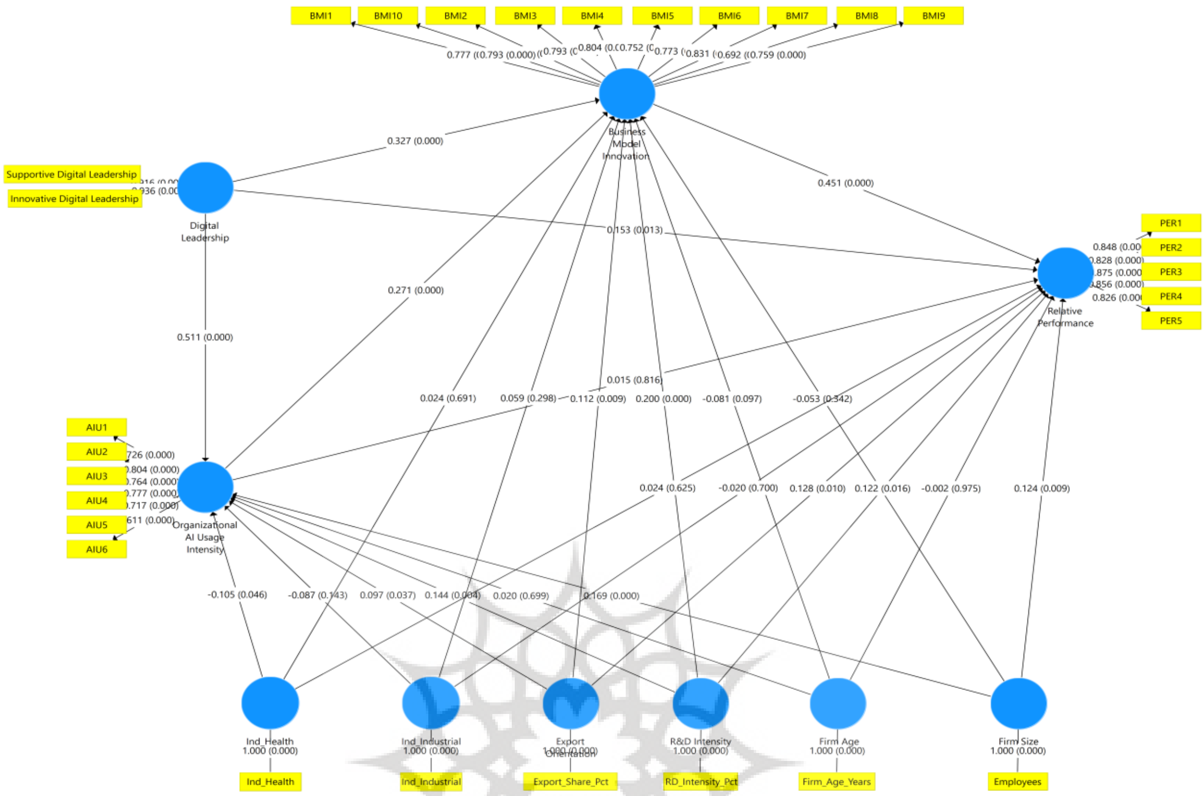
The results in Table 2 show that the diagonal value of each construct is greater than its correlations with the other constructs. Therefore, based on the Fornell–Larcker criterion (1981), the discriminant validity of the main constructs of the model was confirmed. For example, the square root of the average variance extracted for business model innovation is 0.775, which is higher than its correlations with digital leadership, organizational AI usage intensity, and relative performance. Similarly, the diagonal values for digital leadership, organizational AI usage intensity, and relative performance are higher than their corresponding correlations with the other constructs.

## The Assessment of the Structural Model

After confirming the reliability, convergent validity, and discriminant validity of the main constructs, the structural model was evaluated. Before examining the structural relationships, the overall model fit was assessed using the SRMR. The SRMR value was 0.042 for both the saturated and estimated models, which is below the conservative threshold of 0.08 and indicates an acceptable overall model fit.

Figure 2 presents the final research model along with path coefficients and p-values.

**Figure 2.**
**The Results of the Final Structural Model**




**(Source: The Researcher's Findings)**

Figure 2 shows that digital leadership played a central role in the research model, as it had a positive and significant effect on organizational AI usage intensity, business model innovation, and the firm's relative performance. In addition, the business model innovation was the most important variable with a direct effect on the firm's relative performance, whereas organizational AI usage intensity did not show a significant direct effect on relative performance. Therefore, the overall pattern of the model supported the importance of digital leadership and business model innovation in explaining the firm's relative performance.

After examining the path coefficients, the explanatory power of the structural model was assessed using R Square and R Square Adjusted. Table 3 presents the explained variance for the three endogenous constructs of the model, namely business model innovation, organizational AI usage intensity, and relative performance.

**Table 3.**
**The R Square and Adjusted R Square**

| Construct | R Square | R Square Adjusted |
|---|---|---|
| Business Model Innovation | 0.395 | 0.376 |
| Organizational AI Usage Intensity | 0.385 | 0.368 |
| Relative Performance | 0.439 | 0.419 |

**(Source: The Researcher's Findings)**

Based on the results in Table 3, the R Square value for business model innovation is 0.395, and its adjusted R Square value is 0.376. This result indicated that the predictor variables included in the model explain 39.5% of the variance in business model innovation. Considering the adjusted value, the explained variance of this construct is 37.6%.

For organizational AI usage intensity, the R Square value is 0.385, and the adjusted R Square value is 0.368. This showed that the predictor variables in the model explain 38.5% of the variance in organizational AI usage intensity. The adjusted value also indicated that, after adjustment based on the number of predictors, 36.8% of the variance in this construct is explained by the model.

Moreover, the R Square value for relative performance is 0.439, and its adjusted R Square value is 0.419. This value indicated that the predictor variables in the model explain 43.9% of the variance in the firm's relative performance. The adjusted value is 41.9%, indicating the appropriate explanatory power of the model for the final dependent variable of the study.

After assessing the explanatory power of the model, the path coefficients were examined to evaluate the direction, strength, and significance of the relationships among the research variables. Table 4 presents the results of the path coefficients, including the main relationships of the model and the paths related to the control variables.

Based on the results in Table 4, the path from digital leadership to organizational AI usage intensity has a standardized coefficient of 0.511, a standard deviation of 0.046, a t-statistic of 11.050, and a p-value of 0.000. This result indicated that digital leadership has a positive and significant effect on organizational AI usage intensity. Therefore, the first research hypothesis is supported.

The path from digital leadership to business model innovation has a standardized coefficient of 0.327, a standard deviation of 0.052, a t-statistic of 6.297, and a p-value of 0.000. Therefore, digital leadership has a positive and significant effect on business model innovation, and the second research hypothesis is also supported.

The path from organizational AI usage intensity to business model innovation has a standardized coefficient of 0.271, a standard deviation of 0.054, a t-statistic of 4.980, and a p-value of 0.000. This result indicated that organizational AI usage intensity has a positive and significant effect on business model innovation. Therefore, the third research hypothesis is supported.

The path from business model innovation to relative performance has a standardized coefficient of 0.451, a standard deviation of 0.054, a t-statistic of 8.283, and a p-value of 0.000. This result indicated that business model innovation has a positive and significant effect on the firm's relative performance. This path represents the strongest direct effect on relative performance among the main relationships of the model. Therefore, the fourth research hypothesis is supported.

**Table 4.**
**The Results of the Path Coefficients**

| Relationship | Original Sample (O) | Standard Deviation (STDEV) | T Statistics (\|O/STDEV\|) | P Values | Result |
|---|---|---|---|---|---|
| Firm Age → Business Model Innovation | -0.081 | 0.049 | 1.663 | 0.097 | Not significant |
| Firm Age → Organizational AI Usage Intensity | 0.020 | 0.051 | 0.386 | 0.699 | Not significant |
| Firm Age → Relative Performance | -0.002 | 0.049 | 0.031 | 0.975 | Not significant |
| Business Model Innovation → Relative Performance | 0.451 | 0.054 | 8.283 | 0.000 | Significant |
| Digital Leadership → Business Model Innovation | 0.327 | 0.052 | 6.297 | 0.000 | Significant |
| Digital Leadership → Organizational AI Usage Intensity | 0.511 | 0.046 | 11.050 | 0.000 | Significant |
| Digital Leadership → Relative Performance | 0.153 | 0.061 | 2.506 | 0.013 | Significant |
| Export Orientation → Business Model Innovation | 0.112 | 0.042 | 2.633 | 0.009 | Significant |
| Export Orientation → Organizational AI Usage Intensity | 0.097 | 0.046 | 2.094 | 0.037 | Significant |
| Export Orientation → Relative Performance | 0.128 | 0.050 | 2.576 | 0.010 | Significant |
| Firm Size → Business Model Innovation | -0.053 | 0.056 | 0.951 | 0.342 | Not significant |
| Firm Size → Organizational AI Usage Intensity | 0.169 | 0.042 | 4.062 | 0.000 | Significant |
| Firm Size → Relative Performance | 0.124 | 0.047 | 2.618 | 0.009 | Significant |
| Ind_Health → Business Model Innovation | 0.024 | 0.060 | 0.397 | 0.691 | Not significant |
| Ind_Health → Organizational AI Usage Intensity | -0.105 | 0.052 | 1.998 | 0.046 | Significant |
| Ind_Health → Relative Performance | 0.024 | 0.049 | 0.488 | 0.625 | Not significant |
| Ind_Industrial → Business Model Innovation | 0.059 | 0.057 | 1.041 | 0.298 | Not significant |
| Ind_Industrial → Organizational AI Usage Intensity | -0.087 | 0.059 | 1.465 | 0.143 | Not significant |
| Ind_Industrial → Relative Performance | -0.020 | 0.053 | 0.386 | 0.700 | Not significant |
| Organizational AI Usage Intensity → Business Model Innovation | 0.271 | 0.054 | 4.980 | 0.000 | Significant |
| Organizational AI Usage Intensity → Relative Performance | 0.015 | 0.064 | 0.233 | 0.816 | Not significant |
| R&D Intensity → Business Model Innovation | 0.200 | 0.050 | 4.028 | 0.000 | Significant |
| R&D Intensity → Organizational AI Usage Intensity | 0.144 | 0.049 | 2.920 | 0.004 | Significant |
| R&D Intensity → Relative Performance | 0.122 | 0.051 | 2.415 | 0.016 | Significant |

**(Source: The Researcher's Findings)**

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The path from digital leadership to relative performance has a standardized coefficient of 0.153, a standard deviation of 0.061, a t-statistic of 2.506, and a p-value of 0.013. This result indicated that digital leadership, in addition to influencing the organizational AI usage intensity and business model innovation, also has a direct positive and significant effect on the firm's relative performance. Therefore, the fifth research hypothesis is supported.

In contrast, the path from organizational AI usage intensity to relative performance has a standardized coefficient of 0.015, a standard deviation of 0.064, a t-statistic of 0.233, and a p-value of 0.816. This result indicated that the direct effect of organizational AI usage intensity on relative performance is very weak and statistically insignificant. Therefore, the sixth research hypothesis is not supported.

Overall, the results of the path coefficients showed that, among the main relationships of the study, the paths from digital leadership to organizational AI usage intensity, digital leadership to business model innovation, organizational AI usage intensity to business model innovation, business model innovation to relative performance, and digital leadership to relative performance are positive and significant. The only insignificant main path is the path from organizational AI usage intensity to relative performance. This finding indicated that the organizational use of AI alone does not directly improve the firm's relative performance; rather, its performance effect can be explained through the transformation of AI capabilities into business model innovation.

Regarding the control variables, export orientation and R&D intensity exhibited the most consistent positive patterns, as both were positively associated with business model innovation, organizational AI usage intensity, and the firm's relative performance. In particular, R&D intensity showed its strongest association with business model innovation ($\beta = 0.200$, $p = 0.000$), followed by organizational AI usage intensity ($\beta = 0.144$, $p = 0.004$) and relative performance ($\beta = 0.122$, $p = 0.016$), highlighting the importance of sustained investment in knowledge development and innovation-related capabilities. The firm size was positively associated with organizational AI usage intensity and relative performance but not with business model innovation, whereas the firm age showed no significant relationship with any endogenous construct. Industry effects were generally non-significant, except that firms in the health sector exhibited lower organizational AI usage intensity than the reference group ($\beta = -0.105$, $p = 0.046$). Because these variables were included as statistical controls, their coefficients are interpreted cautiously, while the complete results remain reported in Table 4.

Following the assessment of the structural path coefficients, effect sizes ($f^2$) were examined to evaluate the relative contribution of each main predictor to the explained variance of its corresponding endogenous construct. Table 5 presents the $f^2$ values and their associated magnitude classifications for the main structural relationships.

**Table 5.**
**The Effect Sizes ($f^2$) of the Main Structural Relationships**

| Relationship | $f^2$ | Effect Size |
|---|---|---|
| Digital Leadership → Organizational AI Usage Intensity | 0.392 | Large |
| Digital Leadership → Business Model Innovation | 0.117 | Small |
| Organizational AI Usage Intensity → Business Model Innovation | 0.075 | Small |
| Business Model Innovation → Relative Performance | 0.219 | Medium |
| Digital Leadership → Relative Performance | 0.025 | Small |
| Organizational AI Usage Intensity → Relative Performance | 0.000 | Negligible |

**(Source: The Researcher's Findings)**

As shown in Table 5, digital leadership had a large effect on organizational AI usage intensity ($f^2$ = 0.392), indicating its substantial contribution to explaining the organizational AI usage. Business model innovation had a medium effect on relative performance ($f^2$ = 0.219), confirming its central role in explaining the firm-level performance differences. Digital leadership had small effects on business model innovation ($f^2$ = 0.117) and relative performance ($f^2$ = 0.025), while organizational AI usage intensity had a small effect on business model innovation ($f^2$ = 0.075). In contrast, the effect of organizational AI usage intensity on relative performance was negligible ($f^2$ = 0.000), which is consistent with the non-significant direct path reported in the structural model.

After examining the direct effects, specific indirect effects were assessed to test the mediating role of business model innovation and the sequential effect of digital leadership through organizational AI usage intensity and business model innovation. Table 6 presents the results of the specific indirect effects for the main mediating paths of the study.

**Table 6.**
**The Specific Indirect Effects**

| Relationship | Original Sample (O) | T Statistics | P Values |
|---|---|---|---|
| Digital Leadership → Business Model Innovation → Relative Performance | 0.147 | 4.964 | 0.000 |
| Organizational AI Usage Intensity → Business Model Innovation → Relative Performance | 0.122 | 4.499 | 0.000 |
| Digital Leadership → Organizational AI Usage Intensity → Business Model Innovation → Relative Performance | 0.063 | 4.197 | 0.000 |

**(Source: The Researcher's Findings)**

Based on the results in Table 6, the indirect effect of digital leadership on relative performance through business model innovation is 0.147. The t-statistic for this effect is 4.964, and its p-value is 0.000. Therefore, this indirect effect is positive and significant. This result revealed that part of the effect of digital leadership on the firm’s relative performance is transmitted through business model innovation. Given that the direct effect of digital leadership on relative performance was also positive and significant, it can be stated that business model innovation plays a significant mediating role in the relationship between digital leadership and relative performance, while this mediation occurs alongside the direct effect of digital leadership. Therefore, the seventh research hypothesis is supported.

In addition, the indirect effect of organizational AI usage intensity on relative performance through business model innovation is 0.122. The t-statistic for this path is 4.499, and its p-value is 0.000. This result indicated that the indirect effect of organizational AI usage intensity on relative performance through business model innovation is positive and significant. The importance of this finding lay in the fact that the direct effect of organizational AI usage intensity on relative performance was not significant; therefore, the performance effect of AI is mainly realized through its transformation into business model innovation. Accordingly, the eighth research hypothesis is supported.

The results in Table 6 also show that the sequential indirect effect of digital leadership on relative performance through organizational AI usage intensity and business model innovation is 0.063. The t-statistic for this path is 4.197, and its p-value is 0.000. Therefore, the proposed sequential effect is positive and significant. This finding indicated that digital leadership can improve the firm's relative performance by strengthening the organizational AI usage intensity and then transforming it into business model innovation. Accordingly, the ninth research hypothesis is supported.

## Discussion and Conclusion

The main objective of this study was to examine the effect of digital leadership and organizational AI usage intensity on the relative performance of Iranian knowledge-based firms, with an emphasis on the role of business model innovation. The conceptual model of the research was developed based on Upper Echelons Theory, the Resource-Based View, Dynamic Capabilities Theory, and the Technology–Organization–Environment framework, and was tested using the PLS-SEM approach. The results of the model estimation indicated that digital leadership, organizational AI usage intensity, and business model innovation, along with several organizational control variables, play an important role in explaining the relative performance of knowledge-based firms.

From the viewpoint of explanatory power, the R Square outcomes revealed that the predictor variables in the model explained 39.5% of the variance in business model innovation, 38.5% of the variance in organizational AI usage intensity, and 43.9% of the variance in relative performance. The adjusted R Square values for these three constructs were 0.376, 0.368, and 0.419, respectively. The findings indicated that the research model has a sound explanatory capacity especially for relative performance. The combination of digital leadership, organizational AI usage intensity, business model innovation, and control variables can explain a considerable percentage of the variations in performance in knowledge-based firms.

The first main finding revealed that digital leadership positively and significantly impacts organizational AI usage intensity. The path coefficient for this relationship was .511 with $p = .000$. This means that a one-standard deviation increase in digital leadership is related to a 0.511 standard deviation increase in the intensity of organizational AI usage. This finding is consistent with Upper Echelons Theory (Hambrick & Mason, 1984), which proposes that the technological choices made in the organization can be influenced by the orientations and capabilities of top managers.

It is also consistent with Baker's (2012) Technology–Organization–Environment framework, as the adoption of complex technologies such as AI requires managerial support, organizational readiness, and strategic orientation. Thus, in knowledge-based firms, digital leadership is not merely a managerial style but a critical organizational capability for expanding the use of AI.

The second finding revealed that digital leadership has a positive and significant effect on business model innovation. The path coefficient was 0.327, with a p-value of 0.000. Accordingly, a one–standard deviation increase in digital leadership results in a 0.327 standard deviation increase in business model innovation. This finding is consistent with Barney's (1991) Resource-Based View, as digital leadership, as an intangible strategic resource, can coordinate technological, human, and knowledge resources toward the reconfiguration of business logic.

The third finding indicated that digital leadership has a direct, positive, and significant effect on relative performance. The path coefficient was 0.153, with a p-value of 0.013. Thus, a one–standard deviation increase in digital leadership increases relative performance by 0.153 standard deviations. Although this effect is smaller than the effects of digital leadership on AI usage and business model innovation, its significance indicates that digital leadership contributes to better firm performance not only indirectly but also directly—by enhancing strategic orientation, technological decision-making, and organizational adaptability.

The fourth finding was that organizational AI usage intensity has a positive and significant effect on business model innovation. The path coefficient was 0.271 and p value was 0.000. The use of AI in organizations is associated with a 0.271 standard deviation increase in business model innovation for each standard deviation increase in organizational AI use. This finding is in line with the emerging literature on the role of AI in reshaping the logic of value creation. According to some research studies (e.g., Aagaard & Tucci, 2024; Bauer & Wolff, 2022; Di Vaio, Boccia, et al., 2020; Di Vaio, Palladino, et al., 2020), AI can help develop new business models by changing decision-making processes, automating tasks, allowing for data analysis, and transforming organizational relationships.

The present finding confirmed this logic in the context of Iranian knowledge-based firms and showed that organizational AI usage becomes strategically important when it leads to business model reconfiguration.

The most theoretically revealing result concerns the non-significant direct effect of organizational AI usage intensity on relative performance. The path coefficient was 0.015, with a p-value of 0.816. Rather than indicating that AI lacks strategic value, this result suggested that the frequency and breadth of AI use do not automatically translate into superior firm performance. An important distinction should therefore be made between AI usage and AI capability. Whereas usage intensity captures the extent to which AI applications are employed across organizational activities, performance gains depend on the firm's ability to integrate AI-generated insights into decision-making routines, coordinate complementary human and organizational resources, and reconfigure the logic through which value is created, delivered, and captured. This interpretation is consistent with Dynamic Capabilities Theory (Eisenhardt & Martin, 2000; Teece et al., 1997), according to which valuable technological resources generate sustained organizational outcomes only when they are embedded in organizational processes and supported by reconfiguration capabilities. It also refines the argument advanced by Mikalef and Gupta (2021). Their conceptualization of AI capability emphasized the coordinated deployment of AI-specific resources, whereas the present study focused on organizational AI usage intensity. Accordingly, the absence of a significant direct effect does not necessarily contradict prior evidence concerning the performance value of AI capability. Instead, it revealed an important theoretical contingency by indicating that the organizational use of AI must be accompanied by a complementary mechanism of organizational transformation before performance benefits can emerge. The significant indirect effect of organizational AI usage intensity on relative performance through business model innovation ($\beta = 0.122$, $p = 0.000$) supported this interpretation and identified business model innovation as a central value-conversion mechanism in the present model. Therefore, the findings challenged a technology-deterministic view of AI and suggested that competitive value arises not from AI usage alone, but from the organizational capacity to embed such usage within a reconfigured business model.

The sixth and one of the most important findings showed that the business model innovation has a positive and significant effect on relative performance. The path coefficient was 0.451, with a p-value of 0.000. Thus, a one–standard deviation increase in business model innovation led to a 0.451 standard deviation increase in relative performance. This path represented the strongest direct effect on relative performance in the research model. The finding is consistent with Clauss (2017), Boons and Lüdeke-Freund (2013), Madhavan et al. (2022), Shakeel et al. (2020), and Najmaei and Sadeghinejad (2023), all of which emphasized the importance of business model innovation in value creation, sustainability enhancement, and organizational performance improvement. The present result showed that in knowledge-based firms, superior performance arises less from merely possessing or using technologies such as AI, and more from the firm's ability to convert these technologies into innovative business models.

Taken together, these findings revealed a clear distinction between technology use and value realization. Digital leadership functions as an enabling managerial capability that promotes organizational AI usage and directly supports relative performance, whereas business model innovation serves as the organizational mechanism through which technological use is translated into market-relevant and performance-related outcomes. The observed pattern therefore suggests that the performance implications of AI are organizationally contingent: firms may not benefit merely by using AI more intensively, but rather by embedding that use within a revised architecture of value creation, value delivery, and value capture. This interpretation shifts the discussion from whether AI improves the firm performance to how and under what organizational conditions its potential performance benefits can be realized.

In addition to the main paths, the results related to the control variables also revealed important insights. Export Orientation had a positive and significant effect on business model innovation, organizational AI usage intensity, and relative performance. This suggests that firms with a higher export orientation (due to the exposure to international competition, market pressures and higher standards) are more likely to use AI extensively, to innovate more in their business models and to achieve better relative performance. R&D Intensity also positively and significantly influenced all three endogenous constructs. This suggests that investment in research and development leads to increased use of AI, enhances business model innovation and is linked to better relative performance. The firm size had a significant positive effect on organizational AI usage intensity and relative performance. However, its effect on Business Model Innovation was not significant. This indicates that bigger firms could have more resources for AI use and better performance, but the firm size does not necessarily lead to business model innovation. However, the firm age did not have a significant effect on the endogenous variables at the 0.05 level.

Regarding industry, the results showed that firms in the health sector had lower organizational AI usage intensity than firms in the reference group ($\beta = -0.105$, $p = 0.046$), whereas the remaining paths related to Ind_Health and all paths related to Ind_Industrial were not significant. One plausible explanation is that the integration of AI in health-related activities may be more demanding because firms must address sensitive-data governance, privacy and security requirements, ethical considerations, patient-safety concerns, and regulatory compliance before AI applications can be embedded in routine organizational processes (Ahmed et al., 2023). However, because these mechanisms were not directly measured and industry was included only as a control variable, this interpretation remains tentative and should be examined in future industry-specific research studies.

Overall, the findings of the study showed that digital leadership serves as a critical starting point in the digital transformation chain of knowledge-based firms. Digital leadership directly improved relative performance and indirectly created value by increasing organizational AI usage intensity and strengthening business model innovation. However, a key result of the study is that AI alone did not directly improve a firm's relative performance. Its positive performance impact required a complementary mechanism—namely, business model innovation. This finding is highly relevant theoretically and managerially. It demonstrated that the journey to superior performance in knowledge-based firms starts with digital leadership, is strengthened by organizational AI usage, is transformed into value creation logic by business model innovation, and finally, is reflected in relative performance. The theoretical contributions of this study are threefold and collectively provide an integrated process explanation of how digital leadership is translated into the firm's relative performance. First, it extended the application of Upper Echelons Theory to digitally enabled organizational transformation (Hambrick & Mason, 1984) by identifying organizational AI usage intensity as an intermediate organizational mechanism through which top managers' digital orientations are converted into organizational action. Second, it connected the Resource-Based View (Barney, 1991) with Dynamic Capabilities Theory (Eisenhardt & Martin, 2000; Teece et al., 1997) by distinguishing between the availability and use of valuable digital resources and the firm's capacity to reconfigure those resources through business model innovation. The findings indicated that organizational AI usage alone does not directly improve relative performance; rather, value emerges when AI-related capabilities are incorporated into a redesigned logic of value creation, value delivery, and value capture. Third, the Technology–Organization–Environment framework (Baker, 2012) positioned organizational AI usage as a context-dependent organizational process that relied on leadership support and organizational readiness rather than as a stand-alone technological investment. By integrating these perspectives, the study moved beyond the examination of isolated relationships and clarified a sequential mechanism in which digital leadership facilitated the organizational AI usage, AI usage supported business model innovation, and business model innovation became the principal pathway through which these capabilities were translated into the firm's relative performance.

These contributions also position the study within the international literature on digital leadership, AI capability, and AI-enabled business model innovation. Whereas prior research has shown that AI capability can enhance organizational creativity and performance when AI-specific resources are effectively orchestrated (Mikalef & Gupta, 2021), and has emphasized the potential of AI to reshape business models and value creation (Aagaard & Tucci, 2024), the present findings indicated that organizational AI usage intensity alone is not directly related to relative performance. By identifying business model innovation as the mechanism through which organizational AI usage is translated into performance, the study refined this literature by distinguishing technology use from value realization. It also connected the digital leadership literature with research on AI-enabled business model innovation by showing that digital leadership is linked to relative performance through both a direct pathway and a sequential pathway involving the organizational AI usage intensity and business model innovation. The contribution therefore lies not in introducing new constructs, but in clarifying how established managerial and technological constructs operate together to convert digital resources into firm-level value.

Beyond its integrated process contribution, this study also provides a contextual theoretical insight. Iran's innovation system combines comparatively strong innovation outputs with weaker innovation inputs and enabling conditions (WIPO, 2025). Viewed against this contextual background, the non-significant direct effect of organizational AI usage intensity on relative performance, together with its significant indirect effect through business model innovation, is consistent with the interpretation that internal organizational conversion mechanisms may become particularly important when external enabling conditions are uneven. The Iranian context is therefore theoretically informative because it helps reveal the conditions under which the technological use is translated into firm-level value, rather than merely supplying a distinctive empirical setting. Although this interpretation should not be generalized automatically to all emerging economies, it may be relevant to other innovation systems characterized by similar gaps between technological potential and the institutional and organizational conditions required for value realization.

From a practical perspective, the non-significant direct effect of organizational AI usage intensity on relative performance cautions managers against treating broader AI use as an end in itself or as an automatic source of performance gains.

The results are indicative that AI initiatives should be backed up with purposeful re-design of the business model that involves modifications in the ways the firm creates, delivers, and captures value. Thus, managers should assess AI initiatives not only as a matter of the degree or frequency of the use of technology, but also as a matter of integration of AI-generated insights into decision routines, redesign of processes, and new value propositions. That's not to say firms should invest less in AI, but rather that the use of AI needs to be supplemented with digital leadership, employee support, and organizational reconfiguration. Therefore, policymakers who support knowledge-based companies should complement technology access programs with capability building initiatives that improve digital leadership, organizational AI integration, and business model innovation.

Future studies should extend the current model by employing longitudinal designs that reflect the evolution of digital leadership, organizational AI use, business model innovation, and firm performance over time. Studies should also examine organizational culture as a mediating or moderating condition that may affect the extent to which AI-related initiatives are embedded in organizational routines and translated into firm-level value (Isensee et al., 2021).

Despite providing empirical evidence on the roles of digital leadership, organizational AI usage intensity, and business model innovation in explaining the relative performance of knowledge-based firms, the present study was subject to several limitations. First, the research data were collected cross-sectionally; therefore, the interpretation of causal relationships among the variables must be treated with caution. Future studies could employ longitudinal data to examine the dynamics of the effects of digital leadership and organizational AI usage intensity on business model innovation and the firm performance over time.

Second, the data were gathered through a questionnaire and based on the perceptions of key firm respondents. Although relying on well-informed respondents at the firm level is appropriate for measuring constructs such as digital leadership, organizational AI usage intensity, and business model innovation, relying solely on perceptual data can introduce limitations for interpreting the results. Hence, the employment of more objective indicators – such as sales growth, profitability, market share, actual volume of investment in AI, innovative outputs, and secondary financial performance data – could improve the validity of the findings in future research.

Third, this study's statistical population was limited to Iranian knowledge-based firms. Therefore, the generalization of the results to other industries, countries, or types of organizations should be done cautiously. Future research is recommended to validate the current model in other industrial, institutional and geographical contexts and explore the robustness of the relationships found in different settings.

Fourth, the industry sector was included in the present model as a control variable through dummy variables to account for average sectoral differences in the endogenous constructs. A moderation analysis was not conducted because the study's conceptual model was designed to examine the direct, mediating, and sequential relationships among digital leadership, organizational AI usage intensity, business model innovation, and the firm's relative performance, while treating industry as a contextual control rather than as a hypothesized boundary condition. The testing moderation would require the specification and estimation of interaction effects between industry and the focal predictors, which was beyond the scope of the proposed model. Nevertheless, industry differences may condition some of the focal relationships. Future studies should therefore examine industry as a moderator by developing explicit interaction hypotheses and using larger, more balanced industry-specific samples.

Finally, the findings showed that organizational AI usage intensity does not have a significant direct effect on relative performance, but has a positive and significant effect on business model innovation and a significant indirect effect on relative performance through business model innovation. Future research should therefore examine additional organizational mechanisms that may explain when and how AI usage is translated into firm-level value. The organizational culture deserves particular attention because shared values, norms, and behavioral expectations may shape the acceptance, integration, and responsible use of AI and influence the extent to which AI-related initiatives become embedded in organizational routines (Isensee et al., 2021). Accordingly, the organizational culture could be examined as a mediating or moderating mechanism in the relationships among organizational AI usage intensity, business model innovation, and firm performance. Other potentially relevant mechanisms include digital maturity, data-driven capabilities, organizational agility, and market competition intensity.

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