



Digital Capabilities, Family Involvement, and Competitive Performance: A Moderated Mediation Perspective

Rim Gafsi*

¹ Faculty of Business and Computer Science, Leaders University, Nabeul, Tunisia

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Abstract. This study examines how Artificial Intelligence (AI) capability influences competitive performance in family firms through the mediating role of big data capability (BDC) and the moderating effect of family involvement in management. Drawing on survey data from 160 Tunisian family firms that adopted AI technologies between 2021 and 2025, the study employs covariance-based structural equation modeling with bootstrapping. The findings show that AI capability enhances competitive performance indirectly through the development of BDC. In addition, family involvement in management strengthens the positive relationship between AI capability and BDC, thereby amplifying the indirect effect to competitive performance. The results suggest that the performance benefits of AI are more likely to emerge when firms develop complementary data analytics capabilities and maintain strong family managerial involvement. By integrating insights from digital transformation and family business research, this study demonstrates that the business value of AI depends not only on technological capabilities but also on organizational and managerial complementarities that enable firms to transform digital investments into competitive advantage.

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PALABRAS CLAVE
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Capacidades Digitales, Implicación Familiar y Desempeño Competitivo: un Enfoque Relacional

Resumen. Este estudio examina cómo la Inteligencia Artificial (IA) influye en el desempeño competitivo de las empresas familiares a través del papel mediador de la capacidad de big data (BDC) y del efecto moderador de la implicación familiar en la gestión. Basándose en datos de encuesta de 160 empresas familiares tunecinas que adoptaron tecnologías de IA entre 2021 y 2025, el estudio emplea un modelo de ecuaciones estructurales basado en covarianzas con bootstrapping. Los resultados muestran que la IA mejora el desempeño competitivo de manera indirecta mediante el desarrollo de la capacidad de big data. Además, la implicación familiar en la gestión fortalece la relación positiva entre la capacidad de IA y la capacidad de big data, amplificando así el efecto indirecto sobre el desempeño competitivo. Los resultados sugieren que los beneficios de la IA en términos de desempeño son más propensos a materializarse cuando las empresas desarrollan capacidades complementarias de análisis de datos y mantienen una sólida implicación familiar en la dirección. Al integrar aportaciones de la investigación sobre transformación digital y empresa familiar, este estudio demuestra que el valor empresarial de la IA depende no solo de las capacidades tecnológicas, sino también de complementariedades organizativas y directivas que permiten a las empresas transformar las inversiones digitales en ventaja competitiva.

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*Corresponding author:

E-mail: rimgafsi@yahoo.fr

Faculty of Business and Computer Sciences, Leaders University, Nabeul, Tunisia.

1. Introduction

Family firms constitute the dominant organizational form worldwide and play a crucial role in economic growth and employment (Aparicio et al., 2021; Villalonga & Amit, 2020). At the same time, they face increasing pressure to engage in digital transformation to remain competitive in rapidly evolving markets. Prior research on technology adoption in family firms has examined several domains, including innovation management (Calabrò et al., 2019) and business model transformation (Brinkerink et al., 2020). The literature suggests that distinctive family firm characteristics, such as concentrated ownership and centralized decision-making (Soluk & Kammerlander, 2023), strong family influence (Sirmon et al., 2008), succession dynamics (Lannon et al., 2024), and non-financial objectives related to the preservation of socioemotional wealth (SEW) (Gómez-Mejía et al., 2007; Martin et al., 2024), can both facilitate and constrain technological adoption (De Massis et al., 2012). Family firms are commonly defined as organizations in which a family maintains significant ownership and managerial control across generations (Martínez-Romero et al., 2025). Their governance structures typically concentrate authority in owner-managers whose preferences and values strongly influence strategic decision-making. Although such structures promote long-term orientation and organizational stability, they may also encourage risk aversion and resistance to change, particularly regarding advanced digital technologies (Kidwell et al., 2018; Radu-Lefebvre et al., 2024; Ulrich et al., 2023). Consequently, despite their economic importance, family firms often lag non-family firms in the adoption of digital technologies and data-driven practices (Worek & Aaltonen, 2025).

Among emerging digital technologies, artificial intelligence (AI) has become a transformative force with the potential to improve decision-making quality, operational efficiency, and strategic foresight (Chaudhuri et al., 2023; Dwivedi et al., 2021; Gafsi, 2026b). However, AI adoption in family firms is influenced not only by economic considerations but also by emotional, identity-related, and legacy concerns associated with the preservation of SEW. Family involvement in ownership and management therefore plays a critical role in shaping organizational goals, risk preferences, and technology-related behaviors (Chrisman et al., 2012). Although the literature on digital transformation in family firms is expanding, research specifically addressing AI capability remains limited and fragmented (Atienza-Barba et al., 2025; Tuncalp, 2025), creating uncertainty regarding how AI can be

effectively leveraged to enhance competitive performance in family business contexts.

From the perspective of dynamic capability theory (DCT), performance advantages do not arise directly from technological assets, but rather from higher-order capabilities that enable firms to integrate, reconfigure, and deploy resources in response to environmental change (Teece, 2018; 2007). Within this framework, AI should not be viewed as a standalone source of competitive advantage, but rather as an enabling technological resource whose value depends on complementary organizational capabilities (Gandomi & Haider, 2015; Koulis et al., 2025). One such capability is big data capability (BDC), defined as a firm's ability to acquire, integrate, and analyze large and diverse datasets to support strategic and operational decision-making (Xu et al., 2024). BDC is widely recognized as a key mechanism through which AI generates performance outcomes. Strong BDC enhances predictive analytics, improves decision accuracy, optimizes processes and supply chains, and strengthens customer relationships, thereby contributing to sustained competitive advantage (León et al., 2024; Srinivasan et al., 2021). Empirical studies consistently associate BDC with higher efficiency, productivity, and customer satisfaction (Ndou & Beqiri, 2014; Oncioiu et al., 2019). Nevertheless, family firms frequently encounter significant barriers to developing BDC due to limited digital maturity, gaps in data literacy, and resource constraints (Calabrò et al., 2019; Soluk & Kammerlander, 2021).

Despite these insights, an important theoretical gap remains. Existing research has largely examined AI, BDC, and performance either in non-family firms or without explicitly accounting for the distinctive governance logic of family enterprises. Recent reviews highlight the absence of an integrated framework explaining how AI capability translates into competitive performance in family firms and under which governance conditions this relationship occurs (Atienza-Barba et al., 2025; Lannon et al., 2024). Moreover, much of the existing literature remains conceptual or qualitative (Gilani et al., 2023; Upadhyay et al., 2023), providing limited quantitative evidence regarding the mechanisms linking AI capability, BDC, and performance outcomes.

To address this gap, the present study adopts a complementary capability perspective informed by DCT, process theory, and set-theoretic reasoning. Whereas variance-based approaches generally assume symmetric and additive effects, set-theoretic logic emphasizes that certain conditions may be necessary but not sufficient for an outcome to occur (Ragin,

2008). Applied to digital transformation in family firms, this perspective suggests that AI capability may constitute a foundational prerequisite for competitive performance yet may fail to create value unless combined with complementary analytical capabilities and supportive governance structures. Family involvement in management is therefore conceptualized as a critical contextual factor shaping whether AI-enabled capabilities are effectively developed and exploited.

Building on this reasoning, the study investigates the mechanisms through which AI capability contributes to competitive performance in family firms by examining (1) the mediating role of BDC and (2) the moderating role of family involvement in management. Accordingly, the central research question guiding this study is as follows: How does AI capability enhance the family firms' competitive performance through BDC, and how does family involvement influence this relationship?

Responding to recent calls for empirical research on AI in family business contexts (Chaudhuri et al., 2023; Kumar & Ratten, 2025; Ulrich et al., 2023), this study analyzes survey data collected from 160 Tunisian family firms and employs bootstrapped structural equation modeling (SEM) using AMOS (Analysis of Moment Structures) 24.0 software. By jointly examining AI capability, BDC, family involvement, and competitive performance, the study provides novel empirical evidence clarifying the conditions under which AI-driven digital transformation translates into competitive advantage in family enterprises. The paper is organized as follows. Section 1 reviews literature and develops hypotheses. Section 2 presents the methodology. Section 3 reports empirical results. Section 4 discusses the findings. Section 5 outlines the theoretical and practical implications. Finally, Section 6 concludes the study by addressing its limitations and suggesting directions for future research.

2. Literature Review and Hypotheses Development

2.1. The impact of AI capability on big data capability

AI capability, defined as a firm's ability to deploy, integrate, and manage AI technologies, constitutes a dynamic capability that enables the reconfiguration of digital resources within organizational processes (De Fano et al., 2026). In family firms, however, the development and utilization of AI are shaped by distinctive governance structures and SEW considerations, including the preservation of family control, identity, and long-term continuity (Gómez-Mejía et al., 2007; Kumar & Ratten, 2025).

Consequently, decisions regarding AI adoption extend beyond purely technological or efficiency-oriented considerations and are instead evaluated according to their alignment with family values and established decision-making traditions. This orientation often leads family firms to adopt AI incrementally and selectively within existing processes rather than pursue radical digital transformation (Arzubiaga et al., 2021; Ulrich et al., 2023).

Generational involvement further shapes how AI capability is embedded within organizational routines. Senior family leaders may exhibit reservations toward AI due to concerns about authority displacement and the loss of tacit control, whereas younger successors are generally more supportive of AI adoption, particularly when governance structures encourage experimentation and organizational learning (Lannon et al., 2024; Soluk & Kammerlander, 2023). As a result, AI capability in family firms tends to manifest primarily through improvements in internal processes rather than through immediate performance gains.

Prior research consistently demonstrates that AI technologies, such as machine learning algorithms, predictive analytics, and automated data-processing tools, do not create value independently. Rather, they strengthen firms' ability to collect, integrate, process, and analyze large and heterogeneous datasets, which represent the core dimensions of BDC (Gupta & George, 2016). From a dynamic capabilities perspective, AI functions as an enabling mechanism that supports continuous sensing, learning, and resource reconfiguration in complex environments (Teece, 2023; 2007). In this regard, AI capability can be viewed as a lower-order technical capability that facilitates the development of higher-order analytical capabilities by improving data quality, processing speed, pattern recognition, and real-time insight generation (Mikalef et al., 2019; Teece, 2018). Without complementary analytical routines and organizational processes, AI remains underutilized, underscoring its role as a necessary but insufficient condition for the development of data-driven capabilities.

Recent empirical evidence further supports this enabling logic. Hossain et al. (2024) demonstrate that AI strengthens BDC by expanding firms' capacity to manage the scale, variety, and velocity of data flows, thereby improving the accuracy, reliability, and timeliness of analytical outputs. Through advanced computational and predictive techniques, AI enhances BDC by automating data integration, uncovering latent patterns, and generating real-time insights that extend beyond descriptive analysis. Importantly, these effects depend on organizational readiness

in terms of leadership support, human capital, financial investment, and cultural orientation. Accordingly, AI capability enhances BDC by enabling the systematic transformation of raw data into structured, analyzable, and actionable information embedded within organizational processes.

Hypothesis 1. *AI capability positively influences BDC*

2.2. The impact of big data capability on competitive performance

BDC enables firms to transform large volumes of raw data into actionable insights that support strategic and operational decision-making. Through advanced data management, processing, and analytical routines, BDC enhances decision-making speed, improves operational efficiency, and fosters innovation by enabling organizations to identify market trends, optimize resource allocation, and respond effectively to environmental changes (Xie et al., 2024). Firms with strong BDC are therefore better positioned to achieve superior outcomes, including higher profitability, greater market share, and sustained growth, as data-driven strategies are more likely to generate long-term competitive advantages. Building on this logic, Pathak et al. (2025) reconceptualize BDC as a dynamic capability, emphasizing its role in promoting product, process, and business model innovations. From this perspective, BDC extends beyond a purely technical infrastructure and functions as a strategic capability that enables firms to continuously reconfigure resources and adapt to evolving competitive conditions. By supporting innovation as a first-order outcome, BDC indirectly contributes to long-term competitive advantage and enhanced organizational performance. Empirical evidence further confirms the strategic importance of BDC, particularly in highly competitive and resource-constrained environments. Hossain et al. (2024) demonstrate that BDC enhances firm competitiveness by improving decision-making quality, optimizing supply chain operations, and strengthening product development and customer engagement. These findings reinforce the view that BDC should be conceptualized as a dynamic capability rather than merely a technological resource. Accordingly, BDC plays a central role in transforming data into strategic insights and operational improvements, thereby constituting a key driver of competitive performance.

Hypothesis 2. *BDC positively influences competitive performance*

2.3. The mediating role of big data capability

AI capability is increasingly recognized as a transformative force that drives innovation, enhances organizational creativity, and improves performance (Mikalef & Gupta, 2021). More broadly, AI and automation are reshaping business processes, increasing productivity, and accelerating economic transformation (Acemoglu & Restrepo, 2018). However, the strategic value of AI is not inherent. Its impact depends on a firm's ability to embed AI within organizational processes and complement it with other resources and routines that transform technological potential into sustained competitive outcomes (Koulis et al., 2025).

From a process theory perspective, organizational transformation does not occur through simple linear cause-and-effect relationships, but rather through interconnected sequences of events and enabling conditions unfolding over time (Van de Ven & Poole, 1995).

Drawing on necessary-but-not-sufficient logic, AI capability can be conceptualized as an initiating condition within a causal chain rather than as a self-sufficient driver of performance. From this perspective, a condition may be indispensable for an outcome to occur while remaining incapable of producing that outcome independently (Goertz, 2003; Ragin, 2008). Accordingly, although AI capability may be necessary for advanced data-driven competition, it is insufficient to generate superior performance unless combined with complementary organizational capabilities. In this context, BDC represents the critical mechanism through which AI translates into competitive performance. AI systems fundamentally depend on high-quality, integrated, and accessible data. BDC provides firms with the routines, infrastructure, and analytical competencies required to structure, integrate, and exploit data for strategic decision-making (Akter et al., 2016; Gupta & George, 2016). Thus, AI provides computational and learning potential, whereas BDC constitutes the enabling capability that allows this potential to be fully realized. This reasoning is consistent with set-theoretic approaches, which analytically distinguish between necessary conditions and sufficient configurations in explaining organizational outcomes (Goertz, 2003; Ragin, 2008).

This logic is further supported by DCT. Within this framework, AI can be conceptualized as a lower-order technological capability whose performance effects depend on its integration with higher-order dynamic capabilities (Teece, 2007). BDC, as a higher-order capability, enables firms to sense opportunities through data, seize them through analytics-driven decisions, and reconfigure resources in response to environmental change.

Prior research demonstrates that although AI and advanced analytics technologies provide substantial processing power, their value materializes only when embedded within dynamic organizational routines and governance structures (Shamim et al., 2020). When reinforced by AI, BDC strengthens real-time analytics, enhances supply chain resilience, and supports adaptive strategic decision-making (Belhadi et al., 2021). By integrating data flows from acquisition to insight generation, BDC promotes organizational agility, cross-functional coordination, and innovation (Wang et al., 2024; Wang et al., 2016; Xu et al., 2024).

In family firms, however, the transformation of AI capability into performance outcomes is strongly shaped by SEW considerations. SEW priorities, such as the preservation of family control, legacy continuity, and risk aversion, often constrain investments in AI infrastructure, limit openness to external expertise, and weaken data-sharing cultures, thereby hindering the development of strong BDC (Berrone et al., 2012; De Massis et al., 2016; Martínez-Romero & Rojo-Ramírez, 2016). At the same time, SEW can also create favorable conditions for digital transformation. When family goals emphasize transgenerational continuity, reputational capital, and long-term renewal, firms are more likely to invest in digital competencies, modernize legacy systems, and leverage close stakeholder relationships. These behaviors strengthen BDC and amplify the performance implications of AI, particularly during generational transitions that introduce new digital competencies and innovation-oriented mindsets (Åberg et al., 2024; Hernández-Linares et al., 2020; Miller & Le Breton-Miller, 2014; Muñoz-Bullón et al., 2018).

This reasoning suggests that AI capability constitutes a necessary but insufficient condition for superior competitive performance in family firms, whereas BDC serves as the central transformative mechanism through which AI generates performance benefits. Accordingly, we posit that the effect of AI capability on competitive performance is transmitted through BDC. Therefore, the following hypothesis is proposed:

Hypothesis 3. *Big Data Capability fully mediates the relationship between AI capability and competitive performance in family firms*

2.4. The moderating role of family involvement

Family involvement in firms is commonly conceptualized through ownership, control, and management (Chua et al., 1999). Its influence varies according to the presence, authority, and active participation of family members, as well as

the distribution of decision-making rights across governance levels (Muñoz-Bullón et al., 2018). Such involvement affects governance quality and managerial decision-making through mechanisms including ownership concentration (Claessens et al., 2002), managerial participation (Jensen & Meckling, 1976), and board control (Shleifer & Vishny, 1986).

This study focuses specifically on family involvement in management, defined as the active participation of family members in the top management team (TMT) (Martínez-Alonso et al., 2023). This form of involvement is conceptually distinct from passive family ownership or control and represents a central dimension of SEW that directly shapes strategic orientations toward innovation and digital transformation (López-Muñoz et al. 2025; Soluk et al., 2025; 2021). When family members actively occupy managerial positions, they exert direct influence over technology-related decisions, resource allocation, and organizational learning processes. AI capability enables firms to process large volumes of heterogeneous data and generate predictive insights that improve decision quality and operational efficiency (Kumar et al., 2024; Wamba et al., 2016). However, transforming AI capability into effective BDC requires sustained investments in analytics processes, technical skills, governance structures, and organizational learning routines. In family firms, the extent to which AI capability is translated into BDC depends critically on the nature and intensity of family involvement in management. The SEW literature suggests that family involvement may produce both enabling and constraining effects on strategic change. On the one hand, when SEW reflects a stewardship-oriented logic emphasizing family reputation, transgenerational continuity, and long-term value creation, family managers are more likely to support investments that enhance organizational adaptability, even when short-term returns remain uncertain (Berrone et al., 2012; Miller & Le Breton-Miller, 2006). Under such conditions, family managers are more inclined to encourage the integration of AI into analytics processes, thereby fostering the routines, coordination mechanisms, and learning practices that underpin BDC. On the other hand, SEW preservation driven by loss aversion or control-related motives may constrain digital transformation, as family decision-makers may resist initiatives perceived as threats to authority, identity, or established organizational practices (Gómez-Mejía et al., 2007). Importantly, prior research indicates that such constraining effects are more commonly associated with passive family ownership or concentrated control without active managerial engagement, rather than with direct

participation in top management roles (Claessens et al., 2002; Shleifer & Vishny, 1986).

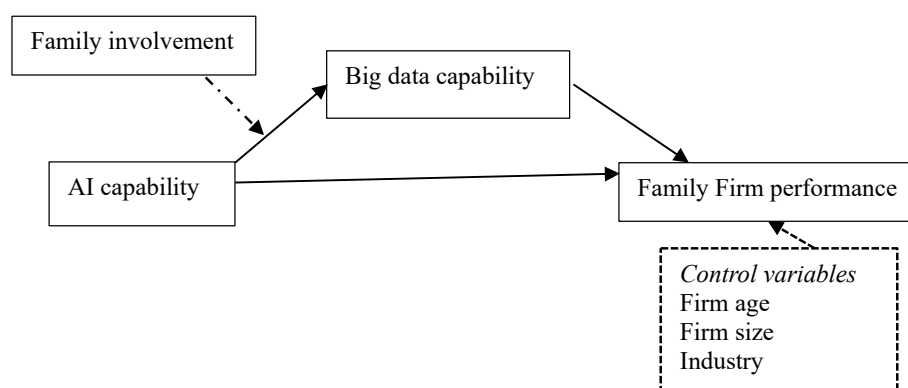
In the present study, family involvement is conceptualized as active participation in top management rather than passive ownership or control, thereby aligning with the stewardship-oriented perspective of SEW. Active family managers typically demonstrate a long-term strategic orientation, patient capital, and a strong commitment to capability development that supports the gradual and synergistic alignment of AI capability and BDC (Miller & Le Breton-Miller, 2006; Soluk et al., 2025). Moreover, their tacit firm-specific knowledge facilitates the conversion of AI-generated insights into actionable analytical routines, thereby reinforcing the development of BDC.

Accordingly, while acknowledging the theoretically dual nature of SEW, this study advances a moderation hypothesis grounded in stewardship-oriented family management. Specifically, under conditions of high family involvement in management, AI capability is expected to be more effectively translated into BDC. The following hypothesis is therefore proposed:

Hypothesis 4. *Family involvement in management moderates the relationship between AI capability and BDC. As family involvement in management increases, the positive effect of AI capability on BDC strengthens*

The research model and proposed hypotheses are shown in Figure 1.

Figure 1. Proposed research model



Source: Author

3. Methodology

3.1. Sample

This study collected data through a survey administered exclusively to Tunisian family firms. According to Alayo et al. (2022), a family firm is defined as an organization in which the founding family retains at least 50% ownership and remains actively involved in management and/or governance. Such firms are characterized by governance structures in which one family, or a small number of families, forms a dominant coalition that intentionally guides strategic decisions to pursue a shared long-term vision and ensure continuity across generations (Sánchez-Peinado & Escribá-Esteve, 2025). The focus on Tunisian family firms is particularly relevant because these businesses constitute a dominant component of the national economy, accounting for nearly 70% of Tunisian GDP (Gafsi, 2024; Gafsi, 2026a).

Data collection was conducted in collaboration with three Tunisian national institutional

partners: the Agency for the Promotion of Industry and Innovation, the Chamber of Commerce and Industry, and the Union of Industry, Commerce, and Craft. These efforts were complemented by the author's professional and personal networks to enhance coverage and participation. The survey targeted family firms operating in the manufacturing and service sectors. These industries provide an empirically rich context for investigating AI capability and BDC because of their relatively high levels of technological adoption. This focus enabled a meaningful examination of how family firms mobilize technological capabilities to improve performance outcomes.

Between August 2024 and March 2025, an online questionnaire was distributed via email and social media to 352 firms. Potential respondents, including CEOs, senior directors, and department heads, were informed of the study's objectives, the voluntary nature of participation, and their right to withdraw at any stage. To ensure content validity, the questionnaire was pretested by

two academic experts in research methodology. Their feedback regarding clarity, relevance, and structure resulted in several minor revisions that improved the instrument's precision and comprehensibility. A total of 170 responses were received, of which 10 were excluded because of incompleteness or inconsistencies, resulting in a final sample of 160 valid responses and an effective response rate of 45.5%.

Table 1 presents the demographic characteristics of the respondents. The typical participant was a highly educated and experienced male manager employed in a manufacturing small - or medium-sized enterprise (SME), most often within a third-generation family enterprise in which the CEO also served as chairperson of the board.

Table 1. Sample characteristics (N=160)

Characteristic	Category	N	%
<i>Gender</i>	Male	100	62.5
	Female	60	37.5
<i>CEO duality</i>	Yes	95	59.4
	No	65	40.6
<i>Age (Mean)</i>		44.3	
<i>Experience</i>	< 10 years	68	42.5
	>10 years	92	57.5
<i>Education</i>	Without degree	10	6.25
	Bachelor's degree	100	62.5
	Master's degree	50	31.25
<i>Family involvement in management</i>	1 family member	30	18.75
	2 family members	45	28.13
	3 family members	40	25
	4 family members	25	15.63
	5 family members	20	12.5
<i>Generational involvement</i>	First generation	10	6.25
	Second generation	40	25
	Third generation	90	56.25
	More than three generations	20	12.5
<i>Firm Size</i>	Small (1-49 employees)	102	63.75
	Medium (50-199 employees)	58	36.25
<i>Industry</i>	Manufacturing	100	62.5
	Services	60	37.5

3.2. Measures

Independent variables: AI capability was measured using the 17-item scale developed by Abou-Foul et al. (2023), grounded in the conceptual framework proposed by Mikalef and Gupta (2021). The items assess the extent to which firms deploy AI technologies across four key domains: (1) enhancing customer value (e.g., personalization, predictive maintenance, and pricing optimization), (2) improving processes (e.g., demand forecasting, robotics, and yield optimization), (3) orchestrating resources (e.g., supplier networks, workforce management, and cybersecurity), and (4) advancing societal good

(e.g., reducing energy consumption, emissions, and waste, or improving workplace safety). In this study, the construct was operationalized as a unidimensional first-order scale, reflecting the holistic and integrative nature of AI capability. Respondents evaluated each item using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

To confirm the one-dimensionality of the construct, a Confirmatory Factor Analysis (CFA) was conducted and demonstrated excellent model fit according to the criteria recommended by Dash and Paul (2021):

- $\chi^2/df = 1.421$ (acceptable threshold < 3)
- CFI (Comparative Fit Index) = 0.994, IFI (Incremental Fit Index) = 0.994, NFI (Normed Fit Index) = 0.979, and TLI (Tucker-Lewis Index) = 0.950 (all ≥ 0.90)
- RMSEA (Root Mean Square Error of Approximation) = 0.051 (≤ 0.08), with PCLOSE = 0.435 (> 0.05)

All 17 items loaded strongly onto a single factor, confirming the construct's one-dimensionality.

Dependent variables: Competitive performance was assessed using a five-item reflective scale adapted from Mikalef et al. (2023). The scale captures respondents' perceptions of how well their organizations perform relative to key competitors across several strategic dimensions, including profitability, market share, growth, overall success, and innovation. Sample items include: "Compared to our key competitors, our organization is more profitable" and "Compared to our key competitors, our organization is more successful." Respondents rated each item on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

Mediating variable: BDC was measured using a five-item scale adapted from Sivarajah et al. (2024). The scale captures a firm's ability to adopt and leverage big data technologies through appropriate technological infrastructure, skilled analytical talent, governance support, and analytics-enabled processes, thereby enhancing organizational efficiency and performance (Gupta & George, 2016). Sample items include: "Adoption of new technologies brings value (technology capability)" and "Efficient use requires trained manpower (talent capability)." All items were assessed using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). BDC was modeled as a reflective first-order construct representing the firm's overall analytics capability.

Moderating variable: Family involvement in management was measured as a continuous variable using a single-item indicator adapted from Martínez-Alonso et al. (2020). Since the sample consisted exclusively of family-owned firms, respondents reported the number of family members occupying top managerial positions, with response options ranging from 1 (one family member) to 5 (more than four family members). This measure captures the degree of family influence over strategic decision-making and reflects the intensity of family participation in management.

Control variables: Three control variables commonly used in family business performance research were included: firm age, firm size, and industry sector. Firm age was measured as the average number of years the firm had been

in operation between 2021 and 2025, while firm size was defined as the average number of employees during the same period. Both variables were log-transformed using the natural logarithm to correct for skewness and capture the diminishing marginal effects associated with additional years and employees (Abou-Foul et al., 2023). This transformation is consistent with prior research suggesting that the early stages of firm development exert a stronger influence on organizational outcomes than later stages (Delmar & Shane, 2006). The industry sector was introduced as a categorical variable using a series of dummy variables, with manufacturing serving as the reference category.

3.3. Data analysis procedures

The data were analyzed using covariance-based structural equation modeling (CB-SEM), which is appropriate for theory-driven and confirmatory research involving well-specified latent constructs as well as hypothesized structural relationships. CB-SEM enables the simultaneous estimation of measurement and structural models, the assessment of overall model fit, and the rigorous testing of mediation and moderated mediation effects. Prior research has demonstrated that CB-SEM provides robust parameter estimates and comprehensive fit indices and performs adequately with sample sizes ranging from 100 to 200 when constructs are reliable and model complexity is moderate (Dash & Paul, 2021).

To implement CB-SEM, this study employed AMOS, which provides well-established support for covariance-based modeling and bootstrapping procedures that enhance the reliability of indirect effect estimation. AMOS is widely used in management and organizational research and facilitates detailed reporting of model fit statistics and parameter estimates, making it particularly suitable for the confirmatory analytical objectives of the present study (Byrne, 2016).

3.4. Common method variance

Common method variance (CMV) was addressed using both procedural (ex-ante) remedies and multiple ex-post statistical techniques, including Harman's single-factor test and the unmeasured latent method factor (ULMF) approach, following Podsakoff et al. (2012; 2003). Ex-ante procedures were implemented to minimize method bias by using clear and concise item wording, assuring respondent anonymity, and reducing evaluation apprehension by keeping respondents unaware of the study's conceptual framework and hypothesized relationships.

As an ex-post analysis procedure, Harman's single-factor test was conducted using CFA. The single-factor model demonstrated poor fit to the

data ($\chi^2/df = 15.625$; CFI = 0.357; TLI = 0.303; IFI = 0.359; NFI = 0.344; RMSEA = 0.303; PCLOSE = 0.000), with all indices falling well outside the recommended thresholds. This result indicates that no single factor accounts for most of the covariance among the measures, suggesting that CMV is unlikely to represent a substantial concern.

To further assess the potential influence of CMV, the ULMF approach was applied by allowing all indicators to load simultaneously onto their theoretical constructs and onto a common method factor. Consistent with Podsakoff et al. (2012; 2003), CMV is considered unlikely to bias results when substantive factor loadings remain statistically significant and when the differences between standardized loadings before and after inclusion of the method factor do not exceed 0.20. In the present analysis, all substantive loadings remained statistically significant, and the observed differences were well below the recommended threshold. Moreover, the inclusion of the method factor did not materially affect the magnitude, direction, or statistical significance of the hypothesized structural relationships. Collectively, these findings indicate that CMV does not pose a serious threat to the validity of the study's conclusions.

4. Findings

4.1. Measurement model

A CFA was conducted to evaluate the measurement model by examining indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. The model fit indices indicate a good fit: $\chi^2/df = 1.384$ (≤ 3.00), CFI = 0.987, TLI = 0.982, IFI = 0.987, and NFI = 0.955 (≥ 0.90); RMSEA = 0.049 (≤ 0.08), and PCLOSE = 0.535 (≥ 0.05).

Table 2 presents the standardized factor loadings, while Table 3 summarizes the descriptive statistics and reliability indicators, including composite reliability (CR), Cronbach's alpha (α), and average variance extracted (AVE) for the three constructs. All standardized factor loadings exceed 0.70 and are statistically significant at $p < 0.001$. Both Cronbach's α and CR exceed the recommended threshold of 0.70, while AVE values are above 0.50, thereby confirming internal consistency reliability and convergent validity (Fornell & Larcker, 1981).

Table 2. Reliability and validity of the measurement scales and construct

Scale composition	Loading	CR	Cronbach's α	AVE
AI capability (Abou-Foul et al., 2023)				
AI1: Our company uses AI to personalize customer experiences and ensure customer success	0.784	0.974	0.973	0.58
AI2: Our team uses AI tools to calculate optimal warranty costs and durations	0.780			
AI3: Our company applies machine learning to optimize pricing and quoting	0.794			
AI4: We analyze embedded sensor data to provide predictive maintenance and operational optimization	0.879			
AI5: We use advanced AI for demand forecasting and inventory stocking.	0.833			
AI6: We acquire strategic data to ensure on-time order fulfillment.	0.795			
AI7: We integrate AI-powered chatbots into our CRM systems.	0.797			
AI8: We use robotics and predictive maintenance in internal operations.	0.806			
AI9: We leverage machine vision and edge analytics for yield optimization.	0.902			
AI10: We use data mining and big data systems to enhance product innovation.	0.842			
AI11: We apply AI to optimize supplier networks through unified data warehouses.	0.766			
AI12: We optimize our labor workforce using AI applications.	0.758			
AI13: We enhance resource optimization, cybersecurity, and data protection with AI.	0.779			
AI14: We use AI to identify the lowest-cost providers.	0.895			
AI15: We train AI assistants to improve workplace safety.	0.834			
AI16: We apply AI to reduce energy consumption, emissions, waste, and operational inefficiencies.	0.763			
AI17: We use data analytics to provide green solutions for societal challenges like decarbonization.	0.765			
Competitive performance (Mikalef et al., 2023)				
PERFORM 1. Compared to our key competitors our organization is more successful	0.839	0.947	0.939	0.553
PERFORM 2. Compared to our key competitors our organization has a greater market share	0.904			
PERFORM 3. Compared to our key competitors our organization is growing faster	0.915			
PERFORM 4. Compared to our key competitors, our organization is more profitable.	0.783			
PERFORM 5. Compared to our key competitors our organization is more innovative	0.868			
Big data capability (Sivarajah et al., 2024)				
BDC1. Adoption of new technologies brings value (Technology capability)	0.765	0.937	0.934	0.611
BDC2. Efficient use requires trained manpower (Talent capability)	0.981			
BDC3. Leadership support for adoption (Governance capability)	0.816			
BDC4. Analytics equips the firm with agility (sense-seize-transform) (Process capability (perceived agility))	0.808			
BDC5. Adoption enhances efficiency (Process capability - analytics exploitation)	0.927			

Table 3. Descriptive statistics and correlation matrix

	Means	SD	AI Cap	BDC	CP	FA	FS	IND
AI Cap	3.81	0.6						
BDC	3.61	0.81	0.193					
CP	3.96	0.75	0.101	0.474				
FA	2.82	0.49	-0.121	0.025	-0.047			
FS	3.59	0.90	-0.044	0.005	-0.016	0.07		
IND	1.14	0.35	-0.049	-0.099	-0.130	-0.13	-0.132	

Note: AI Cap = AI capability; BDC = big data capability; CP = competitive performance; FA = firm age; FS = firm size; IND = industry sector."

Discriminant validity is supported, as the square root of each construct's AVE exceeds its corresponding correlations with the other

constructs, as shown in Table 4. In addition to the Fornell-Larcker criterion, discriminant validity was further assessed using the heterotrait-monotrait (HTMT) ratio of correlations, as recommended by Henseler et al. (2015).

Table 4. Discriminant validity of constructs

Construct	AI capability	Big data capability	Competitive performance
AI capability	0.761		
Big data capability	0.037	0.78	
Competitive performance	0.01	0.225	0.74

The diagonal represents the square root of the average variance extracted, while the other entries represent squared correlations.

As shown in Table 5, the HTMT values for all construct pairs were well below the conservative threshold of 0.85. Moreover, bootstrapping with 5,000 resamples was conducted to derive 95%

confidence intervals for the HTMT estimates. None of the confidence intervals included the value of 1, providing strong evidence of discriminant validity among the constructs.

Table 5. Bootstrapped HTMT confidence intervals (5,000 resamples, 95% CI)

Construct Pair	HTMT	CI 95%
AI - BDC	0.206	(0.092; 0.394)
AI - Performance	0.125	(0.080; 0.336)
BDC - Performance	0.514	(0.334; 0.673)

4.2. Structural model

4.2.1. Partial model analysis (SEM1)

A structural equation model was estimated to examine the hypothesized relationships among AI capability, BDC, and competitive performance in family firms. The results indicate a satisfactory overall model fit. Specifically, $\chi^2/df = 1.329$ is well below the recommended threshold of 3. The incremental fit indices also exceed the

recommended cut-off values (CFI = 0.986, TLI = 0.981, IFI = 0.986, and NFI = 0.947). In addition, RMSEA = 0.046 falls below the recommended threshold of 0.06, while the PCLOSE value of 0.736 indicates a close-fitting model. Collectively, these indicators confirm that the partial mediation model (SEM1) provides an adequate representation of the observed data, consistent with established CB-SEM guidelines.

4.2.2 Full mediation model analysis (SEM2)

To further assess whether the mediating effect of BDC was partial or full, a nested model comparison was conducted by estimating two competing models. In the partial mediation model (SEM1), both the direct path from AI capability to competitive performance and the indirect path through BDC were freely estimated. In the full mediation model (SEM2), the direct path from AI capability to competitive performance was constrained to zero, while the indirect path through BDC was retained.

As reported in Table 6, the chi-square difference test indicates that constraining the direct path does not produce a significant deterioration in model fit ($\Delta x^2 = 0.038$, $\Delta df = 1$, $p > 0.05$). Moreover, the Akaike Information Criterion (AIC) and Expected Cross-Validation Index (ECVI) values are lower for SEM2, indicating a better balance between model fit and parsimony. According

to established SEM guidelines, when a more constrained model does not significantly worsen model fit and demonstrates greater parsimony, it should be preferred (Hair et al., 2017; Kline, 2016).

Consequently, the full mediation model (SEM2) was retained as the final model. Consistent with both the bootstrapping results and the nested model comparison, AI capability does not exert a significant direct effect on competitive performance. Instead, its influence appears to operate through BDC.

Following prior SEM research, the control variables (firm size, firm age, and industry sector) were specified as predictors of the endogenous constructs, namely BDC and competitive performance, while AI capability was modeled as an exogenous construct in accordance with the theoretical framework. None of the control variables exhibited statistically significant effects.

Table 6. Comparison between partial and full mediation models

Model	Mediation type	NPAR	x^2 (CMIN)	df	Δx^2	Δdf	RMSEA	AIC	ECVI
SEM1	Partial mediation (AI $\rightarrow$ CP free)	143	428.057	322	-	-	0.046	714.057	4.491
SEM2	Full mediation (AI $\rightarrow$ CP fixed to 0)	142	428.095	323	0.038	1	0.045	712.095	4.479

4.2.3. Mediation effect analysis

To test the proposed mediation relationships, a bootstrapped SEM approach was employed using AMOS. Following the recommendations of Hayes (2017), mediation effects were assessed using bias-corrected bootstrapping with 5,000 resamples and 95% confidence intervals (CIs). Bootstrapping is a nonparametric resampling procedure that treats the observed sample as a pseudo-population and repeatedly draws subsamples to estimate the sampling distribution of indirect effects, thereby offering greater statistical power and reliability than traditional mediation tests (Hair et al., 2017).

Indirect effects were computed using unstandardized coefficients through the estimands approach to avoid biased estimates (Collier, 2020). A mediation effect was considered statistically significant when the 95% CI did not include zero (Collier, 2020; Hayes, 2017). In addition, following Hair et al. (2010), path coefficients were considered significant when the critical ratio (CR) exceeded 1.96 and the p-value was below 0.05.

The results indicate that AI capability has a positive and significant effect on BDC ($B = 0.22$;

$CR = 2.34$; $p = 0.01$), providing empirical support for Hypothesis 1. Furthermore, BDC exerts a positive and significant effect on competitive performance ($B = 0.39$; $CR = 5.09$; $p < 0.001$), thereby supporting Hypothesis 2.

To assess the mediating role of BDC in the relationship between AI capability and competitive performance, the indirect effect was examined using bootstrapped confidence intervals. The results reveal a statistically significant indirect effect of AI capability on competitive performance through BDC ($B = 0.110$; $p = 0.016$, two-tailed). The 95% bias-corrected bootstrap confidence interval (lower bound = 0.027; upper bound = 0.219) does not include zero, indicating robust mediation.

As shown in Table 7, the effect of AI capability on competitive performance becomes statistically non-significant once BDC is included in the model, indicating that AI capability influences competitive performance exclusively through its impact on BDC.

Therefore, the non-significant x^2 difference, the lower information criterion values, and the significant bootstrapped indirect effect provide strong empirical support for full mediation.

These results confirm Hypothesis 3, namely that BDC fully mediates the relationship between AI capability and competitive performance. Control variables (firm size, firm age, and industry) were included as predictors of both

BDC and competitive performance. None of the control variables exhibited statistically significant effects (see Table 7), suggesting that the observed mediation relationships are not driven by firm-level characteristics.

Table 7. Bootstrap testing

Relationship			Indirect effect	Confidence interval		p-value
				Lower bound	Upper bound	
AI capability →	BDC →	performance	0.110	0.027	0.219	0.016
Control variables						
Firm size →	performance		n.a.	n.a.	n.a.	0.188
Firm age →	performance		n.a.	n.a.	n.a.	0.202
Industry →	performance		n.a.	n.a.	n.a.	0.369
Firm size →	BDC		n.a.	n.a.	n.a.	0.351
Firm age →	BDC		n.a.	n.a.	n.a.	0.371
Industry →	BDC		n.a.	n.a.	n.a.	0.347

4.2.4. Moderating-mediation analysis

To examine Hypothesis 4, which posits that family involvement in management moderates the indirect effect of AI capability on competitive performance through BDC, a moderated mediation model was estimated using the estimands-based approach (Collier, 2020). Bias-corrected 95% confidence intervals (CIs) were generated using 5,000 bootstrap resamples.

Path a: Effect of AI capability on BDC conditional on family involvement

Moderation was specified on path a (AI capability → BDC) through an observed-variable interaction between mean-centered AI capability and family involvement. Because family involvement was measured using a single-item observed indicator, moderation was modeled using a mean-centered observed-variable interaction rather than a latent product-indicator approach, which typically requires multi-item latent constructs (Marsh et al., 2004).

The interaction term between AI capability and family involvement was positive and statistically significant ($B = 0.292$, $CR = 2.956$, $p = 0.003$), indicating that the effect of AI capability on BDC varies according to the level of family involvement in management.

Conditional effect analysis revealed that the relationship between AI capability and BDC was non-significant at low levels of family involvement ($B = -0.11$, $p = 0.826$, 95% CI $[-0.174, 0.116]$) but became positive and significant at high levels of

family involvement ($B = 0.231$, $p < 0.001$, 95% CI $[0.111, 0.434]$). These findings suggest that stronger family involvement enhances firms' ability to translate AI capability into BDC.

Path b: Effect of BDC on competitive performance

Consistent with the mediation model, BDC exerted a positive and significant effect on competitive performance (path b). This relationship was not moderated and therefore remained constant across levels of family involvement, satisfying the conditions required for estimating conditional indirect effects.

Conditional indirect effects ($a \times b$)

The conditional indirect effect of AI capability on competitive performance through BDC was subsequently estimated at different levels of family involvement. As reported in Table 8, the indirect effect was non-significant at low levels of family involvement ($B = 0.014$, 95% CI $[-0.051, 0.076]$, $p = 0.621$), whereas it became positive and statistically significant at high levels of family involvement ($B = 0.110$, 95% CI $[0.027, 0.219]$, $p = 0.016$).

Most importantly, the index of moderated mediation was statistically significant ($B = 0.128$, 95% CI $[0.034, 0.277]$, $p = 0.007$), indicating that the indirect effect of AI capability on competitive performance through BDC varies significantly as a function of family involvement. Because the confidence interval excludes zero, this result provides direct evidence of moderated mediation.

Following Hayes (2015) and Edwards and Konold (2020), the significance of the moderated mediation index supports the presence of conditional indirect effects, regardless of whether the indirect effect is statistically significant at every probed level of the moderator.

Collectively, these findings support Hypothesis 4 and demonstrate that family involvement in management strengthens the indirect effect of AI capability on competitive performance by facilitating the development of BDC.

Table 8. Conditional indirect effects of AI capability on competitive performance through BDC

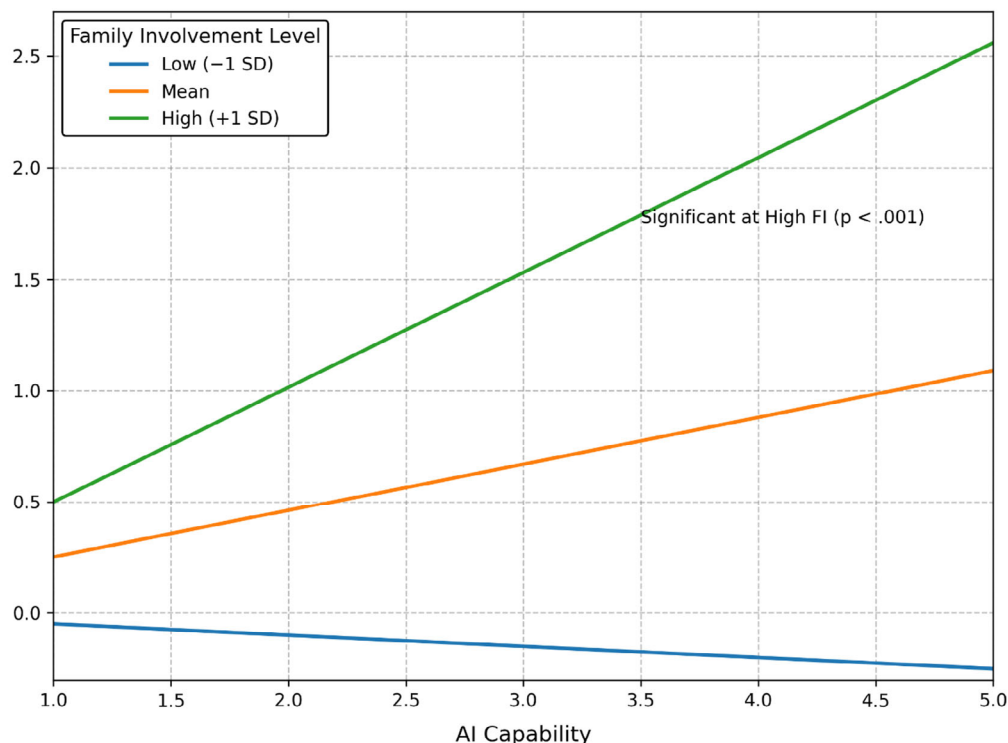
Moderator level (FI)	Path a (AI → BDC)	Indirect effect (a×b)	95% CI (Lower, Upper)	p-value
Low FI	-0.11	0.014	[-0.051, 0.076]	0.621
High FI	0.231	0.110	[0.027, 0.219]	0.016
Index of moderated mediation	—	0.128	[0.034, 0.277]	0.007

Note: All coefficients are unstandardized bootstrap estimates.

As illustrated in Figure 2, the indirect effect of AI capability on competitive performance through BDC is negligible and non-significant at low levels of family involvement but becomes positive and statistically significant at high levels of family

involvement. These results indicate that the indirect effect of AI capability on competitive performance through BDC becomes significant only under conditions of high family involvement.

Figure 2. Conditional indirect effect of AI capability on competitive performance through BDC across levels of family involvement



5. Discussion

This study examines how AI capability contributes to competitive performance in Tunisian family firms by investigating the mediating role of BDC and the moderating influence of family involvement in management. The findings demonstrate that AI capability enhances competitive performance only indirectly through BDC, underscoring that the business value of AI does not arise from technology deployment alone, but rather from the development of complementary data-driven capabilities. In the context of family enterprises, BDC therefore emerges as a critical mechanism through which the technological potential of AI is translated into tangible strategic and operational advantages.

The hypothesized sequence linking AI capability, BDC, and competitive performance is grounded in DCT, which posits that firm performance is shaped not directly by technological resources, but by higher-order capabilities that enable firms to sense opportunities, seize value, and reconfigure resources in response to environmental change (Teece, 2018; 2007). Accordingly, AI capability is conceptualized as an enabling lower-order technological capability, BDC as a higher-order dynamic capability, and competitive performance as a downstream outcome of effective capability deployment.

Empirically, the results provide strong evidence supporting a full mediation mechanism. Although AI capability exerts a positive and significant effect on BDC, and BDC in turn significantly enhances competitive performance, the direct effect of AI capability on performance becomes non-significant once BDC is incorporated into the model. This pattern indicates that AI capability alone is insufficient to generate performance gains unless it is embedded within effective data analytics routines and organizational processes. These findings are consistent with contemporary mediation logic, which emphasizes the importance of indirect effects in explaining how strategic resources influence organizational outcomes (Hayes, 2017).

From a theoretical perspective, these results align closely with DCT, which emphasizes that technological resources do not create value independently but should be integrated into higher-order organizational capabilities to influence performance outcomes (Teece, 2018; 2007). In the present study, AI capability enhances firms' ability to collect, process, and analyze large volumes of data, whereas BDC transforms these data into actionable insights that support strategic and operational decision-making. Without such complementary analytical routines, investments in AI remain

underutilized, thereby explaining the absence of a direct relationship between AI capability and competitive performance.

These findings are also consistent with prior empirical research demonstrating that the performance effects of AI and advanced digital technologies materialize primarily through intermediary capabilities such as data analytics, organizational learning, and process reconfiguration (Gupta & George, 2016; Mikalef et al., 2019). For example, Mikalef et al. (2019) explain that digital technologies contribute to firm performance only when firms possess strong analytical and organizational capabilities that enable effective data exploitation. Similarly, Gupta and George (2016) conceptualize BDC as a multidimensional capability encompassing data, technology, talent, governance, and organizational processes, thereby explaining why data-driven strategies outperform technology-centered approaches.

Further supporting this interpretation, the significant indirect effect confirms that BDC fully mediates the relationship between AI capability and competitive performance, highlighting its pivotal role in transforming AI potential into measurable organizational outcomes. This finding corroborates prior studies showing that BDC enables firms to integrate, analyze, and leverage data insights, thereby converting digital investments into innovation, efficiency gains, and sustained competitive advantage (Ciampi et al., 2021; Ghasemaghaei & Calic, 2020; Sivarajah et al., 2024). Thus, although AI capability represents a necessary condition for improved performance, it is insufficient on its own. BDC operationalizes this technological foundation by enabling data-driven decision-making, predictive analytics, and process optimization. Without robust analytical routines, AI systems provide limited strategic value. This interpretation is consistent with Gao et al. (2025), who argue that AI and IT resources must be embedded within dynamic data-related capabilities to generate tangible business benefits.

Within family firms, the mediating role of BDC assumes particular importance. Family enterprises are often characterized by conservative managerial orientations, centralized decision-making, and limited digital maturity, all of which may constrain the direct performance effects of advanced technologies (Calabrò et al., 2019). In this context, BDC provides a structured pathway for translating AI-generated insights into operational routines, thereby facilitating the transition from intuition-based to evidence-based decision-making. Moreover, BDC enhances the firm's ability to reconfigure resources and adapt to environmental change, reinforcing its dynamic

capabilities (Teece, 2007). As emphasized by Soluk et al. (2025), successful AI integration in family firms typically occurs through gradual digital learning, intergenerational collaboration, and the routinization of knowledge, processes that are central to the development of BDC. Consequently, BDC should be understood not merely as an analytical capability, but also as a critical mechanism for organizational learning and strategic adaptation in family enterprises. The moderated mediation analysis (H4) further reveals that family involvement in management strengthens the indirect effect of AI capability on competitive performance through BDC. Specifically, when family involvement in management is high, AI capability exerts a stronger positive influence on performance by facilitating analytics-driven transformation. In contrast, when family involvement is low, AI capability fails to generate significant performance improvements, even in the presence of advanced technologies. This pattern highlights the enabling role of family governance and long-term commitment in shaping the effectiveness of digital transformation initiatives.

High levels of family involvement in management foster stewardship behavior, long-term orientation, and patient capital, which collectively support sustained investments in digital infrastructure, analytics talent, and data-driven learning processes (Gómez-Mejía et al., 2011; Gupta & George, 2016). Such conditions are particularly conducive to the development and effective deployment of BDC, as analytics capabilities require cumulative learning, organizational alignment, and continuous resource commitment. Family-managed firms are therefore better positioned to transform AI-enabled data resources into actionable insights that enhance strategic decision-making and operational performance.

From a set-theoretic perspective, family involvement functions as a contextual amplifier that strengthens the relationship between the necessary condition (AI capability) and the enabling mechanism (BDC). Although AI capability constitutes a foundational prerequisite for analytics-based transformation, its performance-enhancing potential is realized only when family leaders actively support and guide capability development. High family involvement promotes strategic coherence, continuity of investment, and alignment between AI initiatives and long-term organizational objectives. Conversely, low family involvement is often associated with fragmented governance structures, limited strategic oversight, and resistance to organizational change, thereby weakening the mediating role of BDC.

These dynamics are consistent with SEW theory, which suggests that family-centered governance can either facilitate or constrain strategic renewal depending on the degree of family engagement and control (Gómez-Mejía et al., 2007). When family involvement is strong, SEW preservation motives reinforce commitment to long-term capability development and organizational learning. In contrast, when family engagement is limited, the absence of stewardship-oriented leadership may undermine the institutionalization of analytics routines, thereby reducing the strategic impact of AI investments.

Overall, the findings position family involvement in management as a critical boundary condition determining whether AI capability translates into competitive advantage in family firms. Consistent with Soluk et al. (2025), high family involvement fosters the trust, cohesion, and long-term orientation required to embed analytics routines and sustain AI-driven transformation. By contrast, low family involvement reflects governance fragmentation and short-term orientation, which impede learning, innovation, and effective capability reconfiguration. Consequently, AI capability emerges as a source of sustainable competitive advantage only when combined with robust analytical capabilities and active family stewardship.

6. Implications

6.1. Theoretical implications

This research contributes to the intersection of AI and family business studies by integrating Process Theory, DCT, and necessary-but-not-sufficient logic to explain how AI capability translates into competitive performance. The findings demonstrate that AI capability is a necessary but insufficient resource whose value materializes only when complemented by strong BDC. By conceptualizing BDC as the enabling mechanism that operationalizes AI capability, and family involvement in management as a contextual amplifier, the study extends prior research on IT value creation. This integrative framework clarifies the boundary conditions under which AI investments generate strategic outcomes and advances theoretical understanding of how digital resources, analytics routines, and governance structures interact to shape performance in family firms.

The study proposes a unified model that explains the direct and indirect roles of AI capability, BDC, and family involvement in management. To our knowledge, this is the first empirical investigation to jointly examine these elements by testing BDC as a mediator and family involvement as a moderator within a single integrated framework.

Whereas prior studies have emphasized the performance-enhancing role of BDC in large non-family corporations (Raguseo, 2018; Wamba et al., 2016), the dynamics of the AI-BDC relationship within family-controlled enterprises remain largely underexplored. This study addresses this gap by integrating SEW theory into the digital transformation literature, demonstrating how affective endowments, legacy preservation, and family identity influence big data implementation and AI adoption decisions.

Empirical evidence from Tunisian family firms supports the proposition that BDC serves as the critical dynamic capability enabling the transformation of AI potential into tangible performance outcomes. Moreover, the findings reveal significant heterogeneity in family firms' digital transformation responses. Resistance to digital transformation often stems from governance rigidity, risk aversion, and cultural inertia, whereas successful adaptation is driven by generational succession, digital literacy, and strategic openness. These patterns underscore the importance of a contingency-based, capability-oriented perspective that recognizes variations in family governance and cultural context when explaining digital transformation trajectories.

By emphasizing that family firms differ substantially in their goals, governance configurations, and SEW orientations, this study refines current understanding of digital capability development in family enterprises. Variations in the degree and nature of family involvement shape not only the motivation to adopt AI, but also the effectiveness of analytics integration and the conversion of digital resources into competitive advantage.

6.2. Practical implications

This study offers actionable insights for family firm managers navigating the transition toward data-driven and AI-enabled operations. The results provide strong evidence that developing BDC is a critical enabler of performance improvement, particularly in emerging economies such as Tunisia. This finding underscores the importance for family enterprises of investing in BDC development and continuous organizational learning as foundations for profitability, innovation, and resilience. Although AI holds transformative potential, its benefits materialize only when supported by a robust data infrastructure. Consequently, family firms should prioritize foundational investments in BDC before implementing large-scale AI initiatives, ensuring that digital transformation is grounded in analytical readiness rather than technological enthusiasm.

To achieve this objective, managers should establish a comprehensive BDC framework

encompassing data governance systems, cloud-based infrastructure, and advanced analytics training. Such initiatives help create reliable data pipelines that support effective AI deployment. Simultaneously, firms should strengthen human capital by developing employees capable of interpreting AI outputs and by forming strategic partnerships that facilitate the co-development of integrated AI-BDC solutions. Equally important is the implementation of AI governance mechanisms to ensure algorithmic transparency, validation, and ethical data use. Strategically, AI should not be viewed as an isolated technological investment, but rather as a capability that amplifies the value of BDC. For instance, AI-driven predictive models generate actionable insights only when applied to well-curated, high-quality datasets managed through established BDC systems.

To maximize these synergies, family firm leaders should frame BDC investments as consistent with their legacy preservation and stewardship values, which are central to many family enterprises. Engaging younger and digitally proficient family members as transformation champions can enhance internal legitimacy and accelerate digital adoption. Furthermore, democratizing data access across departments may foster a culture of evidence-based decision-making, thereby reducing resistance rooted in hierarchy or intuition-driven management practices. By emphasizing how AI-BDC integration supports organizational continuity and strengthens SEW, leaders can align digital transformation with enduring family values rather than perceiving it as a threat to tradition.

Recent research also highlights the importance of board-level AI literacy, hybrid governance models, and the alignment of AI initiatives with SEW principles in balancing innovation with continuity (Soluk et al., 2025). Ultimately, positioning BDC as a non-negotiable prerequisite transforms AI adoption from a risky stand-alone initiative into a strategically coherent process that enhances both technological agility and transgenerational resilience. This alignment enables family firms to convert digital capability development into a sustainable competitive advantage while reinforcing the values underpinning their longevity.

7. Conclusion, Limitations, and Future Research

This study enhances understanding of how family firms in emerging economies navigate technological transformation while preserving their SEW. By integrating DCT, Process Theory, and necessary-but-not-sufficient logic, the research clarifies the interdependence between

AI capability and BDC in driving competitive performance. The findings demonstrate that AI capability, although essential, is not a sufficient resource; its performance value materializes only when supported by strong BDC. Moreover, family involvement in management moderates this relationship, illustrating how governance structures and emotional priorities shape digital transformation trajectories. Collectively, these insights advance family business research by revealing how digital resources, analytics routines, and governance mechanisms interact to create performance heterogeneity among family firms.

Although this study makes important contributions, several limitations provide avenues for future research. First, the exclusive focus on Tunisian family firms limits the generalizability of the findings. Future studies should therefore replicate the model across different cultural and institutional contexts to assess how national environments shape the AI-BDC-performance relationship. Second, the cross-sectional design constrains causal inference and does not fully capture the temporal sequencing of AI capability, BDC, and competitive performance. Longitudinal research would help address this limitation. Third, the relatively small sample size, reflecting the early stage of AI and BDC adoption among family firms, may limit statistical generalizability. Future research employing larger samples could apply multi-group SEM and cross-country comparative designs to strengthen robustness and external validity. Fourth, family involvement in management was measured using a single-item indicator capturing active participation in top management. Although this operationalization is appropriate for moderation analysis, single-item measures restrict construct breadth and may attenuate estimated effects. Future research should therefore adopt multi-item measures of family involvement and SEW orientation to better capture heterogeneity in governance motives and examine how distinct SEW profiles condition the AI-BDC-performance relationship. Finally, given the rapid evolution of digital technologies, future research should investigate how emerging technologies such as generative AI, blockchain, and the Internet of Things reshape family governance, legacy preservation, and competitive resilience.

Author contribution statement

The author was solely responsible for all aspects of the study, including conceptualization, data collection, analysis, interpretation of results, and manuscript preparation.

Conflict of interest statement

The author declares no conflicts of interest.

Ethical statement

The author confirms that data collection for this research was conducted anonymously, ensuring that participants could not be identified.

Declaration on the use of generative AI

Generative AI was used solely as a language-support tool during the writing process. It did not generate original ideas, conduct data analysis, or draw conclusions. All intellectual content, interpretations, and responsibility for the manuscript remain with the author.

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Data availability statement

The data supporting the findings of this study are available from the author upon reasonable request.

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