

การเสริมสร้างผู้ประกอบการดิจิทัลและความได้เปรียบในการแข่งขันผ่านการประยุกต์ใช้เทคโนโลยี
ปัญญาประดิษฐ์ นวัตกรรมโมเดลธุรกิจ และขีดความสามารถด้านดิจิทัล
EMPOWERING DIGITAL ENTREPRENEURSHIPS AND COMPETITIVE ADVANTAGE THROUGH AI
TECHNOLOGY ADOPTION, BUSINESS MODEL INNOVATION, AND DIGITAL CAPACITY

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บทคัดย่อ

การศึกษานี้ตรวจสอบว่า การยอมรับเทคโนโลยีปัญญาประดิษฐ์ นวัตกรรมโมเดลธุรกิจ และขีดความสามารถทางดิจิทัล มีอิทธิพลต่อการเป็นผู้ประกอบการดิจิทัล และความได้เปรียบในการแข่งขัน ในหมู่องค์กรในประเทศไทยอย่างไร ข้อมูลถูกรวบรวมจากผู้บริหารจำนวน 276 คนที่มีส่วนร่วมในการเปลี่ยนแปลงทางดิจิทัล และมีการใช้การวิเคราะห์การถดถอยเชิงเส้นพหุคูณ ผลลัพธ์แสดงให้เห็นว่าโมเดลทั้งสองมีนัยสำคัญ โดยมีพลังในการอธิบายสูงสำหรับการเป็นผู้ประกอบการดิจิทัล (R^2 -adjusted = 0.84) และความได้เปรียบในการแข่งขัน (R^2 -adjusted = 0.75) ผลการค้นพบที่สำคัญเน้นให้เห็นว่าทักษะดิจิทัล การสร้างคุณค่า และความเข้ากันได้ ช่วยเสริมสร้างความคล่องตัวทางผู้ประกอบการอย่างมาก ในขณะที่ความสามารถในการปรับตัวขององค์กรและความสามารถของผู้จัดการ แสดงผลที่แตกต่างกันต่อการคงไว้ซึ่งความได้เปรียบในการแข่งขัน การศึกษานี้เน้นความสำคัญของการปรับกลยุทธ์ดิจิทัลให้สอดคล้องกัน เพื่อส่งเสริมทั้งการเป็นผู้ประกอบการและความสามารถในการแข่งขันระยะยาวในเศรษฐกิจดิจิทัลที่มีการเปลี่ยนแปลงอย่างต่อเนื่อง

คำสำคัญ: ผู้ประกอบการดิจิทัล, ความได้เปรียบในการแข่งขัน, การประยุกต์ใช้เทคโนโลยี AI, นวัตกรรมโมเดลธุรกิจ, ขีดความสามารถทางดิจิทัล

ABSTRACT

This study examines how AI Technology Adoption, Business Model Innovation, and Digital Capacity influence Digital Entrepreneurship and Competitive Advantage among organizations in Thailand. Data was collected from 276 executives engaged in digital transformation, and multiple linear regression analysis was employed. The results demonstrate that both models are significant, with high explanatory power for DE (R^2 -adjusted = 0.84) and CA (R^2 -adjusted = 0.75). Key findings highlight that digital skills, value creation, and compatibility strongly enhance entrepreneurial agility, while organizational adaptability and managerial capabilities show differing effects on sustaining competitive advantage. The study emphasizes the importance of aligning digital strategies to simultaneously foster entrepreneurship and long-term competitiveness in an increasingly dynamic digital economy.

Keywords: Digital Entrepreneurships, Competitive Advantage, AI Technology Adoption, Business Model Innovation, Digital Capacity

INTRODUCTION

The transformation of traditional business operations into digitalized systems has rapidly accelerated, presenting enterprises with unprecedented challenges in sustaining growth and maintaining competitive advantage (Bamasoud & Shannak, 2025). The emergence of the digital economy has generated extensive opportunities while simultaneously strengthening market competition. This dynamic coerces organizations to prioritize strategic plans such as facilitating digital entrepreneurship and acquiring sustainable competitive advantage (Koch & Windsperger, 2017). Accomplishing these objectives requires more than organizational initiative; it necessitates a comprehensive and in-depth understanding of the critical factors that support success in the modern digital era. Without such knowledge, enterprises risk misallocating resources, misaligning strategic priorities, and increasing their vulnerability to market uncertainties (Teece, 2018).

To effectively address these challenges, it is essential to conduct a systematic analysis of the key determinants that significantly influence both digital entrepreneurship and competitive advantage. This study focuses on three interrelated constructs that have attracted growing attention in the discourse on digital transformation: Digital Capacity (DC), Business Model Innovation (BMI), and AI Technology Adoption (AI). DC reflects an organization's readiness to deploy digital infrastructure, integrate technology seamlessly into operations, and develop a workforce proficient in leveraging digital tools. BMI entails the strategic reconfiguration of value creation, delivery, and capture mechanisms to address evolving market demands. AI technology adoption augments these capabilities by enabling data-driven decision-making, automating operational processes, and fostering the development of innovative digital solutions (Rai et al., 2019; Dubey et al., 2021).

By exploring the interrelationships among these constructs and their respective impacts, this study aims to deliver insights that extend well beyond academic discourse. The findings are expected to inform policymakers, industry leaders, and entrepreneurs in designing strategies that strengthen digital entrepreneurship ecosystems and sustain competitive advantage in rapidly changing markets. According to recent global reports, a substantial proportion of organizations acknowledge that digital transformation is critical to their survival (Bughin et al., 2018). However, only a limited number of firms have successfully scaled their digital initiatives to achieve measurable business value (Bharadwaj et al., 2019). Similarly, enterprises that continuously innovate their business models are more likely to achieve superior performance compared to their peers (Foss & Saebi, 2017; Clauss et al., 2021). These observations underscore the urgency of identifying the right combination of digital capacity, business model innovation, and AI technology adoption to reduce operational risks, accelerate innovation cycles, and secure long-term growth. Ultimately, this research provides a clear and actionable pathway for organizations to thrive amidst the complexities, competitive pressures, and technological advancements that define the modern business landscape.

RESEARCH OBJECTIVES

1. To examine the direct effects of Digital Capacity, Business Model Innovation, and AI Technology Adoption on Digital Entrepreneurship
2. To examine the direct effects of Digital Capacity, Business Model Innovation, and AI Technology Adoption on Competitive Advantage
3. To compare the differential effects of Digital Capacity, Business Model Innovation, and AI Technology Adoption on Digital Entrepreneurship and Competitive Advantage.

LITERATURE REVIEW

Digital Entrepreneurships and Competitive Advantage

In the contemporary business landscape, organizations face growing pressure to innovate while sustaining market competitiveness. Digital entrepreneurship (DE) has become central to this transformation, as it emphasizes the creation of new ventures, models, and ecosystems through the strategic use of digital technologies (Kraus et al., 2019; Nambisan, 2017; Nambisan et al., 2019). At the same time, competitive advantage (CA) remains a fundamental determinant of long-term success, grounded in the ability to differentiate, achieve efficiency, and adapt to dynamic environments (M. Porter, 2020; M. E. Porter, 1985; Teece, 2018). For modern enterprises, balancing both perspectives is essential; neglecting either risks either short-lived innovation without durability, or strategic rigidity in the face of digital disruption. These perspectives suggest that digital entrepreneurship and competitive advantage are closely interconnected outcomes that may be influenced by common organizational and technological drivers, warranting further empirical investigation.

AI Technology Adoption

AI technology adoption is a multidimensional driver of digital transformation, conceptualized through five dimensions: perceived ease of use (AI1), perceived usefulness (AI2), technological readiness (AI3), compatibility (AI4), and organizational support (AI5). For Digital Entrepreneurship (DE), AI1 and AI2 reduce barriers to experimentation and foster confidence in AI-enabled ventures (Chatterjee, et al., 2021a; Chatterjee, et al., 2021b). AI3 and AI4 ensure scalability and integration of digital offerings (Dubey et al., 2021). For Competitive Advantage (CA), AI5 institutionalizes adoption, embedding AI into organizational routines that enhance efficiency, differentiation, and resilience (Rai et al., 2019). Collectively, these dimensions demonstrate AI's dual role in enabling entrepreneurial agility and sustaining long-term competitiveness. AI's ability to enhance both innovation processes and operational efficiency suggests its critical role in influencing both digital entrepreneurship and competitive advantage.

Digital Capacity

Digital Capacity (DC) represents an organization's readiness to leverage digital resources across multiple dimensions: digital orientation (DC1), digital skills and competence (DC2), resource allocation (DC3), managerial capability (DC4), and environmental influence (DC5). For Digital Entrepreneurship (DE), DC1 and DC2 foster innovation by aligning strategic vision with employees' digital expertise (Ly, 2023). DC3 and DC4 ensure that resources and leadership drive experimentation and scalable growth (Warner & Wäger, 2019). In terms of Competitive Advantage (CA), DC5 enhances adaptability to market and environmental changes, strengthening resilience and differentiation (Bohorquez & Esteves, 2016). Collectively, these capacities provide the foundation for firms to pursue both entrepreneurial agility and sustainable competitive positioning.

Business Model Innovation

Business Model Innovation (BMI) involves the reconfiguration of value creation (BMI1), value delivery (BMI2), value capture (BMI3), organizational adaptability (BMI4), and resources for experimentation (BMI5). Within Digital Entrepreneurship (DE), BMI1 and BMI2 enable entrepreneurs to design novel offerings and reach customers through digital platforms (Foss & Saebi, 2017, 2018). BMI3 strengthens monetization strategies, while BMI4 fosters agility in responding to dynamic markets (Clauss, 2017; Clauss et al., 2021). For Competitive Advantage (CA), BMI5 encourages continuous experimentation, allowing firms to differentiate and sustain profitability (Clohessy et al., 2020). Together, these dimensions highlight BMI as both a driver of entrepreneurial opportunity recognition and a strategic mechanism for achieving long-term competitive positioning. Accordingly, business model innovation is likely to influence both the creation of digital entrepreneurial opportunities and the long-term competitiveness of firms.

Based on the conceptual definitions established from the reviewed literature, the present study proposes a research framework to examine the relationships among Artificial Intelligence Technology Adoption (AI), Business Model Innovation (BMI), and Digital Capacity (DC) as independent variables, and their varying influences on two key dependent constructs: Digital Entrepreneurship (DE) and Competitive Advantage (CA). This framework is designed to illustrate not only the direct associations between the independent variables and each dependent variable but also to capture the distinct patterns of influence that may emerge across the two outcomes. By structuring the model in this way, the study enables a comparative assessment of how AI, BMI, and DC operate in shaping entrepreneurial capacity and competitive positioning within the digital economy. This approach provides a more comprehensive understanding of the interplay between technological adoption, innovation strategies, and organizational capabilities, thereby offering insights that are relevant for both academic inquiry and practical application in business strategy development. Theses research frameworks were developed and described as follows:

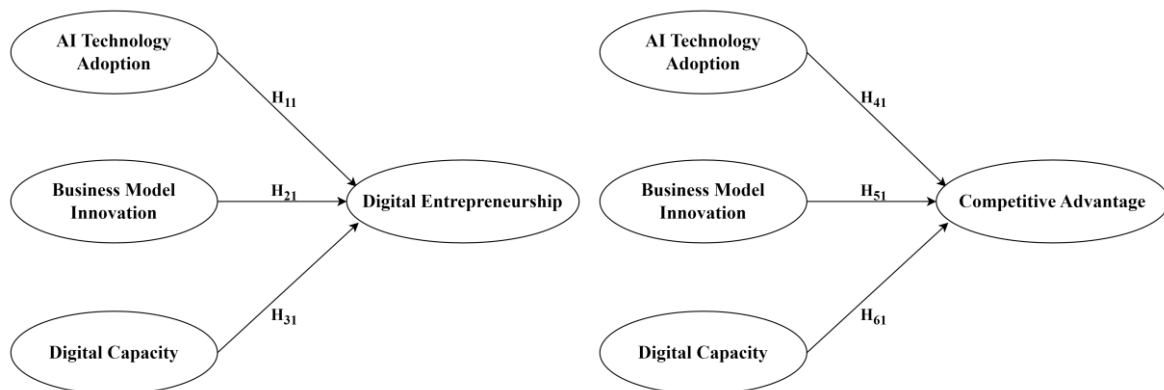


Figure 1. The research framework of this study a) the hypotheses defined for the Digital Entrepreneurships and b) the hypotheses defined for the Competitive Advantage

Moreover, the following hypotheses are formulated for statistical testing using Multiple Linear Regression:

For Digital Entrepreneurship:

H₀₁: AI Technology Adoption has no statistically significant effect on Digital Entrepreneurship ($\beta_{AI}=0$).

H₁₁: AI Technology adoption has statistically significant effect on Digital Entrepreneurship ($\beta_{AI}\neq 0$).

H₀₂: Business Model Innovation has no statistically significant effect on Digital Entrepreneurship ($\beta_{BMI}=0$).

H₁₂: Business Model Innovation has statistically significant effect on Digital Entrepreneurship ($\beta_{BMI}\neq 0$).

H₀₃: Digital Capacity has no statistically significant effect on Digital Entrepreneurship ($\beta_{DC}=0$).

H₁₃: Digital Capacity has statistically significant effect on Digital Entrepreneurship ($\beta_{DC}\neq 0$).

For Competitive Advantage:

H₀₄: AI Technology Adoption has no statistically significant effect on Competitive Advantage ($\beta_{AI}=0$).

H₁₄: AI Technology adoption has statistically significant effect on Competitive Advantage ($\beta_{AI}\neq 0$).

H₀₅: Business Model Innovation has no statistically significant effect on Competitive Advantage ($\beta_{BMI}=0$).

H₁₅: Business Model Innovation has statistically significant effect on Competitive Advantage ($\beta_{BMI}\neq 0$).

H₀₆: Digital Capacity has no statistically significant effect on Competitive Advantage ($\beta_{DC}=0$).

H₁₆: Digital Capacity has statistically significant effect on Competitive Advantage ($\beta_{DC}\neq 0$).

METHODOLOGY

1. Population and Sample

The study's population consists of business executives, managers, and decision-makers in Thailand who are actively engaged in digital transformation initiatives within their organizations. These individuals possess the necessary expertise to provide insights into AI technology adoption, digital capacity, and business model innovation.

A purposive sampling method was employed to select respondents who met specific criteria, including (1) holding a managerial or executive position, (2) working in an organization involved in digital transformation, and (3) having direct involvement in strategic decision-making related to technology adoption, digital capabilities, or business model innovation.

The minimum sample size was determined based on the guideline of at least 10 observations per predictor variable (Kock & Hadaya, 2018). Given that the model includes three main predictors (DC, BMI, and AI), the minimum required sample size was 170 respondents. However, to improve reliability, the target sample size was set at no fewer than 250 respondents.

A total of 312 responses were collected. After screening and removing incomplete responses, 276 valid responses were retained for analysis. This final sample size is sufficient for the statistical analysis conducted in this study.

2. Research Instruments

The primary research instrument was a structured questionnaire developed to collect quantitative data for hypothesis testing and model evaluation. The questionnaire covered three main components: respondent eligibility, demographic and organizational characteristics, and the measurement of key constructs. The measurement items were adapted from validated scales in prior studies, capturing Digital Capacity (DC), Business Model Innovation (BMI), AI Technology Adoption (AI), Digital Entrepreneurship (DE), and Competitive Advantage (CA). All items were assessed using a 7-point Likert scale ranging from strongly disagree to strongly agree.

To ensure content validity, the instrument was reviewed by three academic experts in business administration and digital transformation. A pilot test was conducted with 30 respondents to evaluate clarity and reliability, and minor revisions were made prior to full-scale data collection.

3. Data Collection

Data collection was conducted in July 2025 using a structured online questionnaire to reach respondents who met the defined eligibility criteria. The questionnaire was distributed through professional networks and relevant online channels. A total of 312 responses were received. Following informed consent procedures and the application of screening questions, 276 respondents were confirmed to meet all inclusion criteria, representing a response qualification rate of 88.46%. This final sample size was deemed sufficient for hypothesis testing and structural model analysis based on the research framework.

4. Data Analysis

Descriptive statistics—including frequencies, percentages, means, and standard deviations—were employed to summarize the demographic and organizational characteristics of the respondents. Following this, multiple linear regression (MLR) analysis was performed to examine the influence of Digital Capacity (DC), Business Model Innovation (BMI), and AI Technology Adoption (AI) on the dependent variables, namely Digital Entrepreneurship (DE) and Competitive Advantage (CA). The independent variables were entered into the regression models in

theoretically informed blocks, allowing for the evaluation of incremental variance explained at each stage of the analysis.

Prior to conducting the regression analysis, the standard assumptions of MLR were assessed, including normality of residuals, linearity, and independence of errors. These assumptions were verified using graphical diagnostics such as residual plots and standard probability plots. Statistical significance was determined at an alpha level of $p < 0.05$ for all tests, and effect sizes (ΔR^2 for model blocks) were interpreted to assess the practical significance of the findings. All statistical analyses were conducted using statistical software packages appropriate for behavioral and business research applications.

RESULTS

This study involved 276 participants, the majority of whom were male (54.71%), followed by female (44.93%) and LGBT (0.36%). Most respondents were between 29 and 44 years old (Gen Y; 57.97%), with 35.14% aged 45–60 (Gen X) and 6.88% aged 18–28 (Gen Z). Regarding business experience, 39.13% had been operating for more than 10 years, 32.25% for 4–7 years, 21.01% for 8–10 years, 5.80% for 1–3 years, and 1.81% for less than one year.

In terms of business sectors, the most significant proportion operated in food, service, and tourism (26.09%), followed by technology/software/AI (18.12%), retail and wholesale (17.03%), manufacturing (14.49%), health, wellness, and medical services (10.14%), logistics and transportation (9.42%), and other industries (4.71%). Position-wise, 39.13% were business owners or entrepreneurs, 17.39% were top executives (e.g., CEO, Managing Director), 15.22% were marketing/business development managers, 15.22% were innovation/strategy/IT managers, 9.42% were technology/digital executives (e.g., CTO, CDO), and 3.62% held other positions. Regarding business size, 33.33% of respondents represented small enterprises (11–50 employees), 24.28% large enterprises (more than 200 employees), 23.91% medium-sized enterprises (51–200 employees), and 18.48% micro-enterprises (up to 10 employees). In terms of legal entity type, 65.94% operated as private limited companies, 17.03% as public limited companies, and 17.03% as limited partnerships. When asked about the level of digital technology usage, 37.68% reported moderate usage (e.g., ERP, CRM, website, e-commerce), 32.25% reported basic usage (e.g., Line, social media, e-mail), 27.90% reported advanced usage (e.g., AI, Big Data, automation), and 2.17% indicated no usage of digital technology.

Table 1. Sociodemographic Status of the Participants.

Characteristics	Category	Frequency	Percentage
Gender	Male	151	54.71%
	Female	124	44.93%
	Others	1	0.36%
Age	18–28 (Gen Z)	19	6.88%
	29–44 (Gen Y)	160	57.97%
	45–60 (Gen X)	97	35.14%
Business Experience (Years)	≤3	21	7.61%
	4–7	89	32.25%
	8–10	58	21.01%
	>10	108	39.13%
Industry	Service / Tourism	72	26.09%
	Technology / Digital	50	18.12%
	Retail / Wholesale	47	17.03%
	Manufacturing	40	14.49%
	Others	67	24.27%
Position	Owner / Entrepreneur	108	39.13%
	Top Executive	48	17.39%
	Managerial Level	84	30.43%
	Others	36	13.05%
Firm Size (Employees)	≤10	51	18.48%
	11–50	92	33.33%
	51–200	66	23.91%
	>200	67	24.28%

Table 2. Model Summary of Digital Entrepreneurships and Competitive Advantage

	Digital Entrepreneurships	Competitive Advantage
R-square	0.850	0.760
R-square adjusted	0.841	0.746
Durbin-Watson test	1.754	2.047
S.S.E.	222.637	223.832
F-Test(Sig.)	98.028(0.000)	54.740(0.000)

The multiple linear regression (MLR) analyses were conducted to examine the predictive relationships between DC, BMI, and AI) on two dependent variables: DE and CA. All statistical assumptions relevant to MLR, including linearity, independence of residuals, and homoscedasticity, were evaluated prior to analysis and found to be satisfactory.

For the DE model, the overall regression equation was statistically significant, $F(15, 256) = 98.028, p < 0.001$, indicating that the set of predictors collectively accounted for

a substantial proportion of the variance in DE. The coefficient of determination was $R^2 = 0.850$, with an adjusted R^2 of 0.841, suggesting that approximately 84.1% of the variability in DE was explained by the combined predictors. The Durbin–Watson statistic (1.754) indicated no serious autocorrelation in residuals. Statistically significant predictors ($p < 0.05$) included: AI2 (Digital Skills and Competence, $\beta = 0.146$), BM1 (Value Capture, $\beta = 0.104$), BM3 (Value Creation, $\beta = 0.149$), DC1 (Perceived Ease of Use, $\beta = 0.148$), DC2 (Perceived Usefulness, $\beta = 0.146$), and DC4 (Compatibility, $\beta = 0.261$). All coefficients are interpreted as the expected change in DE per unit increase in the respective predictor, holding all other variables constant.

For the CA model, the regression equation was also statistically significant, $F(15, 256) = 54.740$, $p < 0.001$, confirming that the predictors significantly explained variance in CA. The model yielded $R^2 = 0.760$ and an adjusted R^2 of 0.746, indicating that approximately 74.6% of the variance in CA was explained by the predictors. The Durbin–Watson statistic (2.047) suggested residual independence. Significant predictors ($p < 0.05$) included: AI2 (Digital Skills and Competence, $\beta = 0.261$), AI4 (Managerial Capability, $\beta = -0.116$), BM3 (Value Creation, $\beta = 0.162$), BM4 (Organizational Adaptability, $\beta = -0.156$), DC4 (Compatibility, $\beta = 0.227$), and DC5 (Organizational Support, $\beta = 0.186$). Positive coefficients reflect a direct relationship with CA, whereas negative coefficients indicate an inverse relationship, controlling for other variables in the model.

Collectively, these findings demonstrate that while certain predictors—such as DC4 (Compatibility) and BM3 (Value Creation)—consistently influenced both DE and CA, other predictors exhibited differential effects across the two dependent variables. The high R^2 values for both models indicate that the selected constructs provide robust explanatory power in predicting DE and CA in the context of organizations undergoing digital transformation.

Table 3. Coefficient Table (B, S.E., T, Sig.) of AI, BM, DC for CA and DE

Variables		Competitive Advantage				Digital Entrepreneurships			
		B	Std. Error	T	Sig.	B	Std. Error	T	Sig.
AI	AI Technology Adoption								
AI1	Digital Orientation	-0.006	0.046	-0.128	0.898	-0.063	0.046	-1.371	0.172
AI2	Digital Skills and Competence	0.146	0.041	3.512	0.001***	0.261	0.042	6.274	0.000***
AI3	Resource Allocation	0.010	0.037	0.264	0.792	0.037	0.038	0.990	0.323
AI4	Managerial capability	-0.075	0.047	-1.590	0.113	-0.116	0.047	-2.465	0.014**
AI5	Environmental Influence	0.007	0.044	0.167	0.868	0.050	0.044	1.137	0.257
BM	Business Model Innovation								
BM1	Value Capture	0.104	0.043	2.419	0.016**	0.078	0.043	1.801	0.073*
BM2	Value Delivery	0.058	0.047	1.225	0.222	0.069	0.047	1.463	0.145
BM3	Value Creation	0.149	0.049	3.018	0.003***	0.162	0.050	3.261	0.001***
BM4	Organizational Adaptability	-0.067	0.050	-1.329	0.185	-0.156	0.050	-3.097	0.002***
BM5	Resources for Business Model Experimentation	0.016	0.055	0.287	0.774	0.070	0.056	1.252	0.212
DC	Digital Capacity								
DC1	Perceived Ease of Use	0.148	0.055	2.670	0.008***	0.046	0.055	0.826	0.409
DC2	Perceived Usefulness	0.146	0.059	2.451	0.015**	0.071	0.060	1.186	0.237
DC3	Technological Readiness	0.000	0.057	-0.003	0.997	0.105	0.057	1.836	0.068*
DC4	Compatibility	0.261	0.059	4.394	0.000***	0.227	0.060	3.809	0.000***
DC5	Organizational Support	0.116	0.062	1.881	0.061*	0.186	0.062	3.006	0.003***

*** - p-value <0.01, ** - p-value<0.05, * - p-value<0.1

The regression models were described as follows:

$$CA = 0.146AI_2 + 0.104BM_1 + 0.149BM_3 + 0.148DC_1 + 0.146DC_2 + 0.261DC_4$$

$$DE = 0.261AI_2 - 0.107AI_4 + 0.162BM_3 - 0.156BM_4 + 0.227DC_4 + 0.186DC_5$$

DISCUSSION

The results of this study underscore the differentiated yet interconnected roles that digital transformation factors play in shaping both DE and CA. Specifically, DE was found to be significantly influenced by factors such as digital skills and competence (AI2), value capture (BM1), value creation (BM3), perceived ease of use (DC1), perceived usefulness (DC2),

and compatibility (DC4). These findings suggest that entrepreneurial outcomes in the digital domain are strongly shaped by a combination of human capital, user-oriented technology adoption, and innovative value frameworks. The emphasis on ease of use and usefulness is consistent with the TAM, reinforcing that entrepreneurs tend to prioritize technologies that reduce entry barriers and facilitate rapid experimentation.

In contrast, competitive advantage (CA) demonstrated a different configuration of drivers. It was significantly associated with digital skills and competence (AI2), value creation (BM3), compatibility (DC4), and organizational support (DC5), while managerial capability (AI4) and organizational adaptability (BM4) exerted negative effects. This finding suggests a potential paradox in competitive positioning: although innovation and technological compatibility remain critical, excessive managerial control or overemphasis on structural adaptation may reduce organizational flexibility, which is essential in dynamic digital environments (Warner & Wäger, 2019). From the perspective of the Resource-Based View (RBV), competitive advantage depends not only on the possession of valuable technological and organizational resources but also on the effective alignment and deployment of these resources to sustain differentiation and resist imitation (Barney, 1991; Teece, 2018).

The comparative analysis between digital entrepreneurship (DE) and competitive advantage (CA) reveals both convergences and divergences. Shared predictors, such as value creation (BM3) and compatibility (DC4), indicate common ground where digital opportunity development and competitive positioning overlap. However, the divergence in predictors suggests distinct strategic orientations. DE is primarily opportunity-driven, requiring agility, usability, and continuous experimentation to support venture creation and innovation (Kraus et al., 2019; Nambisan, 2017). In contrast, CA is sustainability-driven, requiring institutionalized support, resource alignment, and controlled adaptation to maintain long-term advantage (M. E. Porter, 1985; Teece, 2018). These findings are consistent with dynamic capabilities theory, which emphasizes that organizations must not only sense and seize opportunities but also reconfigure resources to achieve sustained competitiveness (Teece, 2018).

From a strategic perspective, these results suggest that organizations cannot rely solely on entrepreneurial dynamism or structural consolidation; rather, a balanced approach is required. Firms that overemphasize entrepreneurial agility without sufficient organizational support may struggle to scale innovations effectively, while those focusing too rigidly on stability and control risk constraining experimentation and adaptability (Teece, 2018; Warner & Wäger, 2019). Achieving equilibrium between digital entrepreneurship (DE) and competitive advantage (CA) therefore represents a critical pathway for organizations to sustain growth and remain competitive in dynamic digital environments.

SUGGESTIONS FOR FUTURE RESEARCH

1. Suggestions for Practical Implementation

The findings of this study highlight the importance of a balanced strategy that integrates Digital Capacity (DC), Business Model Innovation (BMI), and AI Technology Adoption (AI) to enhance both Digital Entrepreneurship (DE) and Competitive Advantage (CA). In practice, managers should invest in developing digital skills and managerial competencies (Ariasih et al., 2018; Bharadwaj et al., 2019), experiment with innovative business models aligned with digital transformation (Foss & Saebi, 2017), and adopt AI technologies to improve efficiency and foster innovation (Bughin et al., 2018; Zheng et al., 2022). Such efforts will enable organizations to minimize risks, strengthen agility, and secure sustainable competitiveness.

2. Suggestions for Future Research

Although this study provides valuable insights, further research could expand the framework by incorporating moderating or mediating factors such as leadership style, organizational culture, or environmental turbulence (Teece, 2018). Cross-industry and cross-country comparisons would help identify contextual variations in digital transformation practices (Bican & Brem, 2020; Hajishirzi et al., 2022). Longitudinal studies could capture how relationships between DC, BMI, AI, DE, and CA evolve over time (Clohessy et al., 2020). Additionally, qualitative approaches such as case studies or interviews may enrich the understanding of digital strategies and provide deeper insights into organizational processes (Khin & Ho, 2019; Velyako & Musa, 2023).

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