

Resource-Based View Drivers of Digital Technology Adoption and Financial Performance: Evidence from High-Tech and Non-High-Tech Industries

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Abstract

Digital technology adoption (DTA) strengthens firms' capacity to optimize their operations, improve their products, services, and communication with stakeholders which increases financial performance (FP). However, due to limited financial resources and a fragile structure, some firms, smaller enterprises can encounter several financial obstacles in adoption new technologies for their operations. In this regard, the antecedents of DTA, which are dynamic capabilities based on the Resource-based View (RBV) might help them cope with these financial issues. Drawing on dynamic capabilities of the RBV, this paper identifies three major factors accelerating DTA, namely, digital transformation (DT), digital capabilities (DC), and digital innovation (DI) and evaluates the relationship between these antecedents and FP. This study employs an online survey to collect data from 600 firms operating in different industries across several European countries and applies a purposive sampling method that is based on respondents' job status. Moreover, this paper uses Ordinal Logistic Regression tests to perform research analyses. Unlike other studies that confirm positive associations between the determinants of DTA and FP, the results of this paper verify negative relationships between the antecedents of DTA and FP. Firm-level factors, such as the differences in DT between high tech and non-high tech industries including iron and mining sectors, and country-level factors such as artificial intelligence (AI) and big data adoption by enterprises might be the reasons for the negative associations among the research variables.

Keywords

Financial Risk Management, Financial Performance, Digital Transformation, Digital Capabilities, Digital Innovation, Digital Technology Adoption, Sustainability, Corporate Finance, Financial Technology, High-tech and Non-high tech Industries.



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Introduction

DTA improves firms' ability to optimize their operations, improve their work processes, products and services and communicate with customers, suppliers, creditors, and other external and internal parties which in turn, increase their FP. In addition, DTA enhances information diffusion, increasing efficiency in production and supply chain management (Zeng et al., 2022). Financial success based on DTA also enables firms to improve their sustainable practices in environmental, social, and economic factors (Ayad & Al-Sabi, 2025). However, some enterprises, especially small and medium-sized enterprises (SMEs) may not adopt new technologies due to a lack of financial resources and a less resilient financial structure (Civelek et al., 2025) that lead to low FP (Civelek et al., 2024). In this regard, they can overcome these financial obstacles by developing their dynamic capabilities that are the antecedents of DTA, namely, DT, DC, and DI. In this context, this paper aims to analyze the association between the antecedents of DTA and FP of enterprises.

Firms adopting digital technologies such as artificial intelligence, blockchain, Internet of Things, cloud computing, and big data analytics, can make more effective decisions without involving several staff members in this process. For instance, General Electric has adopted an Internet of Things strategy that assists their customers to maintain products. This strategy has made the company developing service quality and operational efficiency (Liu et al., 2023). DTA also enables firms to cope with obstacles in their business operations and improve their revenues, profitability, and FP (Baabdullah et al., 2021).

Firms need to take an active role in DT process to adopt digital technologies easily for their operations. This is because DT enhances the adoption and integration of new technologies (Křečková et al., 2025) and digital business strategies that develop business services, platforms (Khatami et al., 2024), operations, business functions, and performance (Kraus et al., 2023). Therefore, firms achieving superior performance in DT process can be more successful in DTA, which in turn increase firm revenues, and, thus, FP (Ardito et al., 2025). DT enables firms to gain production information and accurate data (Mtengwane, 2024), and supports intelligent analysis and data-driven operations. This fact makes businesses to optimize resource allocation for intelligent production that shortens production cycles, reduces costs, and improves product quality (Zeng et al., 2022). The integration of these technologies also increases service efficiency and productivity (Duran et al., 2025). DT supports entrepreneurs by transforming everyday work practices, reducing complex operational activities and lessening monitoring and control needs, which in turn help firms save time and costs (Corvello et al., 2022).

Moreover, DTA requires DC since employees with strong digital skills can accelerate firms' DTA process (Verhoef et al., 2021). Thus, employees are required to develop their DC by learning how to use new digital platforms (Xie et al., 2022). Several studies identify DC as a determinant of DTA (Hsu et al., 2014; Garrison et al., 2015) since these capabilities enable organizations to successfully adopt new technologies to achieve greater performance outcomes (Garrison et al., 2015). Firms with stronger DC can both reduce operational costs and more effectively embed AI applications into their operational processes. In turn, AI-enabled applications such as chatbots and intelligent agents can also foster organizational creativity, which further contributes to performance gains (Mikalef & Gupta, 2021). For these reasons firms with stronger DC are more likely to increase their FP (Eller et al., 2020). A positive association between DC-related competencies and DTA has also been confirmed by prior studies (Baabdullah et al., 2021; Xie et al., 2022).

DI also accelerates DTA (Ardito et al., 2025) and has significant effects on DTA process (Raut et al., 2018). This is because DI requires changes to, or creation of, product and services and firms make these changes and creation by adopting new technologies (Liu et al., 2023). DI supports firm development by differentiating firms from their rivals through improved customer experiences and seizing opportunities in hard to access markets. DI also enables firms to collect product and customer related data improving firms' estimation of market trends and competitors' attitudes. (Wang & Liu, 2025). Firms with stronger DI also use digital technologies more extensively (Blichfeldt & Faullant, 2021). In this regard, firms with higher levels of DI are more likely to adopt digital technologies that improve firm performance (Radicic & Petković, 2023). Some researchers also state a positive relationship between DI and DTA (Tronvoll et al., 2020; Blichfeldt & Faullant, 2021).

DT, DC, and DI may be conceptualized as dynamic capabilities of Resource Based View (Yasmin et al., 2023; Davies et al., 2023; Liu et al., 2023; Ardito et al., 2025). This is because dynamic capabilities enable firms to adopt to changing conditions and technologies by using their internal resources and capabilities as explained in RBV (Anwar et al., 2022; Li et al., 2022; Gyamerah et al., 2025) which is one of the most widely used theories to explain differences in firms' financial performance as well. Dynamic capabilities might also shape firms' perceptions of changing environment and determine their response to these changes. Thus, firms can become able to manage uncontrollable risk factors and financial risk under these uncertain circumstances (Ključnikov et al., 2025). According to RBV, firms' internal resources and capabilities that are valuable, rare, inimitable and non-substitutable make them to achieve sustainable competitive advantages (Zeng et al., 2022; Fitong Ketchiwou & Ngulube, 2025) and survive in the long term (Sousa-Zomer et al., 2020).

Although many researchers focus on the relationships between DT and FP (Truant et al., 2021; Peng & Tao, 2022), DC and FP (Cenamor et al., 2019; Silva, 2025), and DI and FP (Scott et al., 2017; Wang et al., 2021) in

their papers, they separately investigate the associations between these variables. This paper differs from those studies by bringing the antecedents of DTA into a unique paper and investigating the relationships between these key determinants of DTA and FP. Accordingly, a research question may be formulated as “Are there positive associations between the antecedents of DTA and FP?”

Moreover, none of prior studies identify DT, DC, and DI as the antecedents of DTA. Therefore, this paper suggests a holistic DTA framework and ground it in dynamic capabilities of RBV. Although many researchers emphasize the role of DTA in FP (Baabdullah et al., 2021; Zeng et al., 2022) identifying the determinant factors of DTA may present another contribution of this paper to academic literature. Since DT, DC, and DI are conceptualized as core antecedents of DTA, this paper also extends the scope of dynamic capabilities based on RBV.

Furthermore, this research offers a new conceptual framework that identifies the determinants of FP. Therefore, this paper presents a unique study that represents RBV-level factors as antecedents of DTA and FP. In this regard, another research question might arise as follows: “What are the antecedents of DTA, and FP?”

In addition, this research investigates the relationships between financial (FP) and non-financial factors (DT, DC, DI). While FP is based on a tangible resource and capability explained in RBV, namely financial capability (Zeng et al., 2022), non-financial factors are dynamic capabilities, and intangible resources of RBV (Navarro-Garcia et al., 2024). Thus, this paper also brings financial, nonfinancial, tangible and intangible factors within a single study.

Although most studies on the relationship between dynamic capabilities and FP analyze firms within a single country (Zhai et al, 2022; Hussain & Papastathopoulos, 2022, Yan et al., 2026), this paper examines enterprises from Western (Germany, Italy) and Central, and Eastern European countries (Czechia, Slovakia, Poland, Hungary) operating in high-tech and non-high-tech industries including iron and mining.

Material and Methods

Material

DT and FP

DT has been a key driver of enterprise development and innovation that strengthens operational efficiency, competitiveness and overall performance particularly in rapidly changing business environments (Kim & Jin, 2024). Entrepreneurs can also achieve sustainable outcomes by adopting digital technologies in their business operations (Gupta et al., 2023). For instance, firms adopting 3D technologies can improve product customization which meets customers’ demand. Moreover, DT enables firms to strengthen connectivity with their customers to generate more secure, efficient, customer friendly (Burkett et al., 2025) and satisfactory user experiences (Zouair et al., 2025). In this regard, customers can personalize services or products firm provide (Zeng et al., 2022). Rather than making large investments for their IT infrastructure, firms can benefit from the usage of cloud computing solutions that include hardware, platform, application services of provider companies. For instance, General Electric’s adoption of Amazon web services for cloud-based application enable this company to reduce cost and to increase operational efficiency and performance. Thus, the role of IT departments has changed from maintenance to assistance as cloud computing facilitates firms’ collaborations and better customer services, increasing customer satisfaction and revenues (Chen et al., 2022).

Furthermore, DT provides a transparent communication mechanism which supports workers to understand firms’ digital operations aiming greater FP (Kraus et al., 2023). The network effects of DT also minimize information asymmetry in business operations helping firms improve their performance under uncertain conditions (Zeng et al., 2022). Frequent interactions and collaborations via digital platforms improve customer experience (Fang et al., 2025) and loyalty, and provide greater operational efficiency supporting higher revenues and profitability (Merín-Rodríguez et al., 2024). DT also enables process redesign, and the development of new products, services, and business models that increase firm performance (Qi et al., 2025). DT reduces cost, increases productivity and operating efficiency, therefore, it increases firms’ revenue potential (Zhai et al., 2022). DT further allows firm to perform more accurate data analysis that improves FP (Huang et al., 2023). Duong (2025) highlights that entrepreneurs who adopt AI technologies can make customer segmentation, enhance business strategies, use data-driven decision-making tools and become agile in changing environments. Thus, they can increase competitive advantage, the number of customers and FP (Duong, 2025). By integrating and acquiring digital technologies, firms can identify market opportunities that enhance performance (Martin-Rojas et al., 2019). Some studies analyzing listed firms in China (Peng & Tao, 2022; Zhai et al, 2022; Zeng et al., 2022) and Italy (Truant et al., 2021), focusing on profitability ratios such as ROA, ROE, and ROI confirm that DT positively enhances FP. Accordingly, firms that perform better in DT process are more likely to achieve superior FP outcomes. These arguments enable this research to present a research hypothesis as follows:

H1: There is a positive relationship between DT and FP.

DC and FP

DC help firms seize market opportunities by gaining information, detecting market and customer trends, making informed decisions, and improving service efficiency, while reducing the time and costs of product and technology development. DC further support opportunity recognition and technology-driven exploitation that

enhances performance (Kim & Jin, 2024). By strengthening supplier–user value creation, DC help firms generate opportunities and sustain competitive advantage and performance gains (Ferreira et al., 2024). DC also enable firms to adopt more easily to changing technologies and customer preferences (Wang & Zhang, 2024), therefore firms benefit from these capabilities to improve performance outcomes (Mangla et al, 2020).

Furthermore, DC motivate firms to use of AI technologies that are positively related to firms' financial outcomes (Gupta et al., 2023) including revenues (Ayinaddis, 2025). DC such as AI-related competencies lower perceived entry barriers, making digital venture creation more attractive for entrepreneurs (Duong, 2025). AI capability also enhances operational efficiency and automates tasks, improving firm performance by lowering costs and production times and strengthening customer relationship management (Mikalef & Gupta, 2021). Firms with greater DC can communicate more effectively through digital tools that reduce information asymmetry. Digital platforms also facilitate communication among internal parties (e.g. workers), thereby, improving team efficiency and enabling more productive resource utilization that increases firm performance (Bhatti et al., 2025). Several studies also emphasize the importance of DC for FP of enterprises.

For instance, Wang and Zhang (2024) observe some Chinese entrepreneurs and argue that DC are a key competency for using IT resources more effectively and building competitive advantages that improve FP. Silva (2025) examines several Portuguese managers in B2B context and vindicate a positive association between their effective use of digital technologies by these managers and FP of enterprises. Using evidence from Swedish SMEs, Cenamor et al. (2019) substantiate the positive impact of DC on FP. According to the researchers, DC strengthen network capability, enabling firms to access information from various sources, reduce transaction costs, and find opportunities that increase FP. Evidence from firms in the UK and Germany further confirms a positive relationship between DC and FP (Davies et al., 2023). Moreover, Ferreira et al. (2024) use World Bank Enterprises Survey data covering firms across 41 countries and territories and report that since DC stimulates data flows, and flexibility, it increases performance of companies. Heredia et al. (2022) use enterprise survey data from 27 countries and verify a positive impact of DC on firm performance. Furthermore, Bitencourt et al. (2020) verify the positive impact of DC on FP by emphasizing their role in strengthening organizational effectiveness via new routines and practices and enabling firms to perceive and seize opportunities under changing conditions. These arguments lead to the following hypothesis:

H2: There is a positive relationship between DC and FP.

DI and FP

Firms with stronger DI capabilities improve the quality their products and services that increase customer satisfaction and loyalty (Ruiz Molina et al., 2025). Moreover, such firms are more likely to implement cost effective product and process innovations that enhance their profitability (Wang & Liu, 2025). Firms with stronger DI can also implement product upgrades and promotes the transformation of value creation process with efficiency advantages that enable to gain excessive profits. (Liu et al., 2023). Since DI improves knowledge sharing, it reduces cost of acquiring information and stimulates knowledge diffusion among external and internal parties, therefore, firms strengthen their reputation to access capital at lower costs (Yan et al., 2026). DI further accelerates information exchange and knowledge management strengthening organization knowledge and innovative value creation which in turn increase FP (Di Vaio et al., 2021). In addition, DI capabilities promote automation and algorithmic decision-making processes which in turn improve operational efficiency (Liu et al., 2023). Since DI is a key competency of firms to obtain accurate information, decision-makers in firms can make responsive decisions that increase FP (Hussain & Papastathopoulos, 2022).

Since firms with stronger DI capabilities can reshape their marketing strategies and businesses models, they can achieve stronger performance (Di Vaio et al., 2021). Zhao et al. (2023) also state that firms with greater DI might achieve greater FP through market orientation. Furthermore, Boudreau et al. (2022) highlight the roles of patents and copyrights in protecting DI and these factors enable firms to gain revenues from their DI.

Hanelt et al., (2021) use profitability ratio to measure FP and confirm a positive association between DI and FP. Research using Bloomberg data on 165 publicly listed banks reports a positive contribution of DI on banks' profitability (Schrieck et al., 2024). Similar to Schrieck et al. (2024), Scott et al. (2017) observe several banks in 29 countries and vindicate a positive impact of DI on profitability. Some researchers focus on digital financial innovations and suggest that DI in fintech technologies increase firms' profitability (Wang et al., 2021), thus improving economic development of countries (Ngware, 2024). Moreover, Yan et al. (2026) examine Chinese listed firms and highlight the importance of DI in the reduction of equity costs for supply chain partners which in turn increases firm value. The authors also state that DI improves product quality, competitiveness and FP of enterprises. Evidence based on the perception of 440 workers of service organizations supports that finance-related DI enhance FP (Hussain & Papastathopoulos, 2022). According to these researchers, firms with stronger DI provide better customer experience, therefore, increase profitability. In line with these arguments, the last hypothesis is formulated as follows:

H3: There is a positive relationship between DI and FP.

Methods

This study examines how the antecedents of DTA affect FP. To achieve this research objective, this research examines 600 SMEs and large firms located in Czechia, Germany, Hungary, Italy, Poland, and Slovakia. The researcher uses an online questionnaire to collect research data. The data collection process took place in the last two months of 2025. A purposive sampling method based on respondents' job status was employed. In this regard, firm executives such as owners, shareholders, CEOs, finance, ICT department managers were the survey respondents. While about 26.17% of respondents (157 survey participants) are between 26 to 35 years old, the rest were older than 35. On the other hand, while 161 respondents have less than a bachelor's degree, 178 have up to ten years of working experience.

Concerning the firm characteristics, while 348 firms are SMEs, the remaining 252 firms are large enterprises. Most of the firms in the sample have been operating more than ten years (458 firms) in service industry (324 businesses). The remaining firms do business in trade and production-based industries such as iron and mining.

Although the questionnaire includes various survey items measuring firm performance, innovation, technology usage, adoption, firm and respondents' characteristics, this study focuses on ten survey questions in line with the research aim. Each independent variable in the research models, namely, DT, DC, and DI are measured by three survey questions, the dependent variable (FP) is measured using a survey statement presented in Tab. 1. The survey questions have been used in prior studies to measure DT (Cubillas-Para et al., 2024), DC (Proksch et al., 2024), DI (He et al., 2024), and FP (Bhatti et al., 2025). These studies have also substantiated reliability and validity of these constructs. Nevertheless, this paper also measures the reliability of each construct and finds that the Cronbach's alpha values for DT, DC, and DI are 0.841, 0.809, and 0.850, respectively. These values also indicate the reliability of these variables and their internal consistency. On the other hand, profitability has been used by several studies to measure FP of enterprises (Hanelt et al., 2021; Truant et al., 2021; Peng & Tao, 2022). Hence, this paper focuses on profitability of firms.

This research also uses a five-point Likert Scale to measure the responses. The response options that survey participants might select are as follows: "1-strongly disagree", "2-disagree", "3-neither agree nor disagree", "4-agree", and "5-strongly agree". Therefore, higher values that survey respondents select represent higher levels of DT, DC, DI, and FP, and vice versa.

Tab. 1. Research variables, survey items and sources

Research Variables	Survey Items	Sources
DT	1- "We aim to digitalize everything that can be digitalized." 2- "We aim to enhance an efficient customer interface with digitality." 3- "We aim at achieving information exchange with digitality."	(Cubillas-Para et al., 2024)
DC	1- "Digital skills are an important selection criterion in recruiting new workers." 2- "Our workers use all digital services and products we offer." 3- "Our workers has the necessary skills to further digitalize our company."	(Proksch et al., 2024)
DI	1- "Our company has achieved innovations incorporating digital technology which is radically new to customers." 2- "Our company has achieved digital innovations introducing completely new digital features to the market." 3- "Our company has achieved digital innovations allowing novel business models."	(He et al., 2024)
FP	"We have better growth in profit than our competitors."	(Bhatti et al., 2025)

Since the independent and the dependent variables are measured by a five-point Likert Scale, they are ordinal and ranked. For this reason, this paper performs Ordinal Logistic Regression analyses via the SPSS program's logit function. This study has three research models, in which DT, DC, and DI separately serve as the independent variables in the first, second, and third research models, respectively. As each research model includes only an independent variable, multicollinearity assumption is not tested in this paper. The research models are presented as follows:

$$\text{"Logit } (P(Y \leq j)) = \beta_{j0} + \beta_{j1}X_1 \text{"} \quad (1)$$

"Y = Ordinal dependent variable" (FP that is same in all research models)

"J = Categories"

"j=1 strongly disagree; j=2 disagree; j=3 neither agree nor disagree; j=4 agree; and j=5 strongly agree".

"X₁ = Independent variable (DT in the first model, DC in the second model, and DI in the third model)"

"β_{j1} = Regression coefficients"

"β_{j0} = Constant term"

"P = Probability"

Concerning the assumptions testing, Tab. 2 is presented below. While p-values from chi-square test are considered to measure overall model fit, Cox & Snell and Nagelkerke measurements are used to evaluate

Goodness of Fit assumption. Moreover, this paper employs Durbin–Watson statistic to assess the Independence of Errors assumption. This paper adopts a 5% significance level not only for Model Fitting assumption but also for hypotheses testing. For example, p-values greater than the selected significance level lead to a failure to support the research hypotheses that assume positive relationships between the independent and the dependent variables.

According to Tab. 2, the p-values from the Chi-square tests are 0.000 for all models, indicating statistical significance at 5% significance level. Hence, DT, DC, and DI are significant predictors to explain the changes in FP. In other words, adding the independent variables to the research models improves the models' ability to explain the changes in FP, thereby, increasing overall model fit. For these reasons, the Model Fitting assumption is not violated.

Tab. 2. Assumptions Testing

Assumptions	Model Fitting				Goodness of Fit Pseudo R-square		Independence of Errors
Models	-2 Log likelihood	Chi- Square	df	p-values	Cox & Snell	Nagelkerke	Durbin-Watson test statistics
Model 1	192.273	84.707	4	0.000	0.132	0.140	1.988
Model 2	202.016	98.664	4	0.000	0.152	0.161	2.027
Model 3	300.867	202.905	4	0.000	0.287	0.305	1.996

Regarding the Goodness of Fit assumption, the results from Cox & Snell and Nagelkerke measures are presented in Tab. 2. The values from these measurements indicate the percentage of variations in the dependent variable that are explained by the independent variables. For example, adding DT to the first model explains 14% of the changes in FP. Likewise, individual addition of DC and DI to the second and third models represents 16.1% and 30.5% variations in FP, respectively. Therefore, including DT, DC, and DI results in meaningful explanatory power for the changes in FP and enables to validate Goodness of Fit assumption.

Moreover, Tab. 2 depicts the results from Durbin Watson test statistics to test Independence of Errors assumption. Durbin-Watson statistics should be close to 2 to satisfy this assumption. This assumption requires that residuals exhibit no autocorrelation implying statistical independence of error terms across observation. Moreover, individual cases and the data should remain statistically independent to support this assumption. As illustrated in Table 2, Durbin-Watson values for 1st, 2nd, and 3rd models are 1.988, 2.027, and 1.996 that are close to 2. For this reason, this paper also meets the Independence of Errors assumption. Since the results from the assumption tests do not violate any assumptions, this paper applies Ordinal Logistic Regression to test the research hypotheses in next section.

Results

All variables in this paper are measured using a five-point Likert scale. Thus, each variable has four cut-off points (thresholds) as presented in Tab. 3, 4, and 5. The first cut-off point represents the transition from “strongly disagree” to “disagree”, where as the second cut-off point indicates the boundary between “disagree” to “neither agree nor disagree”. Similarly, while the third cut-off point marks the transition from “neither agree nor disagree” to “agree”, the fourth cut-off presents the boundary between “agree” to strongly agree”.

Tab. 3. The results regarding DT and FP

Variable	Estimate (β)	S.E.	Wald	df	p-values	95% CI [Lower Upper]
FP = 1	-3.927	0.237	274.844	1	0.000	[-4.392 -3.463]
FP = 2	-2.755	0.182	228.023	1	0.000	[-3.113 -2.397]
FP = 3	-0.881	0.143	37.971	1	0.000	[-1.161 -0.601]
FP = 4	-0.738	0.141	27.488	1	0.000	[-1.014 -0.462]
DT = 1	-3.280	0.834	15.478	1	0.000	[-4.914 -1.646]
DT = 2	-2.493	0.440	32.079	1	0.000	[-3.355 -1.630]
DT = 3	-1.760	0.227	60.335	1	0.000	[-2.204 -1.316]
DT = 4	-0.660	0.174	14.328	1	0.000	[-1.002 -0.318]

Tab. 3 illustrates the results for the 1st research model in which FP is the dependent variable and DT is the independent variable. According to Tab. 3, the p-values for the cut-off points of DT are significant at 5% significance level (p-values = 0.000). Therefore, DT significantly predicts FP. However, as presented in Table 4, the estimated coefficients (β) for DT are all negative (ranging from -3.280 to -0.660), indicating that a one-unit

increase in DT decreases the log-odds of being in a higher FP level. This means that firms with higher levels of DT are less likely to indicate greater FP. For example, with one unit decrease from the fourth cut-off point to the third cut-off points of DT representing a lower DT level, firms have 0.660 times greater odds of being in a higher FP level, with a 95% confidence interval between -1.002 to -0.318. These results confirm a negative association between DT and FP, therefore, this paper fails to support H1 hypothesis.

Moreover, Tab. 4 depicts the results for the 2nd research model in which DC is the independent variable. As presented in this table, the p-values are below the 5% significance level, ranging from 0.000 to 0.035. Thus, DC is a significant predictor of FP. However, the estimated coefficients are all negative differ from -2.601 to -0.879 across to the first through the fourth cut-off points of DC. In this regard, firms with higher levels of DC are less likely to have a greater FP level than those with lower values of DC. For instance, one unit increase in DC decreases the ordered log-odds of higher FP outcomes by -1.617, -2.601, -2.027, and -0.879 for the 1st, 2nd, 3rd, and 4th cut-off points, respectively. These values indicate a negative relationship between DC and FP and cause a failure to support the H2 hypothesis.

Tab. 4. The results regarding DC and FP

Variable	Estimate (β)	S.E.	Wald	df	p-values	95% CI [Lower Upper]
FP = 1	-4.179	0.248	283.565	1	0.000	[-4.666 -3.693]
FP = 2	-3.023	0.199	230.751	1	0.000	[-3.413 -2.633]
FP = 3	-1.010	0.161	39.583	1	0.000	[-1.325 -0.695]
FP = 4	-0.648	0.156	17.271	1	0.000	[-0.954 -0.343]
DC = 1	-1.617	0.767	4.442	1	0.035	[-3.121 -0.113]
DC = 2	-2.601	0.422	38.083	1	0.000	[-3.427 -1.775]
DC = 3	-2.027	0.230	78.019	1	0.000	[-2.477 -1.578]
DC = 4	-0.879	0.187	22.040	1	0.000	[-1.246 -0.512]

Tab. 5 reports the results for the 3rd research model in which DI is the independent variable. Since the p-values for the cut-off points of DI range from 0.046 to 0.000, DI is a statistically significant variable to predict FP. However, the values for the estimated coefficients (β) are negative across all cut-off points of DI, ranging from -4.841 to -1.268. For this reason, a one-unit reduction in DI leads to an increase in the log-odds of falling to a higher level of FP. For example, a one-unit reduction between DI cut-off points such as from the 3rd to 2nd cut-off point is associated with a 2.785 rise in the ordered log-odds of belonging to a higher FP category, with a confidence interval between -3.262 to -2.307. These findings confirm the existence of a negative association between DI and FP and do not support H3 hypothesis.

Tab. 5. The results regarding DI and FP

Variable	Estimate (β)	S.E.	Wald	df	p-values	95% CI [Lower Upper]
FP = 1	-5.163	0.281	336.566	1	0.000	[-5.715 -4.612]
FP = 2	-3.895	0.233	280.305	1	0.000	[-4.351 -3.439]
FP = 3	-1.623	0.186	75.791	1	0.000	[-1.989 -1.258]
FP = 4	-0.230	0.167	1.895	1	0.046	[-0.557 -0.097]
DI = 1	-4.841	0.551	77.312	1	0.000	[-5.920 -3.762]
DI = 2	-3.639	0.380	91.895	1	0.000	[-4.383 -2.895]
DI = 3	-2.785	0.244	130.485	1	0.000	[-3.262 -2.307]
DI = 4	-1.268	0.208	37.256	1	0.000	[-1.675 -0.861]

To sum up, the results for the 1st, 2nd, and 3rd research models indicate a negative association between DTA (DT, DC, DI) and FP. Thus, the research hypotheses are not supported. These findings oppose to the arguments of prior studies cited in the development of research hypotheses which assume the positive relationship between DT and FP, DC and FP, and DI and FP. In this regard, this study will discuss potential reasons for the differences between the findings of prior studies and this research.

Discussion

This paper confirms negative relationships between DT and FP, DC and FP, and DI and FP. Therefore, the findings of this research are not consistent with the results of several studies that substantiate positive associations between DT and FP (Martin-Rojas et al., 2019; Truant et al., 2021; Peng & Tao, 2022; Zhai et al., 2022; Zeng et al., 2022), DC and FP (Cenamor et al., 2019; Heredia et al., 2022; Davies et al., 2023; Ferreira et al., 2024; Wang & Zhang, 2024; Silva, 2025) and DI and FP (Scott et al., 2017; Wang et al., 2021; Hanelt et al., 2021; Hussain & Papastathopoulos, 2022; Schrieck et al., 2024).

The differences in the results of this paper and prior studies might stem from firm-level factors such as sector. The studies mentioned above work on data from high-tech industries such as manufacturing (Cenamor et al., 2019; Hanelt et al., 2021), service (Scott et al., 2017; Hussain & Papastathopoulos, 2022; Schrieck et al., 2024), or technology firms (Martin-Rojas et al., 2019). Firms in high-tech industries are generally more capable of integrating DT into their operations than enterprises operating in non-high-tech industries (Liu & Li, 2023). However, this research's data set includes firms from both high-tech and non-high tech industries such as trade, iron and mining industries that adopt AI, cloud computing, and big data to a lesser extent. The sectoral differences in DT integration and AI, cloud computing or big data adoption may also explain the negative relationships that this paper corroborates.

Moreover, other researchers analyze firms in Italy (Truant et al., 2021), Portugal (Silva, 2025), Germany and the UK (Davies et al., 2023), China (Peng & Tao, 2022; Zhai et al., 2022; Zeng et al., 2022; Wang & Zhang, 2024), 41 countries and territories (excluding Germany and Slovakia) (Ferreira et al., 2024), and 27 countries (excluding Germany and Italy) (Heredia et al., 2022). Since this paper uses data from firms in Czechia, Germany, Hungary, Italy, Poland, and Slovakia, this might be the reason of the negative association between DTA and FP. This is because except for Germany, the share of firms using any AI (DESI, 2025a) and big data technologies in these countries is lower than the EU average that is around 14% (DESI, 2025b). Since the state of DT in an economy and society determines FP of enterprises (Cicchiello et al., 2024), lower usage of big data and AI technologies might contribute to negative relationships between DTA and FP. On the other hand, the results of this paper are compatible with some studies that verify negative associations between dynamic capabilities or digital technology adoption and FP (Zhong & Ren, 2023; Guo et al., 2023; Qi et al., 2025).

Since the adoption, and use of digital technologies and performing DI can be costly for enterprises, increases in operational costs might also reduce their profitability, and in turn FP. Moreover, even some firms have sufficient financial resources to invest in digital technologies, the returns on these investments can be low due to a lack of dynamic capabilities. Since dynamic capabilities accelerate DTA and technological innovation and act as a trigger to enhance firms' efficiency in sustainable innovation, executives should provide training to develop employees' capabilities. Although SMEs may have limited financial sources, capability development may be less costly than the investments in DTA. Governments, particularly in countries where AI and big data adoption is low, can encourage executives to apply for EU funding such as the Digital Europe and the Horizon Europe programs, and the European Regional Development Fund.

Furthermore, universities can provide courses that enhance dynamic capabilities of prospective entrepreneurs. Academicians can also integrate these courses with entrepreneurship education since the interaction of dynamic capabilities with effective entrepreneurial strategies can increase FP. Beyond providing theoretical knowledge, academicians especially in faculties of economics and administrative sciences should educate students in practical skills such as website creation and AI and big data use. In this regard, students can develop digital self-efficacy to take entrepreneurial actions. Group projects can also motivate students to engage with these technologies since network effect can also facilitate capacity development.

Conclusions

DTA is one of the vital factors determining firms' operational efficiency and FP since the adoption of digital technologies improves user and customer experiences and saves costs. However, some firm may not have the required financial sources to adopt new technologies. Therefore, dynamic capabilities based on RBV may motivate them to reduce financial concerns, since DT, DC, and DI which are the antecedents of DTA, are effective competencies that increase firms' competitiveness. In this context, this paper evaluates the relationships between the determinant factors of DTA and FP by analyzing 600 SMEs and large high-tech or non-high-tech firms operating in several Eastern, Central, and Western European countries.

The results from the Ordinal Logistic Regression analyses indicate a negative relationship between DTA and FP. Differences in AI and big data adoption across industries and countries might lead to the negative association that this paper confirms. In this regard, policy makers, academicians, and firm executives need to provide financial and advisory support to increase dynamic capabilities of existing and prospective entrepreneurs. While academicians can teach courses that improve entrepreneurial and digital literacy and use of technologies by prospective entrepreneurs, firm executives and policymakers can motivate existing entrepreneurs or workers to apply for EU funding or participate trainings that increase digital capabilities.

Except practical contributions, this paper makes several theoretical contributions by extending the scope of dynamic capabilities of RBV, suggesting a novel framework for DTA, and including tangible and intangible factors that determine DTA and FP. However, this paper has some limitations. First, although this paper measures FP by focusing on profitability, it is just based on the perceptions of survey respondents and is not based on any financial ratios. Thus, further research should focus on profitability ratios such as ROA and ROE. Moreover, researchers can create research sample based on listed firms that may provide accurate financial statements which enable to analyze performance by using profitability ratios. Although this paper investigates firms of different sizes, across different industries, and from different countries, it does not include these factors

into the analyses. In this regard, new papers can make comparisons by firm size, industry and country when investigating the relationship between dynamic capabilities and FP.

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