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# Swift organizational adaptation through digital scanning and analytical culture

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## Abstract

**Purpose** – Digital advancements have altered how companies collect, process, and interpret information about the environment, enabling them to better adapt. Through the lens of information processing, this paper examines how organizations achieve adaptive performance in navigating a brittle environment in the digital era.

**Design/methodology/approach** – The study utilizes data from a cross-sectional questionnaire survey of 293 medium- and large-sized companies, employing the Partial Least Squares-Structural Equation Modeling (PLS-SEM) technique.

**Findings** – We reveal the nuanced role of digitally enabled scanning and an analytical culture in how companies successfully adapt to their environment. We also argue that this does not eliminate, but rather reshapes, the role of top management in scanning the environment and interpreting the collected information. Moreover, our findings suggest that this adaptive performance may not necessarily yield immediate financial benefits.

**Originality/value** – By emphasizing the role of digitally enhanced organizational information processes, our insights extend the discourse on adaptive mechanisms and information management. Our results challenge adaptation theories that focus on individual capabilities by refuting the prevailing notion that employee-level adaptive capacity ensures better adaptation at the organizational level.

**Keywords** Information processing, Digital scanning, Analytical culture, Adaptive capacity, Adaptive performance, Financial performance

**Paper type** Research article

## 1. Introduction

Informed by both the information management and the strategic management literature, this study explores how information processing and interpretation, reshaped by digital advancements, serve as effective adaptation mechanisms for contemporary organizations. We demonstrate that digital scanning of the internal and external organizational environment, combined with an analytical culture, is a crucial enabler of swift organizational adaptation; however, it does not necessarily lead to improved financial performance. By this, we aim to contribute to the literature in three ways. First, we theoretically derive and empirically evidence those adaptation mechanisms that provide an explanation for the heterogeneity in firms' performance in adapting to uncertain conditions. In discussing organizations as interpretive systems, we demonstrate why and how leveraging digital advances can enhance interpretive capacity, and as a result, how the role of top management has evolved to continuously scan their environment and interpret the collected information. Second, we show that adaptive ability, i.e., the' capacity of employees to perform well in adaptation, does not enable organizational adaptation *per se*; rather, it plays a key role in building and maintaining digitally advanced information processes and a culture to systematically interpret and use this information. Third, we refute the idea that adaptation performance and financial success are necessarily linked. It reinforces the reported ambiguous link between digital advances and



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immediate financial performance (Benedek *et al.*, 2025) and aligns with the concept of resilience theory, which suggests that adaptation in crisis situations often prioritizes survival and continuity over short-term financial gains (Duchek, 2020).

Organizational adaptation is a strategic response to uncertain conditions (Andersen, 2023), involving the alignment of an organization with a changing environment through a series of managerial choices (Levinthal, 2021; Sarta *et al.*, 2021), which ideally results in improved financial performance (Chakrabarti, 2015). Therefore, we conceptualize organizational adaptation to environmental changes as an intentional shift resulting from various decisions made by organizational members (Hrebiniak and Joyce, 1985; Sarta *et al.*, 2021). Recently, adaptation studies have increasingly focused on explaining general responsiveness to highly unpredictable events such as the COVID-19 pandemic (Krammer, 2022; Hansson and Abrantes, 2023), the Ukrainian war (Obłój and Voronovska, 2024), and related geopolitical tensions (Charpin *et al.*, 2024). In these unforeseen situations, characterized by a sudden onset, disruption of normal operation, and a high level of uncertainty in duration and impact (Hansson and Abrantes, 2023), foresight and specific deliberate preparation may seem unrealistic. Instead, continuous effort is required to scan the environment effectively and utilize tools and resources that enable swift and adequate responses. Thus, the primary question motivating our study is *what effective, context-independent mechanisms an organization can maintain that help with scanning and swift responses* to the volatile, uncertain, complex, and ambiguous (VUCA) environment of today, *thereby enabling better adaptation performance*.

Swift organizational adaptation is a response that occurs quickly in relation to the pace of environmental change, and it aims to maintain or enhance outcomes, such as financial performance, even in the short term. Following an accounting approach, short-term performance adjustments are considered to occur within a year. Moreover, we delineate and separate the mechanisms that predict better alignment of the organization with its environment, the adaptive performance resulting from it, and the financial success, thereby avoiding the conflation of causes and effects (Sarta *et al.*, 2021). This separation raises a second question, namely, *to what extent is the enhanced adaptive performance of an organization reflected in an ex-post evaluation of its financial performance-based outcomes*?

We embed this discussion into the latest global discourse on how digitalization provides opportunities and also challenges in adaptation (Lim *et al.*, 2022; Yadav *et al.*, 2023; Sun *et al.*, 2023; Őri *et al.*, 2024). We explain the mechanism of adaptation by utilizing Galbraith's (1973) extended organizational information processing theory (OIPT) and Daft and Weick's (1984) related conceptualization of organizations as interpretation systems. In this view, organizations tend toward a dynamic equilibrium with their environment, i.e., maintaining an alignment with the volatile environment (Xie *et al.*, 2022). This alignment occurs by answering the four key challenges of the information environment: uncertainty, complexity, equivocality, and ambiguity (Zack, 2007). We hypothesize that digitally enabled scanning of the environmental reality can manage issues arising from uncertainty and complexity. At the same time, the establishment of an analytical culture, associated with the collective and systematic interpretation of available information, is a means of mitigating equivocality and ambiguity (Cao *et al.*, 2019). Thus, *we suggest that digital scanning and analytical culture are adaptation mechanisms that ensure better adaptation performance under new conditions of unprecedented uncertainty.*

We interpret digital scanning as the systematic use of digital technologies to identify, monitor, gather, and filter information from both internal and external environments, uncovering trends, risks, and opportunities. While digital scanning enables the provision of the input data, an analytical culture established at the organizational level ensures that this input is interpreted and embedded systematically for informed decision-making (Popovič *et al.*, 2012; Kulkarni *et al.*, 2017). Additionally, we introduce *adaptive capacity of organizational members as a precursor to establishing effective organizational information processes and excelling in adaptation.* Adaptive capacity describes employees' skills and dispositions referring to overall ability and tendency to engage in adaptive performance (Jundt *et al.*, 2015; Cedergren and Hassel, 2024).

To test our hypotheses, we utilized data from a 2022 questionnaire survey conducted among Hungarian mid-sized and large companies. We asked senior executives one month after the outbreak of the Ukrainian war, in the midst of geopolitical conflicts surrounding the war-torn country, which was experiencing remarkable disruptions in supply chains and related discontinuities in the operations of several companies, as it entered a high-inflation era unprecedented in the preceding decade (Benczúr and Kónya, 2024). The results of the PLS-SEM analysis indicate that maintaining adaptive capacity does not directly impact adaptive performance. At the same time, digital scanning and analytical culture fully mediate the relationship between adaptive capacity and performance. The findings did not confirm that better adaptive performance is followed by increased financial performance, but rather reinforce theories that adaptation does not always lead to positive financial outcomes, especially in the short term and in VUCA environments, where the process of adaptation can be divergent or maladaptive due to the difficulty of perceiving the environment.

## 2. Theoretical background

### *2.1 Information processing theory and adaptation*

OIPT provides a framework for understanding how organizations process and utilize information. Organizations collect and store data from their external environments and internal operations, process the data to gain information, and based on that, exploit opportunities and avoid threats (Galbraith, 2014). Organizations face problems of uncertainty and equivocality that need to be mitigated through their information flows (Brown *et al.*, 2015). In the broader context of an external environment, uncertainty is perceived as a lack of information, which can be addressed by acquiring additional information. At the same time, the increasing availability of information leads to a greater variety of information, potentially creating a new problem of complexity, where more information is available than can be easily processed (Zack, 2007). Moreover, acquiring more information does not alleviate interpretation problems of equivocality and ambiguity (Daft and Lengel, 1986).

The four problems arising around information processing, namely uncertainty, complexity, equivocality, and ambiguity of the environment, present an increasing challenge for organizations experiencing turbulent times. Uncertainty arises when a new context renders an old set of information obsolete, resulting in a shortage of information relevant to the new context (Galbraith, 1974). Complexity increases because the number and variety of elements to be considered grow (Campbell, 1988) when organizations perceive an environment with multiple changes. New, unpredictable events may present poorly understood situations, as organizations either lack understanding (in the case of ambiguity) or collective interpretations differ (in the case of equivocality) due to their novelty. Equivocality describes situations where multiple, parallel, and divergent interpretations of the same information exist, while ambiguity refers to the inability to interpret something in any way (Zack, 2007).

Responding to these four challenges creates new and increased needs for collecting, interpreting, and utilizing information. To satisfy the needs, organizations can invest in information technology, thereby increasing their capacities and enabling more efficient information processing (Fairbank *et al.*, 2006). More recently, the importance of data-centric mechanisms enabled by digital advancements were emphasized, such as big data, advanced analytics (Kowalczyk and Buxmann, 2014; Dubey *et al.*, 2021). These digital advancements, which enable the digital scanning of reality, support the effective collection and processing of information (Lu *et al.*, 2023). Thus, we introduce digital scanning of the environment as a key enabler for successful adaptation.

The positive impact of incorporating digital technologies has been supported beyond the predominantly Western European and North American literature, as evidenced in Asia (Jain *et al.*, 2025) and in the Central and Eastern European (CEE) context (Tutak and Brodny, 2024). Evidence from CEE B2B firms suggests that digital/Industry 4.0 adoption is typically incremental yet constrained primarily by skills shortages and financial limitations

(Szabo *et al.*, 2020), as well as by supply chain, sovereignty, and security policy decisions that vary from country to country (Szunomár, 2024). Thus, while CEE digital trajectories share common historical and economic roots and face similar structural weaknesses and below-average EU digital competitiveness (Buglea *et al.*, 2025), the level of digitization in these countries and the companies within them is highly differentiated and size-dependent.

Adaptation choices are preceded not only by (digital) scanning the environment, during which data is collected, but also by interpreting the data, where the data is given meaning (Daft and Weick, 1984; Thomas *et al.*, 1993; Brown *et al.*, 2015). While digital advancements increasingly support the scanning process through enhanced data collection, interpretation remains a socially embedded process. Interpretation requires developing models and procedures that ensure a shared understanding among organizational members, at least among top management (Choo, 1996). To support interpretation, we introduce the concept of analytical decision-making culture (Popovič *et al.*, 2012) as another key enabler for organizational adaptation to change.

Analytical decision-making culture refers to the shared organizational mindset and associated practices that emphasize the use of data, evidence, and rigorous analysis in guiding decisions (Popovič *et al.*, 2012). It reflects a collective orientation toward systematic and evidence-based decision processes (Kulkarni *et al.*, 2017). We emphasize that – beyond the increasing importance of IT tools enabled by digitalization – organizations must also cultivate behavioral mechanisms that enhance their capacity to process complex and uncertain information. In this regard, technological and behavioral mechanisms play complementary roles: while digital tools expand data availability and accessibility, an analytical decision-making culture ensures that such data is interpreted and acted upon thoughtfully. These two mechanisms reinforce each other in building the organization's overall information processing capacity. This co-production of technological and social components gains renewed importance in the surge of AI, as the new and closer-than-ever collaboration between humans and technology in the interpretation process is expected to result in complementary performance (Bansal *et al.*, 2021).

While recent OIPT literature is mainly focused on organizational-level tools that mitigate problems arising from the ever-growing information processing needs, it is the collective of individual employees who design and maintain these organizational mechanisms. This implies that the role of human actors, specifically employees, should also be taken into consideration. OIPT suggests that the variety of tasks that an employee should accomplish in an organization is dependent upon the frequency of unforeseen events (Haußmann *et al.*, 2012). Turbulent times lead to a higher variety of tasks that require a set of cognitive, skill-based characteristics that enable employees to succeed in the face of new or changing task demands. Thus, it necessitates their cognitive, skill-based adaptation (Jundt *et al.*, 2015). Therefore, we capture these work-related cognitive skills and work-related attitudes that enable us to adapt and denote them as adaptive capacity in our further investigation.

Moreover, adaptive performance is expected to be related to financial success (Chakrabarti, 2015), although the reasonably expected timeframe for financial effects is a matter of controversy. The impact of adaptation through digital means varies over time and with the type of expected outcome, known as the digitalization paradox (Guo *et al.*, 2023). During major shocks, organizations monitor environmental changes in the short term through intelligent sensing, absorb shocks to maintain environmental alignment, and adapt to the new environment through rapid response (Park *et al.*, 2023). These efforts should yield reasonably immediate financial gains. At the same time, the financial impact may be delayed in the short term or may even be completely absent (Bresnahan *et al.*, 2002; Benedek *et al.*, 2025). The economic impact does not appear to be evident even in the long term when short-term responses do not lead to long-lasting transformations, which require significant changes in business models and structures, and the establishment of a new stable state (Park *et al.*, 2023).

Grounding the choice of predictor constructs in OIPT, we explain the adaptive performance of organizations in terms of their individual adaptive capacity, digital scanning, and analytical culture. We conceptualize adaptive performance as an organizational-level phenomenon,

characterized by a reactive nature that captures a company's success in responding to often-unanticipated environmental changes. Appendix 1 contrasts our approach to recent organizational-level adaptation literature and describes how these studies connect to or reinforce the central ideas of our investigation.

### *2.2 Hypotheses development*

Adaptive performance can be considered on both an organizational and individual employee level (Shoss *et al*., 2012). The latter captures the proficiency with which individuals adjust their behavior to satisfy environmental demands, such as solving problems in novel ways, dealing with unexpected work situations, and learning new tasks and technologies (Pulakos *et al*., 2000; Charbonnier-Voirin and Roussel, 2012). This set of properties enables adaptation and is essential for employees to thrive in the face of new or modified task requirements (Jundt *et al*., 2015). Adaptive capacity ensures that employees are able and willing to fit their behavior (Shoss *et al*., 2012). It does not describe the extent or quality of adaptation, but rather the conditions that are necessary for employees to engage in adaptive behavior when task variety is increased. Next, when these individual-level adaptive capacities are aggregated and interact at an organizational level, they will enable organizations to adapt successfully to changes. Hence, we propose that the source of variation in organizations' ability to adapt is their adaptive capacity, considered at the employee level.

*H1*. Adaptive capacity is positively associated with adaptive performance.

Digitalization can be described as the utilization of digital technologies, a combination of information, computing, communication, and connectivity technologies (Vial, 2019). These enable the digital scanning of reality and may also be capable of replicating and even replacing human involvement in information processing (Constantiou *et al*., 2023). As an extreme view, it leads to "a progressive replacement of humans by digital technologies in … the processes of scanning, interpretation, and learning that encompasses an organization's interaction with its environment" (Constantiou *et al*., 2023). In a more prudent approach, employees as human resources appear as enablers for implementing digital improvements. In the future, it is expected that technology and people will increasingly work together in collaboration to process and interpret information (Kolbjørnsrud, 2024). For this, indispensable prerequisites include their basic knowledge (Oberländer *et al*., 2020), willingness to develop, openness to change (Osmundsen *et al*., 2018; Trenerry *et al*., 2021), and cognitive behaviors and attitudes that allow for self-directed workplace learning (Trenerry *et al*., 2021). In line with this view, we see the adaptive capacity of employees, i.e., their knowledge, skills, and attitudes, describing employees' ability and willingness to engage in novel ways of working as a necessary precondition.

Digital scanning can be seen as an adaptation mechanism if it decreases the distance between the environment and the organization. Through enhanced capabilities in gathering, storing, and processing larger amounts of data, digital solutions can bridge the gap between possessed and required information (Moeuf *et al*., 2020), thereby reducing uncertainty. A much higher amount and diverse set of data can also be easily processed through more advanced analytical solutions, i.e., reducing complexity (Cao *et al*., 2019). By reducing uncertainty and complexity, digital scanning enables the management of indeterminacy in information processes (Zack, 2007), resulting in enhanced information processing capacities that facilitate better alignment. Accordingly, we suggest that digital scanning serves as an adaptation mechanism that explains how employee-level adaptive capacity results in better organizational adaptive performance.

*H2*. The relationship between adaptive capacity and adaptive performance is mediated by digital scanning.

While technology can help cope with uncertainty and complexity, it might not be enough to mitigate other forms of information-based indeterminacy (Zack, 2007). Establishing a

converging interpretation of existing information, i.e., mitigating ambiguity and equivocality, must be achieved by other means, namely, organizational practices, policies, and procedures promoting well-established and shared information processes and a comprehensive analysis of available information (Zack, 2007). In the decision-making literature, this organizational attitude toward the information environment is often referred to as analytical culture (Popovič *et al.*, 2012; Szukits and Móricz, 2023) or analytical orientation (Kulkarni *et al.*, 2017).

The establishment of an analytical culture brings a systematic approach to decision-making processes, prioritizing data-driven insights that are underpinned by thorough analysis (Popovič *et al.*, 2012) and disseminating knowledge (Medeiros and Maçada, 2021), thereby minimizing the risk of ambiguity, i.e., the inability to interpret something in any clear way. This culture also promotes collaborative frameworks, such as personal interaction with analysts, that are essential for utilizing analytic results (Kowalczyk and Gerlach, 2015), reducing equivocality where multiple divergent interpretations of the same information exist. Thus, we suggest that analytical culture, by its ability to mitigate ambiguity and equivocality, serves as an adaptation mechanism explaining how employees' adaptive capacity contributes to organizational excellence in adaptation.

*H3.* The relationship between adaptive capacity and adaptive performance is mediated by analytical culture.

A volatile environment compels managers to actively monitor their environment (Choo, 1996) and to make rapid judgments, leaving little time for processing available information (Singh *et al.*, 2002). Digitalization supports the technological foundation, the abundance of data, and advanced analytical solutions, enabling efficient scanning of the external environment and providing rapid, data-driven insights for quick responses. Although the benefits from more informed decisions are repeatedly evidenced in the literature (Gupta and George, 2016; Oesterreich *et al.*, 2022), we know that "good data won't guarantee good decisions" (Shah *et al.*, 2012, p. 2). The primary reason for the lack of guarantee is that even if scanning and data collection are accomplished, they need to be given meaning. This interpretation extends not only to the individual level, but also requires "developing shared understanding and conceptual schemes among members of upper management" (Daft and Weick, 1984, p. 284). This is an important phase of sense-making, where the equivocality of information about the environment is reduced by extensive discussions to arrive at a common interpretation (Choo, 1996). It happens in the supportive environment established by analytical culture (Popovič *et al.*, 2012; Kulkarni *et al.*, 2017), which also creates an atmosphere of continual experimentation and learning, enabling performing better in adaptation to uncertain conditions (Mikalef *et al.*, 2019; Oesterreich *et al.*, 2022; Chatterjee *et al.*, 2024). Thus, we suggest that analytical culture facilitates the positive impact of digitalization on adaptive performance.

*H4.* The relationship between digital scanning and adaptive performance is mediated by analytical culture.

Adaptation to environmental changes is often presented as a positive and desirable phenomenon in organizational studies; however, opinions differ regarding its positive impact. The simple survival of companies can be seen as a sign of successful adaptation (Bradley *et al.*, 2011; Quansah and Hartz, 2021) or as the alteration of business behavior to accommodate challenging circumstances (Obłój and Voronovska, 2024). Perceived competitive advantage, as a relative firm performance compared to competitors (Navarro *et al.*, 2010) and growth of the organization (Chakrabarti, 2015), are often claimed to be an indicator of adaptation. Endeavors to link adaptation with objective measures of financial success introduce profitability measures to evidence adaptive performance (Adner and Helfat, 2003). In contrast to that approach, we consider financial performance as a separate construct that is a consequence of adaptive performance (Powell, 1992). We propose that superior adaptation does not equate to financial success but rather serves as a prelude to it.

*H5.* Adaptive performance is positively associated with financial performance.

We summarize our research model in Figure 1.

## 3. Research method

Despite growing interest in digital advances and organizational adaptation, most empirical studies have focused on Western European or North American contexts, neglecting other regions such as Central and Eastern Europe (CEE). To address this gap, we present contextually rich research conducted among Hungarian firms during a period of high demand for adaptation. As a neighboring country to Ukraine, Hungary experienced direct and immediate exposure to the economic, geopolitical, and logistical consequences of the Russia–Ukraine war. The outbreak of war in early 2022 triggered a cascade of challenges for firms operating in CEE (Benczúr and Kónya, 2024). The timing of the survey enables us to study short-term responses and minimize recall bias by surveying respondents immediately after the event.

Beyond the region's strategic relevance and the temporal relevance of addressing adaptation, the sample also allows us to study adaptation-enabling mechanisms related to digital advances. Although the pace of digitalization in this region has accelerated significantly in recent years, the necessary technological tools (infrastructure) are usually available for medium and large companies, and they also exhibit uneven adoption, resulting in varied levels of digitalization and analytical capabilities (OECD, 2021; Kovács *et al*., 2023; Tutak and Brodny, 2024). This variety makes Hungary an ideal context in which to examine the diversity of organizations' capacities to utilize digital scanning and an analytical culture amid change.

### *3.1 Data collection and sample characteristics*

A questionnaire was developed by a team of academics representing various management-related subfields. A professional research company was then involved in pre-testing and conducting the survey. After the pre-test with invited companies, the wording of the questions was adjusted, and the order of the different types of questions was changed to reduce monotony. Given the cross-sectional nature of the survey, we targeted companies registered in Hungary across all industries. Defining the size of the companies by their number of full-time employees, we limited our research to medium-sized (50–249 employees) and large

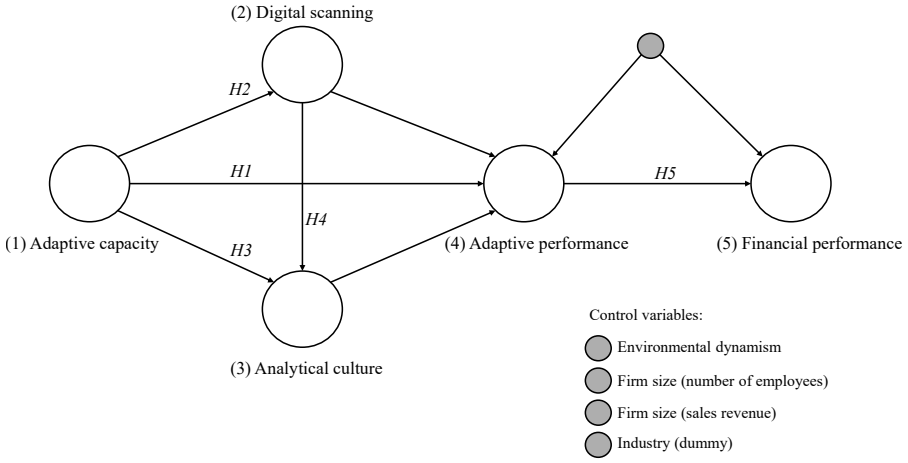



**Figure 1.** Research model. Source: Authors' own work

enterprises (250+ employees). The total population of nearly 6,000 companies was stratified by quotas defined for size and region based on data from the Central Statistical Office. A random sampling was applied per quota cell to select 1,369 companies to be contacted from the Dun & Bradstreet company database. The cross-sectional questionnaire survey was conducted by a professional market research company in March and April 2022.

To improve response rates and data quality, and to reduce self-selection bias, we collected data via the Computer-Assisted Telephone Interviewing (CATI) method (Groves *et al.*, 2009). Interviews were conducted by trained interviewers from a market research company, with repeated call attempts where necessary (mean 1.8 contacts per firm). Participation was fully voluntary and anonymous; respondents received standardized information about the study and provided verbal consent. Overall, 306 firms completed the interview (response rate 22.35%). The database of the questionnaire survey, which reflects the perceptions of senior executives, has been supplemented with financial data for the companies for the years 2017–2020, available via the Business Information and Electronic Commerce Business Intermediary Service of the Hungarian Ministry of Justice. In the second phase, in November 2023, we could complete the database with the financial statements published for the years 2021 and 2022. We used the financial data for the preceding years to check whether the firm has consistently operated or not. We excluded 13 companies from further investigation due to incomplete financial statements. The industry and size characteristics of the final sample, including 293 companies, are remarkably close to those of the total population (Table 1).

The research targeted senior executives, with 40% of the respondents holding the position of chief executive, and the remaining 60% occupying diverse senior-level positions. The respondents have an average of 25 years of work experience, with one-third of them being female. We could rule out systematic distortion by position with the Kruskal Wallis H test executed for the four items of the key target construct of adaptive performance. The $p$ values ranging from 0.297 to 0.861 suggest retaining the null hypotheses; that is, none of the items of adaptive performance is significantly differentially perceived by respondents in the three executive positions.

**Table 1.** Sample characteristics

| | Final sample | | Total population |
|---|---|---|---|
| | Frequency | Percent (%) | Percent (%) |
| Medium-size companies (50–249) | 239 | 81.6 | 83.5 |
| Big-size companies (250+) | 54 | 18.4 | 16.5 |
| *Industry (NACE code)* | | | |
| Agriculture and Mining (01–09) | 21 | 7.2 | 5.4 |
| Manufacturing (10–33) | 112 | 38.2 | 36.9 |
| Electricity, Gas, Steam and Water Supply, Waste (35–39) | 10 | 3.4 | 2.7 |
| Construction (41–43) | 22 | 7.5 | 4.9 |
| Wholesale and Retail Trade (45–47) | 43 | 14.7 | 15.1 |
| Transportation and Storage (49–53) | 14 | 4.8 | 7.1 |
| Accommodation and Food Service (55–56) | 11 | 3.8 | 3.9 |
| Information and Communication (58–63) | 12 | 4.1 | 3.5 |
| Financial, Insurance and Real Estate Activities (64–68) | 9 | 3.1 | 4.1 |
| Professional, Scientific and Technical Activities (69–75) | 11 | 3.8 | 4.5 |
| Administrative and Support Service Activities (77–82) | 19 | 6.5 | 9.4 |
| Other Services (84–96) | 9 | 3.1 | 2.4 |
| Total | 293 | 100.0 | 100.0 |

**Source(s):** Authors' own work

To mitigate common method bias, we designed the survey following the suggestions of Podsakoff and Organ (1986), Podsakoff *et al.* (2012). To prevent erroneous relationships between causes and consequences, we separated the measurement of the two key target constructs: adaptive performance and financial performance. The former was measured by senior management opinions, while the latter was measured by objective financial data. Moreover, we reversely worded the items of the exogenous construct, adaptive capacity, and then transformed the scale to measure in the same direction as the dependent variables. Finally, we assessed the common method bias resulting from having single respondents in the questionnaire survey by executing Harman's Single Factor Test and Kock's (2015) approach. As the total variance extracted by one factor (33.2%) is less than the critical threshold (50%) and all VIF values of the inner model are far below 3.3, no difficulties with common method bias are reported that may distort the perceptional data because of relying on the same measuring instrument used for the constructs (1)–(4).

### *3.2 Measurement properties*

The measurement model (see Figure 1) involves 26 manifest variables loading onto 5 latent constructs: (1) Adaptive capacity, (2) Digital scanning, (3) Analytical culture, (4) Adaptive performance, and (5) Financial performance. Where available, we adopted established scales. For the operationalization of the key constructs measuring adaptivity, we developed our own measurement scales, which are most suitable for the study's objectives (see Appendix 2). Constructs (1)–(4) rely on senior executives' perceptions, where respondents were asked to rate statements about their own organization on a scale of 1–5. While perceptual measures may be superior to objective measures in predictive relevance (Kayser *et al.*, 2025), to mitigate potential random measurement errors introduced by subjective judgments, we used multi-item scales for each subjectively measured construct. (5) Financial performance is measured with objective data.

We developed *adaptive capacity* as an ex-ante measure focusing on the employee level. Jundt *et al.* (2015, p. 55) denoted it as "adaptability" and explained it as "a multidimensional composite of knowledge, skills, and dispositions that influence an individual's general capability and proclivity to engage in adaptive performance". It captures the employee-level capacity to manage dynamic work situations, described by the (1) abilities and (2) willingness of employees that enable adaptation (Pulakos *et al.*, 2002). Abilities call for skill- and knowledge-based inquiry, and willingness requires more attitude-related inquiry, suggesting together an individual capacity for adaptation. Accordingly, we measure employees' adaptive capacity using seven items that describe their existing field-specific expertise, their ability to absorb new knowledge, managerial knowledge at the middle level, their ability to innovate, resistance to change, motivation, and work morale.

In contrast to the capacity established at the organizational level (Soparnot, 2011), we focus on the workforce level. But unlike psychology-related and behavioral investigations of individual adaptivity, we do not rely on behavioral self-reports from individuals. We use executives' general perceptions of organizational members in terms of their knowledge, skills, and dispositions, which are scattered and associated with change in the literature. In this setting, executive judgment serves as a proxy for the aggregated judgments of all employees that would be hardly accessible. Each item has been worded in reverse to minimize potential problems associated with common method bias.

*Adaptive performance* is an ex-post composite measure on the organizational level that captures multiple facets of adaptive performance theorized in prior literature. Adaptive performance is associated with competitive advantages (Navarro *et al.*, 2010), the ability to both exploit existing and explore new opportunities by scanning, i.e. sensing the environment, and acting, i.e. seizing (O'Reilly and Tushman, 2011; Kumkale, 2022), and the ability to respond to significant and unexpected events (McCarthy *et al.*, 2017; Duchek, 2020). Accordingly, we asked senior executives about the sustainable competitive advantages gained

over competitors, excellence in efficiently executing and further improving standard work processes, excellence in exploring entirely new possibilities and experimenting, and the ability to meet even significant and unexpected environmental challenges. By this, we arrived at adaptive performance items that capture organizational achievements that (1) do not relate to financial gains, but (2) are still general enough that they are meaningful for all companies (i.e., not listing concrete actions, responses).

The model identifies digital scanning and collective interpretation as mediators. *Analytical culture* is measured using a scale developed and first introduced by Popovič *et al*. (2012) in the context of business intelligence. To operationalize the concept of digital scanning, we adopted the scale developed by Mhlungu *et al*. (2019) for measuring strategic initiatives that enhance an organization's digital capability. It captures the level of advancements that allow digital scanning. Beyond the general resource attainment abilities of the companies, they identified three aspects of successful digital developments: customer centricity, governance, and innovation, measured by 12 items. Two indicators (DIG_11 and DIG_12) were removed due to weak loadings and their internal consistency. Following Hair *et al*. (2021), we did not mechanically drop all indicators with loadings between 0.4. and 0.7. We measure the digital scanning construct by 10 items and retain DIG_1, DIG_5, and DIG_10 as they do not compromise construct reliability, i.e., they do not weaken the values of the three reliability measures (see Table 2).

We used the year-end financial numbers, representing data with a time lag of 8–9 months, to objectively measure the performance effect in financial terms. *Financial performance* was assessed by two return ratios, capturing vastly different aspects of profitability. Return on sales (ROS, earnings before interest and taxes divided by sales revenue) reports about operational efficiency in terms of how much profit is produced per unit of sales revenue. Return on assets (ROA, profit after tax divided by total assets) indicates how effectively a company utilizes its assets to generate profit, a metric widely used in organizational adaptation literature (Zajac *et al*., 2000; Adner and Helfat, 2003; Thongpapanl *et al*., 2012). In Appendix 3, we report on the statistics for these two financial measures for the period 2017–2022.

By evaluating the results, we controlled for environmental dynamism, industry, and company size. Both the number of employees and the net revenue of the fiscal year 2022 were used as continuous control variables, controlling for size effects. A dummy variable has been established to control for the effect of the manufacturing industry, as 38.2% of the companies are active in this industry, which closely approximates the rate in the population as a whole (see Table 1). Moreover, we added environmental dynamism as a control variable to reflect the extent of vulnerability of the organizations, thereby ruling out the potential confounding effect of it. Environmental dynamism is confined to unpredictable changes that increase uncertainty for organizational members (Dess and Beard, 1984). War-related environmental dynamism covers the perceived impact of changes related to (1) "market for our products/services", (2) "market for the inputs we need to operate", (3) "labor market", and (4) "financial market" (including inflation, foreign exchange rates). It is developed as a four-item formative construct, as turbulence in the different sub-environments does not necessarily move together.

**Table 2.** Reliability measures of the digital scanning construct

| | Digital scanning<br>Construct measured by 10 items | Construct measured by 7 items |
|---|---|---|
| Chronbach Alfa | 0.890 | 0.874 |
| Composite reliability (rho_a) | 0.897 | 0.879 |
| Composite reliability (rho_b) | 0.910 | 0.903 |

**Source(s):** Authors' own work

The partial least squares structural equation model (PLS-SEM) was calculated in SmartPLS 4. The missing data, ranging from 0 to 2.4% per variable, were imputed using the mean value replacement method. The sample size of 293 companies exceeds the minimum sample size requirements calculated using the inverse square root method. The lowest statistically significant path coefficient in the model (0.179) and the suggested significance level of 5% require a sample size of 193 or higher.

## 4. Results

### *4.1 Measurement model assessment*

Table 3 presents the key statistics used to assess the reflective measurement model. Outer loadings on all constructs are significant, and their value exceeds the threshold of 0.708 for each indicator of (1) Adaptive capacity, (3) Analytical culture, and (5) Financial performance, signaling that the associated indicators have much in common. We decided to retain items in the model with weaker outer loadings after investigating their effects on the

**Table 3.** Reliability, validity, and collinearity measures

| Items and constructs | Outer loadings | Cronbach's alpha | Composite reliability (rho_a) | Composite reliability (rho_c) | Average variance extracted (AVE) | Collinearity statistics (VIF) |
|---|---|---|---|---|---|---|
| *(1) Adaptive capacity* | | 0.933 | 0.940 | 0.946 | 0.716 | |
| ADA_1 | 0.886 | | | | | 3.032 |
| ADA_2 | 0.731 | | | | | 1.871 |
| ADA_3 | 0.800 | | | | | 2.233 |
| ADA_4 | 0.902 | | | | | 4.210 |
| ADA_5 | 0.894 | | | | | 4.108 |
| ADA_6 | 0.846 | | | | | 2.776 |
| ADA_7 | 0.869 | | | | | 3.165 |
| *(2) Digital scanning* | | 0.890 | 0.897 | 0.910 | 0.504 | |
| DIG_1 | 0.657 | | | | | 1.476 |
| DIG_2 | 0.751 | | | | | 1.966 |
| DIG_3 | 0.757 | | | | | 2.010 |
| DIG_4 | 0.723 | | | | | 1.840 |
| DIG_5 | 0.537 | | | | | 1.415 |
| DIG_6 | 0.716 | | | | | 1.918 |
| DIG_7 | 0.719 | | | | | 1.764 |
| DIG_8 | 0.742 | | | | | 1.799 |
| DIG_9 | 0.786 | | | | | 2.253 |
| DIG_10 | 0.682 | | | | | 1.836 |
| *(3) Analytical culture* | | 0.817 | 0.833 | 0.891 | 0.732 | |
| AC_1 | 0.814 | | | | | 1.601 |
| AC_2 | 0.898 | | | | | 2.096 |
| AC_3 | 0.853 | | | | | 1.960 |
| *(4) Adaptive performance* | | 0.702 | 0.727 | 0.816 | 0.529 | |
| AP_1 | 0.773 | | | | | 1.345 |
| AP_2 | 0.769 | | | | | 1.494 |
| AP_3 | 0.769 | | | | | 1.426 |
| AP_4 | 0.579 | | | | | 1.184 |
| *(5) Financial performance* | | 0.829 | 0.986 | 0.917 | 0.847 | |
| ROA | 0.880 | | | | | 2.005 |
| ROS | 0.958 | | | | | 2.005 |

**Source(s):** Authors' own work

reliability and validity measures of the constructs (2) Digital scanning and (4) Adaptive performance. While assessing the constructs' internal consistency reliability, the traditional criterion of Chronbach's alfa was supplemented with rho_a and rho_c measures with reassuringly high values (above 0.7). To establish convergent validity at the construct level, the average variance extracted (AVE) is reported, with values above 0.5 for each construct. This indicates that each latent variable explains more than 50% of the variance of its indicators.

The extent of dissimilarity of the constructs was assessed by both the Fornell-Larcker criterion of discriminant validity (Fornell and Larcker, 1981) and the heterotrait-monotrait ratio (HTMT) proposed by Henseler *et al*. (2015). Table 4 shows that the indicators' loadings on the associated constructs are higher than those on other constructs, as reflected in the diagonal values being the highest. HTMT Matrix reports values far below the conservative threshold of 0.85, indicating that the constructs are conceptually dissimilar to each other. Finally, we can exclude critical collinearity issues among predictors as the values reported for outer model variance inflating factors (VIF) in Table 3 are all below 5, and the majority of them do not even exceed the more preferable threshold of 3.

### *4.2 Structural model assessment*

Assessment of the structural model started with evaluating the research model as displayed in Figure 1, without introducing control variables (Table 5). Based on this significance criterion, $p < 0.05$, we must reject H1 and H5: adaptive capacity does not directly impact the adaptive performance of companies, and adaptive performance does not significantly increase financial performance.

Path coefficients indicate the extent to which the related constructs are associated with each other. The path coefficients of the direct effects in Table 5 range from 0.179 to 0.459. Based on Cohen (2013), we can conclude that adaptive capacity is associated with digital scanning at a medium-to-strong level, and digital scanning has a strong impact on adaptive performance. The results also show that adaptive capacity contributes to establishing an analytical culture to a lesser extent, as does the relationship between analytical culture and adaptive performance, which is medium-moderate. The direct effect of digital scanning on analytical culture is significant, with a weak effect size.

We assessed mediation using bootstrapped specific indirect effects (Table 5). Digital scanning (H2) and analytical culture (H3) jointly mediate the relationship between adaptive capacity on adaptive performance. The direct effect is insignificant while the indirect effects are significant, indicating full mediation. Analytical culture also mediates the relationship

**Table 4.** Discriminant validity assessment

| | (1) Adaptive capacity | (2) Digital scanning | (3) Analytical culture | (4) Adaptive performance | (5) Financial performance |
|---|---|---|---|---|---|
| *Fornell-Larcker criterion* | | | | | |
| (1) Adaptive capacity | *0.846* | | | | |
| (2) Digital scanning | 0.323 | *0.727* | | | |
| (3) Analytical culture | 0.296 | 0.358 | *0.856* | | |
| (4) Adaptive performance | 0.404 | 0.546 | 0.270 | *0.710* | |
| (5) Financial performance | 0.142 | 0.102 | 0.047 | 0.079 | *0.920* |
| *Heterotrait-monotrait ratio (HTMT) - Matrix* | | | | | |
| (1) Adaptive capacity | | | | | |
| (2) Digital scanning | 0.377 | | | | |
| (3) Analytical culture | 0.329 | 0.459 | | | |
| (4) Adaptive performance | 0.431 | 0.665 | 0.302 | | |
| (5) Financial performance | 0.162 | 0.157 | 0.100 | 0.095 | |

**Source(s):** Authors' own work

**Table 5.** Evaluation of the structural model: model 1 without controls

| | Path coefficients | $f^2$ effect sizes | T statistics | *p*-values | Confidence intervals 2.5% | 97.5% | Significance $p < 0.05$ |
|---|---|---|---|---|---|---|---|
| *Direct effects* | | | | | | | |
| (1) Adaptive capacity → (2) Digital scanning | 0.404 | 0.195 | 7.061 | 0.000 | 0.296 | 0.518 | Yes |
| (1) Adaptive capacity → (3) Analytical culture | 0.224 | 0.047 | 2.964 | 0.003 | 0.075 | 0.367 | Yes |
| (1) Adaptive capacity → (4) Adaptive performance | 0.074 | 0.007 | 1.385 | 0.166 | −0.030 | 0.179 | No |
| (2) Digital scanning → (3) Analytical culture | 0.179 | 0.030 | 2.703 | 0.007 | 0.052 | 0.311 | Yes |
| (2) Digital scanning → (4) Adaptive performance | 0.459 | 0.263 | 9.122 | 0.000 | 0.362 | 0.557 | Yes |
| (3) Analytical culture → (4) Adaptive performance | 0.212 | 0.061 | 4.160 | 0.000 | 0.109 | 0.308 | Yes |
| (4) Adaptive performance → (5) Financial performance | 0.102 | 0.011 | 1.601 | 0.109 | −0.054 | 0.229 | No |
| *Specific indirect effects* | | | | | | | |
| (1) Adaptive capacity → (2) Digital scanning → (4) Adaptive performance | 0.185 | | 5.245 | 0.000 | 0.126 | 0.263 | Yes |
| (1) Adaptive capacity → (3) Analytical culture → (4) Adaptive performance | 0.048 | | 2.423 | 0.015 | 0.014 | 0.090 | Yes |
| (2) Digital scanning → (3) Analytical culture → (4) Adaptive performance | 0.038 | | 2.351 | 0.019 | 0.010 | 0.072 | Yes |
| (1) Adaptive capacity → (2) Digital scanning → (3) Analytical culture → (4) Adaptive performance | 0.015 | | 2.220 | 0.026 | 0.004 | 0.031 | Yes |
| *Total effects* | | | | | | | |
| (1) Adaptive capacity → (2) Digital scanning | 0.404 | | 7.061 | 0.000 | 0.296 | 0.518 | Yes |
| (1) Adaptive capacity → (3) Analytical culture | 0.296 | | 4.448 | 0.000 | 0.165 | 0.425 | Yes |

(*continued*)

**Table 5.** Continued

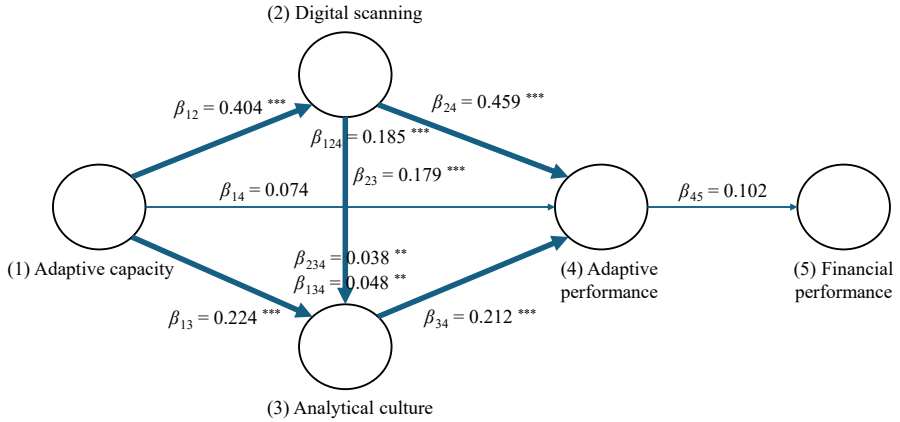
| | Path coefficients | $f^2$ effect sizes | T statistics | *p*-values | Confidence intervals 2.5% | 97.5% | Significance $p < 0.05$ |
|---|---|---|---|---|---|---|---|
| (1) Adaptive capacity → (4) Adaptive performance | 0.323 | | 5.552 | 0.000 | 0.211 | 0.437 | Yes |
| (1) Adaptive capacity → (5) Financial performance | 0.033 | | 1.465 | 0.143 | −0.017 | 0.082 | No |
| (2) Digital scanning → (3) Analytical culture | 0.179 | | 2.703 | 0.007 | 0.052 | 0.311 | Yes |
| (2) Digital scanning → (4) Adaptive performance | 0.497 | | 10.328 | 0.000 | 0.403 | 0.592 | Yes |
| (2) Digital scanning → (5) Financial performance | 0.051 | | 1.604 | 0.109 | −0.028 | 0.111 | No |
| (3) Analytical culture → (4) Adaptive performance | 0.212 | | 4.160 | 0.000 | 0.109 | 0.308 | Yes |
| (3) Analytical culture → (5) Financial performance | 0.022 | | 1.434 | 0.152 | −0.010 | 0.055 | No |
| (4) Adaptive performance → (5) Financial performance | 0.102 | | 1.601 | 0.109 | −0.054 | 0.229 | No |

**Source(s):** Authors' own work

between digital scanning and adaptive performance (H4). As the direct path remains significant here, this represents partial mediation. Table 5 additionally reports the serial indirect effect from adaptive capacity to adaptive performance via both mediators.

Overall, the total effects interpreted as the sum of direct and indirect effects signal a medium to strong relationship between the predictors and the target construct of adaptive performance, while adaptive performance does not significantly contribute to enhanced financial performance (Figure 2).

To eliminate the influence of firm size, industry, and environmental dynamism as potential confounding factors, the model was extended to include control variables related to both key target constructs: adaptive and financial performance. Results for model 2 with controls are reported in Table 6. The introduction of the control variables has no impact on either the significance of the paths or the magnitude of the significant path coefficients. Models 1 and 2 are remarkably similar, so the relationships reported as significant in Model 1 are not confounded by the differences between the two models. At the same time, one of the control variables, environmental dynamism, is highly associated with adaptive performance, showing that the higher the perceived firm-level impact of environmental changes, the higher the perceived performance in adaptation. Even more importantly, incorporating this control into the model results in a somewhat increased effect size between adaptive performance and financial performance ($\beta = 0.141$, $p = 0.050$), but it still lacks convincing significance. At the same time, environmental dynamism is not associated with the dependent construct of financial performance; therefore, it does not act as a confounder but as a suppressor. The suppressor variable, environmental dynamism, controls for the extraneous variance of adaptive performance that is unrelated to financial performance. Thus, adjusting for this control, the relationship is somewhat stronger than initially observed.




$\beta_{xy}$: Path coefficient representing the value of direct effect of the construct X on Y

$\beta_{xzy}$: Path coefficient representing the value of the specific indirect effect of the construct X on Y via the mediator construct Y

***: Path coefficient is significant at the 1% level ($p < 0.01$)

** : Path coefficient is significant at the 5% level ($p < 0.05$)

**Figure 2.** Summary of results. Source: Authors' own work

Given the non-significant association with financial performance, we evaluate the explanatory and predictive power primarily of adaptive performance. The model shows moderate explanatory power for this key target construct (R square, 0.351). We assess out-of-sample prediction using $PLS_{predict}$ (Shmueli *et al.*, 2016). Table 7 reports $Q^2$ and root mean square error (RMSE) for the PLS mode relative to the linear-model benchmark (Hair *et al.*, 2021). We conclude that all indicators except one (AP_4) in the PLS-SEM analysis have lower prediction error statistics values compared to the LM benchmark, indicating that the model has moderate predictive power.

Finally, we checked and corrected for endogeneity bias by implementing the Gaussian Copula approach (Eckert and Hohberger, 2023). All the Copula parameters are non-significant ($p > 0.05$ in the case of each GC estimate), indicating that the endogeneity problem is not present. Overall, we found that the model is robust and has an adequate level of explanatory and predictive power.

The results suggest that the adaptive capacity of companies does not automatically and directly lead to better adaptive performance (Figure 2). At the same time, this relationship is fully mediated by two mechanisms of digital scanning and analytical culture. Through their abilities to advance information processes, they support higher performance in adaptation. Interestingly, this adaptive performance does not significantly improve performance measured in financial terms, at least not in the measured period.

## 5. Discussion

While seeking to understand why organizations perform differently in adapting, we focus on the information processes that link organizations with their environment, as recent technological advances have fundamentally changed the information routines of organizations (Riedl *et al.*, 2017). Organizations scan their environment, and the collected data needs to be interpreted; they must make sense of it and leverage the insights gained. Companies utilizing digital advances argue that they will increasingly replace human processes, such as scanning, interpreting, and learning, with digital practices (Constantiou *et al.*, 2023). Our results revealed that these information processes, jointly constituted by humans and digital practices, enable organizations to better adapt to their environment.

**Table 6.** Evaluation of the structural model: model 2 with controls

| Direct effects | Path coefficients | $f^2$ effect sizes | T statistics | *P* values | Confidence intervals 2.5% | 97.5% | Significance $p < 0.05$ |
|---|---|---|---|---|---|---|---|
| (1) Adaptive capacity → (2) Digital scanning | 0.404 | 0.195 | 7.063 | 0.000 | 0.296 | 0.518 | Yes |
| (1) Adaptive capacity → (3) Analytical culture | 0.224 | 0.047 | 2.963 | 0.003 | 0.074 | 0.367 | Yes |
| (1) Adaptive capacity → (4) Adaptive performance | 0.066 | 0.006 | 1.284 | 0.199 | −0.036 | 0.166 | No |
| (2) Digital scanning → (3) Analytical culture | 0.180 | 0.030 | 2.706 | 0.007 | 0.052 | 0.311 | Yes |
| (2) Digital scanning → (4) Adaptive performance | 0.383 | 0.191 | 7.787 | 0.000 | 0.287 | 0.477 | Yes |
| (3) Analytical culture → (4) Adaptive performance | 0.192 | 0.055 | 3.967 | 0.000 | 0.096 | 0.284 | Yes |
| (4) Adaptive performance → (5) Financial performance | 0.141 | 0.016 | 1.960 | 0.050 | −0.013 | 0.272 | Yes |
| Environmental dynamism → (4) Adaptive performance | 0.276 | 0.121 | 5.217 | 0.000 | 0.183 | 0.391 | Yes |
| Environmental dynamism → (5) Financial performance | −0.071 | 0.004 | 0.618 | 0.537 | −0.259 | 0.160 | No |
| Industry → (4) Adaptive performance | −0.031 | 0.000 | 0.329 | 0.742 | −0.218 | 0.149 | No |
| Industry → (5) Financial performance | 0.014 | 0.000 | 0.074 | 0.941 | −0.338 | 0.379 | No |
| Size be revenue → (4) Adaptive performance | 0.041 | 0.003 | 1.366 | 0.172 | −0.010 | 0.119 | No |
| Size be revenue → (5) Financial performance | −0.019 | 0.000 | 0.427 | 0.670 | −0.108 | 0.076 | No |
| Size by employee → (4) Adaptive performance | 0.032 | 0.002 | 0.807 | 0.419 | −0.043 | 0.103 | No |
| Size by employee → (5) Financial performance | −0.074 | 0.005 | 1.631 | 0.103 | −0.194 | 0.004 | No |

**Source(s):** Authors' own work

**Table 7.** Predictive power assessment

| | $Q^2$ predict | PLS-SEM RMSE | PLS-SEM MAE | LM RMSE | LM MAE |
|---|---|---|---|---|---|
| *Adaptive performance* | | | | | |
| AP_1 | 0.095 | 0.848 | 0.697 | 0.861 | 0.704 |
| AP_2 | 0.017 | 0.807 | 0.647 | 0.817 | 0.648 |
| AP_3 | 0.061 | 0.799 | 0.634 | 0.814 | 0.650 |
| AP_4 | 0.009 | 0.843 | 0.665 | 0.822 | 0.654 |

**Source(s):** Authors' own work

*5.1 The indirect role of employee-level adaptive capacity*

The findings suggest that employee-level adaptive capacity to manage dynamic work situations, on its own, does not guarantee higher organizational adaptive performance. The lack of a direct relationship contradicts the population ecology approach, emphasizing that organizations adapt to change either by replacing their members or through the adaptive capacity of their employees (Hannan and Freeman, 1977; Sternad, 2011). Our results suggest that adaptation is a more complex process. Employees' capability to cope with a wider variety of tasks is, in itself, not sufficient, but it is a necessary precondition for engagement in digital initiatives, resulting in improved digital scanning ability within the company and the establishment of an analytical culture.

*5.2 Digitalization and analytical culture as adaptation enablers*

Our results confirmed that digital scanning and related analytical culture mediate the relationship between adaptive capacity and organizational adaptive performance. Information technology has long been argued to enhance the increasing information processing capacity of organizations (Fairbank *et al*., 2006), and recent findings support that digital advances have a similar effect (Dubey *et al*., 2021). Accordingly, digital scanning is conceptualized here as an adaptation mechanism shaped by the extensive diffusion and use of digital technologies (Hanelt *et al*., 2021). The adoption of digital technologies facilitates better adaptation by being highly effective in scanning, outperforming human data collection (Chatterjee *et al*., 2024), particularly in fast-paced and ambiguous environmental changes (Ali and Wood-Harper, 2022).

While the benefits of digital scanning in terms of efficiency and precision of information collection are unquestionable, it has its limitations: it is confined to using preprogrammed rules recorded in algorithms, targeting only explicitly available and codifiable information, allowing the business to adapt to recurring changes (Constantiou *et al*., 2023). This limitation calls for another adaptation mechanism of analytical culture that can reinforce and complement the benefits of digitalization. We found that analytical culture facilitates both the relationship between adaptive capacity and organizational adaptive performance, as well as the relationship between digital scanning and adaptive performance. This dual mediator role of analytical culture is explained by the inability of digital technologies to cope with all indeterminacies of information processes.

We observe a positive yet modest association between the two mediators, namely digital scanning and analytical culture. This pattern aligns with OIPT, suggesting that technology-driven, data-centric mechanisms and human-enabled mechanisms in information processing are linked but separate (Kowalczyk and Buxmann, 2014). Digital advances increase information capacity, enabling but not determining the development of analytical culture, as some organizations possess substantial technological resources but lack robust cultural frameworks, while others have strong cultural attributes but limited technological tools.

*5.3 Ambiguous link between swift adaptation and financial performance*

Our result refutes the idea that organizations that excel at adaptation also necessarily have superior short-term financial performance. We also identify a minor suppressor effect of environmental dynamism on whether good adaptive performance leads to good financial performance. Companies that perceive a highly turbulent immediate environment put increased efforts to adapt; thus, the higher the perceived firm-level impact of environmental changes, the higher the reported adaptive performance. Controlling for the perceived environmental dynamism slightly strengthens the impact and significance of how adaptive performance results in better financial performance; however, the link remains insignificant.

Our null finding supports the view of resilience theory that during shocks, adaptation primarily manifests itself in organizational continuity, rather than in immediate financial performance (Duchek, 2020; McCarthy *et al*., 2017). The "payoff" of adaptation may not necessarily be captured by near-term ROA and ROS. As reported in the context of the COVID-19

pandemic, adaptation through digital means prioritizes continuity over short-term profit (Park *et al.*, 2023). Although both operational and financial performance are expected by firms, the positive effect is significant mostly on non-financial performance (Iftikhar *et al.*, 2021). The focus on operational performance under adversity manifests in both preserving core functions and enhancing existing organizational processes (Ortiz-de-Mandojana and Bansal, 2016).

In an era marked by a rising frequency of environmental shocks, adaptation that yields short-term economic benefits is gaining importance. Still, costs of responding might be high, and such costs can offset or delay observable returns. Thus, adaptation may occur without substantial short-term financial benefits. The financial benefits of investments in information technology and complementary intangible assets may only become discernible over an extended period (Jardak and Ben Hamad, 2022). Investing in digitalization may cost more than it yields, failing to improve financial performance, at least in the short term (Benedek *et al.*, 2025).

Moreover, high perceived adaptive performance without enhanced financial performance may indicate that adaptation efforts did not result in a better fit (Sarta *et al.*, 2021). The fit often cannot be established because it fails to consider the parallel development of the environment and the actions taken by peer companies (Durand and Jourdan, 2012). Maladaptation, conceptualized as an insufficient change to establish fit, may display insufficiencies related to the timing, magnitude, or direction of change (Zajac *et al.*, 2000). Maladaptation may occur under challenging environmental conditions of multiplicity, where simultaneous adaptation to different sub-environments necessitates divergent actions (Sarta *et al.*, 2021). In the special context of war-related uncertainties, recent literature addressed another form of maladaptation that may explain our results. Maladaptive convergence is the tendency of firms to respond similarly in the face of uncertainty, such as firms over-complying with sanctions to avoid reputational risk, which may harm short-term financial results. This behavior results in actions that are collectively and/or individually suboptimal. In this case of maladaptation, the direction of change is correct, but the magnitude is incorrect (resulting in failures of over- or under-reacting). In the current context of the Russian-Ukrainian war, the strategic responses to sanctions imposed on Russia have often resulted in overcompliance with these sanctions, a behavior shaped by multiple external pressures, including legal, public, and pressure from business partners (Stępień *et al.*, 2024). Over-complying through adaptive actions, such as full-suspension, is well-reasoned in terms of reducing reputational risk (Fang *et al.*, 2025), but not necessarily implemented by considering the immediate financial performance effects (Patel and Richter, 2025).

## 6. Conclusions, implications, and limitations

### *6.1 Theoretical implications*

While digital advances and organizational adaptation exhibit a bidirectional relationship (Sun *et al.*, 2023), a stream of research is engaged with adaptation to technological change (Aggarwal *et al.*, 2017; Eggers and Park, 2017). This paper focuses on and nuances existing literature on how utilizing digital tools and related analytical culture contribute to better adaptation. We emphasize the necessary but insufficient role of adaptive capacity at the employee level and conclude that it is the environmental digital scanning and collective interpretation that establishes adaptive performance. By this, our study extends the traditional approach to organizational adaptation as a strategic process determined by top-level managerial decisions (e.g. Levinthal, 2021; Sarta *et al.*, 2021) and supports the idea that successful adaptation is increasingly based on organizational routines that are deeply rooted at the individual level (Aggarwal *et al.*, 2017). This implies that research efforts should be directed at understanding the systemic integration of organizational routines in leveraging individual-level capabilities at the organizational level.

By theorizing adaptation as a continuous information processing challenge where digital processes prevail over human information processes, the role of top executives needs to be reinterpreted, potentially requiring different managerial skills. Earlier empirical studies

suggested that managerial cognitive capabilities are highly important, as they lead to diverse strategic decisions that either favor or hinder adaptation (Adner and Helfat, 2003) and result in differential firm performance (Helfat and Peteraf, 2015). Now, theoretical endeavors should focus on the qualities that facilitate the interplay between human decision makers and digital information processing (Cui *et al*., 2024), resulting in adaptive performance.

In this study, we theoretically decouple adaptive performance from immediate financial results, as suggested more recently (Sarta *et al*., 2021), but found no significant relationship. On the other hand, the empirical illustration of decoupling adaptive and short-term financial performance supports to view of resilience theory that outcomes extend beyond financial gains and are dependent on the temporal window of observation (Ilseven and Puranam, 2021). On the other hand, it implies that we need to better understand the organization-specific patterns that enhance this relationship, particularly in VUCA environments, where accurately assessing the environment is challenging, and the costs associated with exploring new information and knowledge are increased (Srikanth and Ungureanu, 2025).

### *6.2 Managerial implications*

The original privilege of top management in interpreting information and making subsequent decisions (Daft and Weick, 1984) is diminished due to digital scanning and interpretation (Constantiou *et al*., 2023). Still, it is the managerial level's responsibility to identify relevant aspects of the environment that should be scanned and codified (Constantiou *et al*., 2023). Moreover, under highly uncertain conditions, digital scanning and interpretation do not outperform humans in every quality. Although digital technologies are argued to successfully cope with uncertainty and complexity issues (Cao *et al*., 2019), their capacity to capture new, unexpected information is limited. That is, while digital technologies can quickly process the enormous amounts of data collected through digital scanning, the critical role of human decision-makers remains in situations where interpretation and a deeper understanding of context are required. The difficulties of the interpretation phase are twofold when environmental changes are unprecedented. First, digital interpretation encounters its limits as past patterns become obsolete. Second, decision-makers' experience also does not provide guidance (Ali and Wood-Harper, 2022).

This ambiguous situation can be addressed by emphasizing hard evidence, accompanied by processes and policies that facilitate common interpretation among senior executives, i.e., establishing an analytical culture. While resources, including technical expertise, data, and human skills, can be readily and swiftly copied or obtained from the market (Mikalef *et al*., 2019), establishing and developing these patterns of shared behaviors and collective practices related to information processes is a lengthy process (Kiron *et al*., 2013). Hence, their efforts should be focused on enhancing an analytical culture. Moreover, managers must learn when to trust digital systems and when to prioritize human intuition and experience. Therefore, it remains challenging for senior executives to decide where to let technology act without human intervention and, most importantly, where not to use technology.

Finally, top managers should exercise prudence. A key assumption of organizational adaptation is that successful adaptation ultimately leads to higher financial performance (Chakrabarti, 2015). According to our results, there is a missing link between adaptive performance as perceived by senior management and the ex-post evaluation of financial outcomes. This suggests organizations should exercise caution if high investments in digital advancements and analytical culture might leave firms without generating higher returns.

### *6.3 Limitations and future research*

When evaluating the results of this paper, several limitations should be taken into account.

Employing a cross-sectional survey design and a Structural Equation Modeling (SEM) imposes limitations on causal inference. While we theoretically postulate causal relationships and discuss the underlying logic, the calculated path coefficients should be regarded as

theoretical associations rather than causal relationships (Hair *et al.*, 2021). Consequently, we interpret our findings as patterns consistent with the theory that require validation through longitudinal methodologies. The cross-sectional designs also fail to establish temporal precedence and explain the phenomenon of adaptation as a process. Thus, our findings cannot be considered as evidence of processual dynamics. Future research may employ panel designs or event-history methodologies to investigate the timing and potential reciprocal effects among the examined constructs.

A further limitation concerns our measurement of adaptive capacity and adaptive performance. As we relied on self-developed scales, our operationalization may be affected by construct validity risks. While common statistical measures confirm the internal consistency of the applied items, incomplete domain coverage is still a risk. Future research should therefore seek to validate and refine these items. We relied on single informants, who were top executives of the firms. While key-informant designs are prevalent and justifiable when respondents possess role-relevant knowledge (Krause *et al.*, 2018), single-source reporting introduces risks of measurement errors (Podsakoff *et al.*, 2012). Despite our ex ante and ex post efforts to mitigate these, we cannot rule out the possibility that perception bias and response tendencies of the responding individuals may impact our results and inferences. Single-source method biases could be mitigated by utilizing distinct data sources, such as gathering multi-informant data and triangulating perceptual measures with objective indicators about digital advances of the firms.

The single-region sample may limit the applicability of the findings to CEE or other non-conflict-affected contexts. The questionnaire survey yielded a representative sample of Hungarian companies across various industries and sizes. By not limiting our focus to specific industries, we did not account for the potentially varying depths and sizes of war-related uncertainties across industries. Although the effects of subgroups could not be identified in the current sample, unobserved heterogeneity may still exist. Future research with either a much larger overall sample size or with focused data collection within specific industry contexts across regions may help identify whether sector-specific patterns exist, i.e., whether firms with different sub-environments and structural dependencies require different adaptation strategies.

## Appendix 1

**Table A1.** Relating our research to organizational adaptation literature (2015–2025)

| Author (date) | Title | Main aim and concepts | Main findings | Relation to our research |
|---|---|---|---|---|
| Aggarwal *et al.* (2017) | Adaptive capacity to technological change: A microfoundational approach | Explaining the microfoundational origin of heterogeneity in firms' capacity to adapt to technological change | Individual-level learning, along with organizational routines, produces heterogeneity in firms' adaptive capacity | Our findings support that organizational adaptive capacity is established on an individual level but exerts its effect via organizational-level practices |
| Andersen (2023) | Adaptive Strategy-making and Left-skewed Performance Outcomes | Explaining the left-skewed performance outcomes and inverse risk–return relationships based on the dynamic response capabilities perspective | Heterogeneous dynamic response capabilities and related diverse adaptive strategy-making processes explain divergent performance outcomes in a dynamic environment | Our findings add to the idea that firms' response capabilities are heterogeneous, resulting in divergent outcomes; however, we could not confirm that it is directly related to financial outcomes |
| Cedergren and Hassel (2024) | Building organizational adaptive capacity in the face of crisis: Lessons from a public sector case study | Better understand the preconditions that are necessary to adapt to an unfolding crisis in the context of COVID-19 pandemic | Preconditions to adaptation exist before the change occurs. A range of enabling factors is identified, such as trust, coordination, clear objectives, and asset literacy | We also argue that enabling factors are established before the change occurs, and we complete the preconditions enabling successful adaptation with digital scanning and analytical culture |
| Chakrabarti (2015) | Organizational adaptation in an economic shock: The role of growth reconfiguration | Exploring adaptation to economic shock and improvement of performance through growth | During an economic shock, firms' growth resulted in decreased performance and increased the risk of failure. Organizational resources played a minor role in their successful adaptation compared to developed external institutions | In contrast to external conditions, our findings emphasize the importance and positive role of organizational internal mechanisms in successful adaptation |

(*continued*)

**Table A1.** Continued

| Author (date) | Title | Main aim and concepts | Main findings | Relation to our research |
|---|---|---|---|---|
| Eggers and Park (2017) | Incumbent Adaptation to Technological Change: The Past, Present, and Future of Research on Heterogeneous Incumbent Response | Building a holistic, cross-industry picture and linking different mechanisms explaining which firms survive a technological discontinuity | There exist various antecedents to incumbent adaptation. The nature of technological change needs to be understood before theorizing the necessary capabilities | Instead of explaining adaptation to external technological change, we theorize and study how technology can act as an enabling mechanism in adaptation |
| Hansson and Abrantes (2023) | Strategic Adaption (Capabilities) and the Responsiveness to COVID-19's Business Environmental Threats | Understanding how contemporary firms strategize to prepare and accommodate a sudden and unpredictable environmental change | Companies are a long way from being able to respond quickly enough Adaptation capabilities are built by experience or exposure | We also emphasize and investigate rapid adaptive responses, but we theorize underlying capabilities that are established *a priori*, instead of focusing on how they can develop under threat conditions |
| Krammer (2022) | Navigating the New Normal: Which firms have adapted better to the COVID-19 disruption? | Examining firm innovation, knowledge sources, management practices, and gender issues related to firms' adaptation during crisis | Young innovators, firms that rely on internal sources of knowledge, and firms with better management practices are more likely to successfully adapt | We extend Krammer's paper that emphasizes the importance of strong internal knowledge capabilities in relation to adaptation by arguing that digital scanning and analytical culture are mechanisms to develop these capabilities |
| Sarta *et al.* (2021) | Organizational Adaptation | Reviewing organization adaptation literature to better understand the concept and identify difficulties in research | Adaptation is interpreted "as intentional decision making undertaken by organizational members, leading to observable actions that aim to reduce the distance between an organization and its economic and institutional environments" | We share the suggested interpretation of adaptation and support the idea of a non-deterministic relationship between adaptation and outcomes |

(*continued*)

**Table A1.** Continued

| Author (date) | Title | Main aim and concepts | Main findings | Relation to our research |
|---|---|---|---|---|
| Srikanth and Ungureanu (2025) | Organizational adaptation in dynamic environments: Disentangling the effects of how much to explore versus where to explore | Exploring the diverse roles of two facets of exploration–propensity and breadth–and related different decision-making processes (evaluative or non-evaluative) in relation to adaptation | With increasing environmental dynamism, the exploration breadth of firms always increases. Exploration propensity may increase, decrease, or stay constant depending on the firm's decision-making process. In case of a turbulent environment, it is more important to identify the correct level of exploration propensity | We argue in line with the idea that evaluative decision making matters, and it is the senior manager level that first decides how much to explore (exploration propensity). We add that digital scanning is able to decrease exploration costs |
| Sun *et al.* (2023) | Getting organizational adaptability in the context of digital transformation | Understanding how manufacturing companies establish organizational adaptability during the digital transformation process | All three dimensions of adaptability, namely structural adaptability, operational adaptability, and governance adaptability, can be mutually reinforced with digital capabilities | While we also rely on linking organizational adaptation and digital advances, we do not theorize this link in a bidirectional relationship; rather, we investigate digitalization's role in facilitating organizational adaptability |

**Source(s):** Authors' own work

## Appendix 2

**Table A2.** Questionnaire items

| Construct | Label | Indicator wording | Literature |
|---|---|---|---|
| | | To what extent are the following inhibiting factors present in your organization?<br>Please indicate your answer using the following scale: 1 - not at all, 5 - very typical | Items informed by or adapted from |
| (1) Adaptive capacity | ADA_1 | Low work morale of employees | Jundt *et al.* (2015), Pulakos *et al.* (2002) |
| | ADA_2 | Lack of specific expertise | |
| | ADA_3 | Insufficient management knowledge and leadership skills of middle managers | |
| | ADA_4 | Lack of employees' motivation | |
| | ADA_5 | Low ability of employees to innovate | |
| | ADA_6 | Employees' resistance to change | |
| | ADA_7 | Employees's inability to absorb new knowledge | |
| | | In the following, I will read some statements to you. Please rate them according to how true they are for your organization<br>Answer 1 means: strongly disagree, answer 5 means: strongly agree | |
| (2) Digital scanning | DIG_1 | Our organization has transformational culture that embracing change and high performance | Mhlungu *et al.* (2019) |
| | DIG_2 | Our organization implements process digitalization and re-engineering (both internal services and customer services) | |
| | DIG_3 | Our organization has prioritisation and roadmap of digital projects | |
| | DIG_4 | Our organization has guiding policies and decision structures to steer digital transformation | |
| | DIG_5 | Our organization has security policies, standards and practices used to secure data | |
| | DIG_6 | Our organization has evaluation of IT controls, that means security metrics, vulnerability assessment | |
| | DIG_7 | Our organization is characterized by purposeful and frequent experimentation with new technologies | |
| | DIG_8 | Our organization has well-structured innovation throughput mechanism (from idea generation to implementation of new ideas) | |
| | DIG_9 | Our organization explores new digital business model (s) enabled by digital technology | |
| | DIG_10 | Our organization established a dedicated unit to promote corporate innovation | |
| | DIG_11 | Our organization has mechanisms to keep abreast with the changing "customers" needs (both internal and external customers) | |
| | DIG_12 | Our organization has customer-centred approach in offering design (for both internal and external customers) | |
| (3) Analytical culture | AC_1 | The decision-making process is well established and known to its stakeholders | Popovič *et al.* (2012) |
| | AC_2 | It is an organization's policy to incorporate available information within any decision-making process | |
| | AC_3 | We consider the information provided regardless of the type of decision to be taken | |

(*continued*)

**Table A2.** Continued

| Construct | Label | Indicator wording | Literature |
|---|---|---|---|
| (4) Adaptive Performance | AP_1 | Our organization constantly seeks to achieve sustainable competitive advantages over the competitors through new strategic initiatives | Duchek (2020) Kumkale (2022) McCarthy *et al.* (2017) |
| | AP_2 | Our organization excels at efficiently executing and further improving usual work processes | Navarro *et al.* (2010) |
| | AP_3 | Our organization excels at exploring completely new possibilities and experimenting | O'Reilly and Tushman (2011) |
| | AP_4 | Our organization can effectively meet even significant and unexpected environmental challenges | |
| (5) Financial performance | ROS | Return on Sales: Earning before interest and taxes/ Sales revenue | Adner and Helfat (2003) |
| | ROA | Return on Assets: Profit after Tax/Total assets | Thongpapanl *et al.* (2012) Zajac *et al.* (2000) |
| | | To what extent do the following changes affect your organization? Answer 1 means: no effect at all; Answer 5 means: very strong effect | |
| Environmental dynamism | ED_1 | Changes in the market for our products/services | |
| | ED_2 | Changes in the market for the inputs we need to operate (availability and prices of raw materials, energy, etc., and suppliers) | |
| | ED_3 | Changes in the labour market (the availability and changing expectations of an adequate workforce) | |
| | ED_4 | Changes in financial markets (borrowing and investment opportunities, inflation, exchange rates) | |

**Source(s):** Authors' own work

## Appendix 3

**Table A3.** Financial performance of the sample firms (2017–2022)

| | | Mean | Percentile 25 | Percentile 50 | Percentile 75 | Std. Deviation |
|---|---|---|---|---|---|---|
| Return on Sales | 2017 | 6.39% | 2.01% | 4.65% | 9.28% | 0.125 |
| | 2018 | 5.92% | 2.01% | 4.33% | 9.72% | 0.120 |
| | 2019 | 6.28% | 1.71% | 4.39% | 9.85% | 0.096 |
| | 2020 | 5.15% | 2.07% | 4.79% | 9.72% | 0.129 |
| | 2021 | 6.94% | 2.14% | 5.92% | 11.23% | 0.114 |
| | 2022 | 6.77% | 2.34% | 5.97% | 11.05% | 0.944 |
| Return on Assets | 2017 | 7.77% | 1.54% | 5.08% | 11.55% | 0.134 |
| | 2018 | 8.24% | 1.40% | 5.55% | 12.27% | 0.137 |
| | 2019 | 8.41% | 1.58% | 5.71% | 13.04% | 0.154 |
| | 2020 | 6.86% | 1.78% | 6.09% | 11.67% | 0.179 |
| | 2021 | 8.72% | 2.09% | 6.78% | 14.55% | 0.126 |
| | 2022 | 9.07% | 1.69% | 7.44% | 16.01% | 0.140 |

**Source(s):** Authors' own work

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