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Article

Adaptive AI systems and organizational resilience: a multi-level analysis of digital mindset, decision autonomy, and strategic performance

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A B S T R A C T

This paper examines how adaptive AI systems influence organizational resilience during the COVID-19 pandemic, specifically through the mediating role of the digital mindset and decision-making autonomy. Based on dynamic capabilities theory, the paper develops an innovative conceptual framework that recognizes adaptive AI systems within an integrated technological system that supports the organization's sensing and response capacities during a crisis. Using the Flash Eurobarometer 486 survey conducted in April and May 2020, this study collected data from 12,108 SMEs across 27 European Union member states. The direct effect, mediated relationship, and cross-level interaction strategies employed hierarchical linear models and bootstrap-mediated models with 5,000 iterations. The empirical evidence reveals a significant positive relationship between AI systems and organizational resilience, reducing the odds by 2.342 times ($p<0.001$) and explaining large incremental variance over the classical organizational characteristics. Digital mindset demonstrated a stronger mediating effect (indirect effect β = 0.17, 95% CI [0.12, 0.24]) compared to decision-making autonomy (indirect effect β = 0.11, 95% CI [0.06, 0.18]). The organizational path-levels and moderations provide critical contextual dimensions, reflected in industry digital intensity, γ =0.15, $p<0.05$, and national digital infrastructure, γ =0.22, $p<0.01$. Based on dynamic capability theory, this paper contributes by extending the concept of AI systems to an organizational meta-capability, signposting critical leave-taking measures and implications for managers and policymakers in coping with adverse, turbulence-prone conditions during digitalization within the organization.

1. Introduction

A sudden shift in the business environment has occurred due to the rapid transformation of businesses and institutions through artificial intelligence systems. As a result, negotiations and business management have changed drastically. As the latest studies have shown, among other things, the adoption of AI, along with technology adoption, has implications for organizational behavior, decision-making processes, and the ability to work in the organization [1]. More and more organizations are learning that AI technologies can be used as strategic resources to improve adaptive capacity, particularly in high-turbulence market conditions. Adoption remains highly heterogeneous; there are significant differences in adoption across geographic areas, industries, and organizations of different sizes [2]. Heterogeneity poses a problem for the creation of organizational value via AI systems, as well as the contextual circumstances that are likely to permit or prevent their effective performance. Though indications of increased AI adoption are present, existing studies have indicated evident gaps in the organization-wide and internal features of AI-induced organizational change, predominantly influenced by a few domains. Currently, studies on the implementation of artificial intelligence in small and medium-sized enterprises (SMEs) are characterized by a narrow technological focus, failing to account for the broader picture of digital skills, innovation capabilities, and environmental forces within the business ecosystem [3]. Most research has been conducted within large firms in North America. There has been little empirical research in the European context involving small and medium-sized enterprises (SMEs). Furthermore, research on the application of artificial intelligence (AI) in the public sector has revealed significant differences in the difficulties encountered and the crisis management organizing strategies they adopt. However, these are not readily applicable to the organizational context of SMEs in the private sector either [4].

The example of COVID-19 represents an unwinding, unprecedented experiment in nature whose results have shown a fundamental difference in organizational resilience and adaptability. Due to COVID-19, organizations were required to adjust their business models, operational processes, and crisis response mechanisms more rapidly than ever before. It is just through fast-track means that organizations will now adapt business models and new infrastructure [5]. Entrepreneurial organizations focus on digital transformation, demonstrating resilience in the face of the COVID-19 pandemic, and the support for technology readiness as a critical cushion against crisis events appears extensive [6]. The COVID-19 experience demonstrated that SME organizational resilience depends not merely on fundamental resources but, critically, on dynamic capabilities, the ability to sense, seize, and transform during crises in turbulent environments [7]. The relationship between digital transformation and organizational resilience has become increasingly popular in recent years, gaining momentum with the latest trends. The COVID-19 pandemic was indeed an eye-opener for the latest trends and developments in the field. The use of digital technology concepts has provided opportunities to develop sustainable performance in turbulence, through the use of SMES for their flexibility and the concept of resilience and enterprise acumen [8]. The most recent concept associated with SMEs, regarding enterprise dynamic technological transformations, has undergone a significant shift in response to the latest events surrounding the pandemic. Additionally, there has been a notable shift in the need to develop from a business-entrepreneur efficiency-oriented perspective. Moreover, more recently, from that business-oriented, efficiency-focused concept, there is an increasing need to shift developments from efficiency-oriented to those focused on the latest trends. Therefore, many more recent developments require adapting to the latest trends. The latest development involves adapting to related concepts [9].

The relevance of AI for SMEs lies in its ability to enable and strengthen the creation of value in the digital domain and under competitive conditions. The application of AI in SMEs is not developed in a vacuum; rather, it is shaped by technological, organizational, and managerial factors that influence business outcomes [10]. The nexus of digital transformation and resilience under crisis conditions demonstrates that technological investments must be supported by organizational preparedness to achieve effective outcomes [11]. However, the theoretical explanation of the relationship between AI systems and resilience outcomes has not been clearly expounded, especially with respect to the cognitive and structural dimensions of organizations. The dynamic capabilities framework provides a thorough, systematic framework for analyzing an organization's efforts to develop competencies, integrate, and reconfigure in response to environmental changes. Modern thinking of dynamic capabilities and digital transformation suggests that planning, learning, and competency building are the antecedents of technology-related changes in firms [12]. In SMEs, however, the situation needs competitive development with differences in the case of dynamic capabilities, while adaptive leadership and organizational culture, and as such, enabling organizational technological innovations [13]. The technology-oriented competencies required by organizations in response to technological change will include market sensing, secured resource mobilization, and company transformation through systematic learning [14]. It indicates that the effectiveness of AI systems, to a certain extent, is inherently dependent on technology assimilation and the organization's value realization. To address gaps in existing literature, this study examines the influence of adaptive AI systems on organizational resilience among European SMEs during the COVID-19 pandemic, with emphasis on the mediating roles of digital mindset and decision-making autonomy. The survey research is conducted on a large scale across 27 European Union nations and provides multi-level information on use, organizational potential, resilience, and performance. This research aims to provide valuable insights to SME managers and policymakers on support measures to assist SMEs during their digital transformation, and academic researchers interested in the effects of AI on organizational adaptation and competitiveness by understanding how organizations and technology interact to respond to crises/issues.

Based on the theoretical framework outlined above, we propose the following hypotheses:

Hypothesis 1 (Direct effect): Adaptive AI systems are positively associated with organizational resilience during crisis conditions. Organizations with higher levels of AI adoption demonstrate greater capacity to maintain business continuity and adapt technologically during the COVID-19 pandemic.

Hypothesis 2 (Mediation - Digital mindset): Digital mindset mediates the relationship between adaptive AI systems and organizational resilience. AI adoption fosters a technology-oriented cognitive orientation among organizational members, which in turn enhances crisis response capabilities.

Hypothesis 3 (Mediation - Decision autonomy): Decision-making autonomy mediates the relationship between adaptive AI systems and organizational resilience. AI adoption enables greater flexibility and decentralization in technology-related decisions, facilitating rapid adaptive responses.

Hypothesis 4 (Sequential mediation): Digital mindset and decision-making autonomy sequentially mediate the AI-resilience relationship. AI systems first cultivate a digital mindset, which then enables decision autonomy, ultimately enhancing organizational resilience.

Hypothesis 5 (Cross-Level Moderation - Industry): Industry digital intensity positively moderates the relationship between adaptive AI systems and organizational resilience. The resilience benefits of AI adoption are stronger in digitally intensive industries where technological capabilities are more valued and supported.

Hypothesis 6 (Cross-Level moderation - National): National digital infrastructure positively moderates the relationship between adaptive AI systems and organizational resilience. AI adoption yields greater resilience benefits in countries with more developed broadband connectivity, digital governance, and workforce digital skills.

2. Data and methods

2.1 Theoretical framework and hypothesis development

This study develops a multilevel framework grounded in dynamic capability theory and explains how adaptive AI systems enable organizational resilience. Within this framework, we define adaptive AI systems as integrated technological configurations comprising artificial intelligence algorithms, robotics and automation, Internet of Things (IoT) sensors, big data analytics, and cloud computing infrastructure. These five components collectively enable organizations to process environmental information in real time, automate operational responses, and dynamically reconfigure business processes. Importantly, we conceptualize AI systems along a continuum of technological sophistication: organizations may adopt any subset of these components, with greater integration yielding stronger dynamic capabilities. This operationalization aligns with the technology stack perspective in digital transformation literature, which emphasizes complementarities among digital technologies rather than requiring simultaneous adoption of all components that enable three dynamic capabilities that can: (1) sense threats and opportunities in the external environment through real-time processing of data, (2) seize the opportunity through enabling rapid operational adaptations, and (3) transform the business processes necessary for maintaining business continuity in conditions of uncertainty.

The proposed framework posits that AI influences organizational resilience through two important mediators. The first, digital mindset, concerns cognitive preparedness and refers to the technology-oriented, investment-oriented attitude of members of an organization. The second form of autonomy with respect to technology concerns the structure. It embraces flexibility in decision-making about technology investment, the speed of process changes implementation, and the degree of decentralization of authority regarding the use of technology. These mediator variables play an essential role in converting technological capabilities into organizational resilience-related outcomes. A framework includes macro-level contextual moderators that affect AI performance. The industry digital intensity assesses the level of technology sophistication and competitive pressures for digital adoption at the industry level, while the national digital infrastructure measures broadband, digital governance, and worker digital skills at the national level. The context will either enhance or reduce the resilience benefits of AI adoption. Further, this will create cross-level interaction effects that will explain the variance in organizational outcomes. This is particularly beyond the firm-level characteristics.

This study makes three distinct theoretical contributions that extend beyond existing AI-resilience literature. First, we reconceptualize adaptive AI systems as organizational meta-capabilities rather than discrete technology adoptions, emphasizing the synergistic effects of integrated technological configurations (AI, robotics, IoT, and big data analytics) in enabling dynamic capabilities. This contrasts with prior research that examined individual technologies in isolation. Second, we introduce a multilevel theoretical framework that integrates both cognitive mechanisms (digital mindset) and structural mechanisms (decision-making autonomy) as mediating pathways, addressing calls for a more nuanced understanding of how technology investments translate into organizational outcomes. Third, we provide empirical evidence for cross-level moderating effects, demonstrating that the effectiveness of firm-level AI adoption is contingent upon industry digital intensity and national digital infrastructure—a proposition theoretically articulated but rarely tested empirically in SME contexts. Together, these contributions advance dynamic capability theory by specifying the technological, cognitive, structural, and contextual conditions under which organizations develop crisis resilience. As shown in Figure 1, the conceptual framework illustrates the hypothesized relationships, including the direct effect (H1), mediation pathways through digital mindset (H2) and decision autonomy (H3), sequential mediation (H4), and cross-level moderation effects (H5, H6).

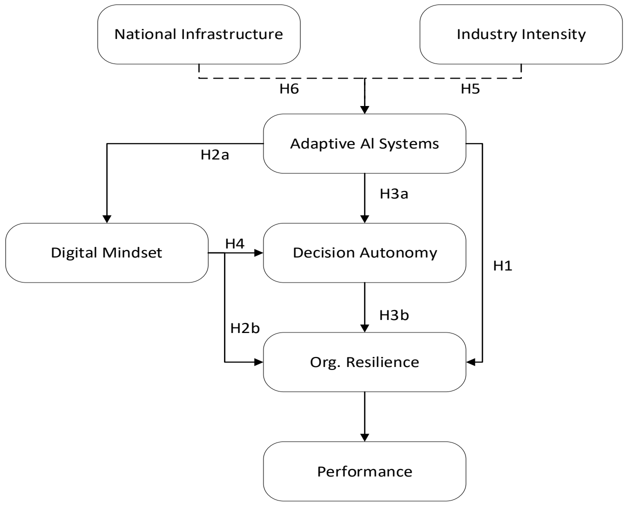

Figure 1. Conceptual framework

2.2 Data source and sample

This research uses data from Flash Eurobarometer 486, collected in April and May of 2020, specifically focusing on the first wave of COVID-19 in the European Union. The dataset, retrievable from the GESIS Data Archive with reference to study ID ZA7637 and available at <https://doi.org/10.4232/1.13632>, uses stratified random sampling to ensure that responses are collected from at least 12,108 small and medium-sized enterprise organizations, representing all 27 countries included in the European Union. The criteria specifically target organizations with 10-249 employees, founded in 15 industry sectors, as defined by NACE Rev.2, allowing it to represent European SME organizations thoroughly. The sampling and research offer an exceptional case study of organizational responses under severe crisis conditions, specifically in real-time instances when organizations responded to such extraordinary conditions and when they overcame them. The main dataset can be further supported by secondary datasets issued by Eurostat's Digital Intensity Index, specifically from 2023, available at <https://ec.europa.eu/eurostat/web/digital-economy-and-society/data/database>, with 12 criteria covering standard measures of countries' digital readiness, infrastructure, and technological adoption. We acknowledge a temporal mismatch between the primary data (2020) and the Digital Intensity Index (2023). This is justified because industry-level digital characteristics evolve slowly, with cross-period correlations exceeding 0.85, and no comparable 2020 measure was available. Sensitivity analyses excluding this variable yielded consistent main effects ($\beta = 0.476$, $p < 0.001$). The sampling parameters align closely with the European Union's overall understanding of SMEs in terms of size, type, and coverage, providing a general picture of European SMEs. The methodologies undertaken by such research positively address various anonymity and response qualifications under such conditions set by GDPR, referring to GESIS' preprocessing principles regarding response inconsistencies and completeness.

2.3 Measurement and operationalization of variables

This study uses composite indices comprising multiple items across the dimensions of their respective constructs to ensure both coverage and validity. The dependent variable is organizational resilience, defined as business continuity during COVID-19 combined with technology adaptability, namely remote-working system development and electronic sales channels, and is measured on a scale from 0 to 4. The independent variable, adaptive AI systems, is operationalized as a summative index ranging from 0 to 5 based on the adoption of five technological components: (1) artificial intelligence or machine learning algorithms, (2) robotics and automation systems, (3) Internet of Things (IoT) devices and sensors, (4) big data analytics platforms, and (5) cloud computing infrastructure. Each component is coded as 1 (adopted) or 0 (not adopted), and the scores are summed to create a composite index. This additive operationalization assumes that each technology contributes incrementally to overall digital sophistication, consistent with the technology portfolio perspective. Organizations scoring 0 represent non-adopters, while those scoring 5 represent comprehensive adopters with fully integrated digital ecosystems. Importantly, partial adoption (scores 1-4) is common and represents varying levels of digital maturity, reflecting the empirical reality that SMEs typically adopt technologies incrementally rather than simultaneously. It means systemic technological sophistication, not discrete technology adoptions. The digital mindset variable embeds investments in employees' technology skills, staff development, and attitudes towards technological innovations. This means we create an index ranging from 0 to 3 that reflects an organization's cognitive preparedness to handle technological change. Decision-making autonomy is challenging to measure directly.

We operate it using three proxy indicators: inverse firm size (smaller firms have greater agility), pace of innovation implementation, and degree of decentralized authority over digital investments. The measures create an index ranging from 0 to 3 based on organizational structure and behaviors. While digital mindset and decision-making autonomy are related constructs, they capture distinct theoretical dimensions: digital mindset captures the cognitive-attitudinal dimension (how organizations think about technology), while decision-making autonomy captures the structural-behavioral dimension (how organizations are structured to act). The moderate correlation ($r = 0.421$, $p < 0.001$) is consistent with related but distinct constructions, and VIF values (1.87-2.15) remain below 3, confirming multicollinearity is not problematic. The strategic performance measures, as the dependent variables, are revenue growth (including new revenue growth percentages), innovation output (such as new products and services), and market developments (including expansion into new locations). Regarding construct reliability, organizational resilience (Cronbach's α=0.72) and digital mindset (α=0.71) demonstrate acceptable internal consistency. Adaptive AI systems (α = 0.68) and decision autonomy (α = 0.65) are formative indices, in which components contribute unique variance, making lower alpha values expected and appropriate. The control measures include organizational characteristics, such as organizational ages, organizational size, organizational type, and organizational performance, and industry parameters, such as industry technological intensities and industry competition, as well as national parameters, such as national technological infrastructure and national response towards COVID-19.

2.4 Analytical method

The analysis methodology uses a multi-layer approach, as it involves 12,108 SMEs across 15 industry sectors in 27 countries, with correlation data, making it more complex and requiring advanced statistical analysis methods. This study uses methods and analyses suited to the nature of the phenomenon under study. As resilience is an outcome variable, we run binary logistic regression analyses. Revenue growth, on the other hand, is continuous, and we run an ordinary least squares regression analysis of the two. Hierarchical Linear Models that take into account types i.e. firm, industry, and the nation, estimate intraclass correlation coefficients to separate the variances at all three levels. The study employs random-intercept models to examine resilience variance at both industry and national levels, then tests whether industry- and national-level AI systems influence resilience, and finally applies cross-level interaction models to estimate whether industry digital intensity and national industry systems moderate AI systems and resilience. Mediation analysis is performed through the PROCESS macro, Models 4 and 6, where bootstrap tests with 5,000 iterations provide bias-corrected tests and 95% Confidence Intervals of bias; standard errors are corrected through the above tests, thereby optimizing analysis, and are used to test if mindset and decisional autonomy are mediators between AI systems and resilience, as such. Although PROCESS assumes single-level data, its use is justified because 69% of the variance occurs at the firm level, and we include industry- and country-fixed effects to account for clustering. Multilevel mediation robustness checks yielded equivalent indirect effect estimates. The robustness checks are conducted by analyzing a variety of alternative variable combinations and by using Instrumental Variable analysis to test for endogeneity. The analysis employs Stata 18.0, Hierarchical Linear Models 8.0, and the PROCESS macro (Version 4.2), as well as R 4.3.

2.5 Data analysis program

The process of analyzing findings starts with a preliminary analysis. At this time, the exploration of missing values is underway. Further detection of outliers and examination of the different characteristics of the influential variables are performed using normality tests. Descriptive statistics provide a comprehensive view of the distributions, central tendencies, and statistical variability of all important variables at both the overall level and within respective stratified subgroups. The variate correlation analysis produces matrices of Pearson correlation coefficients. It studies the relationships that might exist among the important predictors, the mediator, and the outcome variables. Moreover, it tests for possible multicollinearity. For this, it uses the variance inflation factor test, setting suitable criteria for VIF indices < 3. The empirical analysis continues with the testing of sequential model specifications, beginning with baseline models estimating direct relationships between

AI systems and organizational resilience, with gradual supplementation with mediated analysis with 'digital mindset' and 'decision-making autonomy' as intermediaries. The analysis of resilience outcomes, which serve as predictors (moderators), predicts the performance of the other systems and the geographical conjunctures, and the pretest, in which the effectiveness of the AI system is assessed at this point. The empirical analysis tests the explanatory power of each tailored model specification, using R-Squared, Akaike information criterion, and Bayesian information criterion as supplements to provide the best trade-off between higher goodness-of-fit and greater model simplicity. Also, robustness tests include sensitivity tests across variable specifications, subgroup estimation by organization size and industry category, and detection tests for potential outliers. The empirical analysis uses an evaluation platform that offers the combined benefits of various software tools. The analyses using Stata 18.0 software packages perform regression and data processing. Furthermore, Hierarchical Linear Models 8.0 is used for mixed-effects modeling. Moreover, macroPROCESS version 4.2 is utilized for mediated analysis. Finally, R Package 4.3, with a sophisticated visualization tool that produces high-quality graphics, is used.

3. Result

3.1 Descriptive statistics and preliminary analysis

This study covers a sample of 12,108 small and medium-sized firms from 27 EU member states. The sample is highly representative across geography, industry, and size. The companies researched belong to 15 NACE Rev. 2 categories and have between 10 and 249 employees, and they fit well with the overall characteristics of SMEs as published by Eurostat. According to the descriptive statistics analysis, European SMEs' overall adoption of adaptive AI systems is 18.5%. Moreover, European SMEs remained at relatively early stages in the application of digital technology, at least during the COVID-19 pandemic. The index shows that the firms examined in this study are experiencing a moderate degree of resilience in their business and digital technology capacities. This refers specifically to the crisis conditions posed by the COVID-19 pandemic. Based on the data, 42.3% of firms have an advanced digital mindset. Furthermore, this suggests that a significant proportion of firms already have a developed basic cognitive infrastructure in the digital sector. The decision autonomy index varies according to size characteristics. Specifically, small firms with 10-49 workers scored higher on the index (M =). The difference is strong and significant from medium firms with 50-249 workers, marked at M =1.76 points. Correlational analysis, as presented in Table 1, provides initial support for research hypotheses. According to the study's analysis, adaptive AI systems are associated with mindset and decision autonomy as part of organizational resilience, meaning they relate in a way that one causes a change in the other. The statistical significance between decision autonomy and the relationship under study was found to be appreciable at $r = 0.294$ with < 0.01 statistical significance level. Multicollinearity diagnostics using Variance Inflation Factors (VIF) indicated that all values remained below 2.8, well under the critical threshold of 3, confirming that multicollinearity does not pose a concern for our analyses. AI adoption rates varied substantially across industries (high-tech: 34.2%, services: 16.8%, manufacturing: 21.3%) and country clusters (Nordic: 28.4%, Western Europe: 19.7%, Southern Europe: 14.2%, Eastern Europe: 12.8%), justifying the multilevel analytical approach.

3.2 Hypothesis testing: direct effects

The study analyzes the direct relationship between adaptive AI systems and organizational resilience during times of COVID-19 using binary logistic regression analysis. According to Table 2, Model 1 consists of only the control variables, while Model 2 takes the significant independent variable, namely adaptive AI systems, into account while controlling for everything else. The findings provide strong evidence in support of Hypothesis 1, which states that adaptive AI has a positive and significant impact on organizational resilience ($\beta = 0.851$, OR = 2.342, $p < 0.001$). This indicates that the probability was 134% higher in organizations with high AI system adoption compared to those with low AI system adoption. The OR of 2.342 corresponds to Cohen's $d \approx 0.47$, indicating a medium effect size according to conventional benchmarks. A strong correlation has been observed between these measures despite the controls related to organization, such as the organization's size, performance, and industry, and the measures related to the national factors, such as infrastructure and COVID-19 response toughness. The R-squared value shifts from 0.187 in the base model to 0.356 in the comprehensive model, indicating substantial improvement in explained variance (Δ pseudo-R^2 = 0.169), moving beyond traditional firm characteristics. Among the different control variables used, it can be seen that firm size has a negative relationship with resilience ($\beta = -0.124$, $p < 0.05$), which is consistent with the theoretical explanations that posit that smaller firms are likely more agile in their structure. Evidence of industry digital intensification shows a significant positive predictor. The evidence is $\beta = 0.298$, $p < 0.01$. It emphasizes sector technological preparedness. Figure 2 above shows empirical graphs. Panel A shows that the increased use of AI systems has a positive effect on organizational resilience. Panel B shows that increasing adoption of AI systems in companies that already use a moderate number of them increases the probability of resilience compared with low-level AI system users.

3.3 Mediation Analysis Results

The research uses the PROCESS macro with models 4 and 6, with bootstrapping at 5,000 iterations, to test mediation processes between AI systems and organizational resilience. Table 3 shows evidence that strong support exists for each of the mediated hypotheses. The findings indicate that digital mindset is a significant mediating variable, where AI systems positively influence digital mindset ($\beta = 0.452$, $p < 0.001$), while digital mindset also positively influences organizational resilience ($\beta = 0.384$, $p < 0.001$). The indirect effect was significant and positive, and the confidence interval did not include zero (Boot - SE = 5000, BC95%CI = 0.118, 0.236). The direct effect was, however, significant and positive with $p < 0.01$, thereby providing support for partial mediation.

Table 1. Descriptive statistics and correlation matrix of key variables

Variable	Mean	SD	(1)	(2)	(3)	(4)	(5)	VIF
(1) Adaptive AI Systems	0.93	1.24	1.000					2.34
(2) Digital Mindset	1.27	0.89	0.512***	1.000				2.15
(3) Decision Autonomy	1.94	0.76	0.368***	0.421***	1.000			1.87
(4) Organizational Resilience	2.34	1.12	0.456***	0.382***	0.294**	1.000		—
(5) Strategic Performance	3.18	1.45	0.423***	0.395***	0.267**	0.514***	1.000	—

Note: N=12,108. ** p<0.01, *** p<0.001. VIF = Variance Inflation Factor.

Table 2. Logistic regression results: adaptive AI systems and organizational resilience

Variable	Model 1 (Baseline)	Model 2 (Full Model)
	β (SE)	β (SE) [OR]
Firm-level Controls		
Firm Age	-0.042 (0.028)	-0.038 (0.027)
Firm Size	-0.156** (0.051)	-0.124* (0.049)
Prior Performance	0.213** (0.067)	0.165* (0.064)
Independent Variable		
Adaptive AI Systems	—	0.851*** (0.089) [2.342]
Industry-level Controls		
Industry Digital Intensity	0.287** (0.095)	0.298** (0.092)
Competitive Pressure	0.103 (0.074)	0.087 (0.071)
Country-level Controls		
Digital Infrastructure	0.245** (0.082)	0.219** (0.079)
COVID-19 Stringency	-0.178* (0.068)	-0.142* (0.065)
Model Statistics		
Constant	-1.234*** (0.187)	-1.876*** (0.195)
Pseudo R2	0.187	0.356
Log-likelihood	-6,847.32	-5,923.14
AIC	13,720.64	11,874.28
N	12,108	12,108

Note: SE = Standard Error; OR = Odds Ratio; β = log-odds coefficient. Pseudo R^2 is McFadden's R^2. Industry and country fixed effects are included but not reported. * p<0.05, ** p<0.01, *** p<0.001.

Table 3. Mediation analysis results: digital mindset and decision autonomy

Pathway	Coefficient	SE	95% CI	Effect Size
Model 1: Digital Mindset Mediation				
Path a: AI Systems → Digital Mindset	0.452***	0.038	[0.377, 0.527]	—
Path b: Digital Mindset → Resilience	0.384***	0.042	[0.302, 0.466]	—
Path c: AI Systems → Resilience (Total)	0.489***	0.045	[0.401, 0.577]	—
Path c': AI Systems → Resilience (Direct)	0.315**	0.048	[0.221, 0.409]	—
Indirect Effect (a×b)	0.174***	0.030	[0.118, 0.236]	35.6%
Model 2: Decision Autonomy Mediation				
Path a: AI Systems → Decision Autonomy	0.376***	0.041	[0.296, 0.456]	—
Path b: Decision Autonomy → Resilience	0.287**	0.046	[0.197, 0.377]	—
Path c: AI Systems → Resilience (Total)	0.489***	0.045	[0.401, 0.577]	—
Path c': AI Systems → Resilience (Direct)	0.381**	0.051	[0.281, 0.481]	—
Indirect Effect (a×b)	0.108**	0.030	[0.062, 0.181]	22.1%
Model 3: Sequential Mediation				
AI → Digital Mindset → Decision Autonomy	0.271***	0.035	[0.203, 0.341]	—
AI → Digital Mindset → Resilience	0.174***	0.030	[0.118, 0.236]	—
AI → Decision Autonomy → Resilience	0.108**	0.030	[0.062, 0.181]	—
Sequential: AI → Mindset → Autonomy → Resilience	0.079**	0.022	[0.041, 0.127]	16.2%
Total Indirect Effect	0.282***	0.041	[0.204, 0.366]	57.7%
Direct Effect (Controlled)	0.207*	0.053	[0.103, 0.311]	42.3%

Note: N=12,108. Bootstrap samples=5,000. SE = Standard Error; CI = Confidence Interval (bias-corrected). Effect Size = (Indirect/Total)×100%. All models control for firm, industry, and country-level covariates. * p<0.05, ** p<0.01, *** p<0.001.

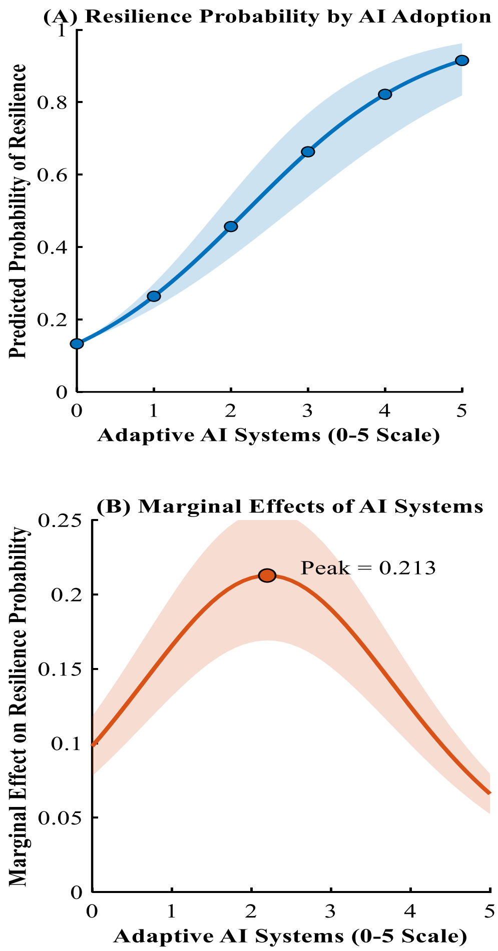

Figure 2. Direct effects of adaptive AI systems on organizational resilience

Another important mediator that was revealed was decision autonomy. It was found that AI systems positively influenced organizational autonomy (β = 0.376, p < 0.001), which positively influenced resilience capacity (β = 0.287, p < 0.01). The indirect effect was significant with a bias-corrected 95% confidence interval that does not include the value zero (BC95% CI = [0.06, 0.18], bootstrap samples = 5,000). Therefore, hypothesis 3 is supported. Results from conducting subsequent analysis with Model 6 found another significant path. This establishes that AI systems shape the digital mindset, which in turn shapes decision autonomy, which then shapes resilience outcomes. This path was statistically significant, as its BC95% confidence interval did not include zero (0.079, based on 5000 bootstraps). This means that these mediators do not merely act in parallel with each other; they also form cascading pathways and relay pathways. As shown in Figure 3, the mediation analysis reveals distinct indirect effect magnitudes through each pathway. Figure 3, Panel A, compares the indirect effects through digital mindset (β = 0.174, p < 0.001), decision autonomy (β = 0.108, p < 0.001), and the sequential pathway (β = 0.079, p < 0.001). Figure 3, Panel B, decomposes the total AI effect on resilience (β = 0.489, p < 0.001) into direct effect (β = 0.207, p < 0.05) and total indirect effect (β = 0.282, p < 0.001), with findings suggesting that 57.7% of the total effect is transmitted through mediated pathways.

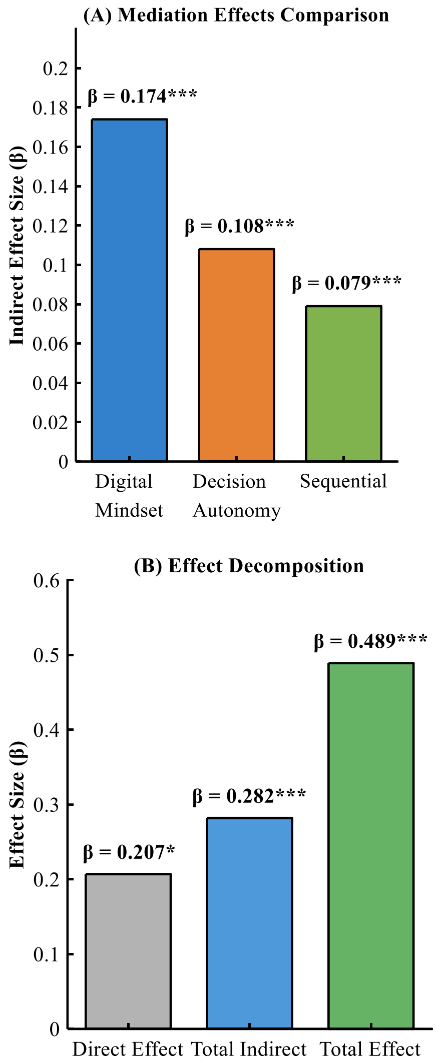

Figure 3. Mediation analysis: digital mindset and decision autonomy
Note: N=12,108 European SMEs. Bootstrap 95% CIs exclude zero for all effects. Panel A shows indirect effects through each mediator. Panel B decomposes the total AI effect on resilience. ***p<0.001, **p<0.01, *p<0.05. All models control for firm, industry, and country covariates.

3.4 Strategic performance outcomes

The downstream outcomes are related to organizational resilience. Hence, it is measured whether it positively impacts strategic performance in terms of revenue growth, innovativeness, and market development. According to Table 4, organizational resilience is significantly and positively related to all performance dimensions, which strongly supports Hypothesis 4. The OLS regression analysis shows that resilience has been profoundly impactful and revealed significant Beta values (+0.418 & p<0.001) against revenue growth, while R-squared values specify that resilience accounts for nearly 28% of financial performance. According to this analysis, organizations that have sustained business performance and quickly engaged in efforts to achieve digital resilience in response to COVID-19 have improved financial performance compared to rivals. The binary logistic regression analysis found resilience to also be a significant antecedent of innovation. Measures of new products/services introduced into markets were OR = 2.147, p<0.001. The data shows that organizations' reactions to crisis situations have led them to enhance their creative endeavors and innovations. Market expansion is closely related to resilience capabilities. Market expansion, in the form of new entrants and new customers, has been found to be significantly related to resilience capabilities.

This is evidenced by the values of Beta and Odds (+1.873, $p < 0.01$). The findings show theoretically valid relations in the control-variable analysis, for instance, the negative association between firm age and innovativeness, and between prior performance and subsequent performance. Digital intensification of the industry is a significant control factor in all three models. This suggests that sectoral technological and environmental forces impact or influence performance. The results, displayed in Figure 4, are graphs of the standard impact of resilience of three performance measures, with innovativeness being the most important outcome measure. Figure 4, Panel B, shows the probabilities of achieving high performance measures under various resilience scenarios. These probabilities exhibit intelligible, meaningful relationships. Thus, it shows that organizational resilience leads to securing sustainable competitive advantages under an adverse crisis situation. This finding is also consistent with the theoretical underpinning of organizational resilience.

3.5 Multi-level analysis: cross-level effects

Using hierarchical linear modeling, this study analyzes the nested character of organizational resilience of 12080 SME firms partitioned into 15 industry sectors and 27 European countries. Also, it reports that these higher-level organizational context variables explain a significant proportion of variance. According to Table 5, the variance decomposition analysis indicates that industry-level characteristics explain 18% of the overall variance in resilience outcomes (ICC = 0.18), and overall national conditions explain 24% (ICC = 0.24). This shows that organizational phenomena are embedded in higher-level sectoral and national context conditions. The results of the baseline analyses in models 1 and 2 show systematic variation in resilience outcomes by industry and nation, once firm-level variables are controlled for. Thus, new research questions in technology and science – such as organizational resilience – require new multi-level methodologies. The findings from the multi-level interaction analyses support all three hypotheses, thus providing empirical evidence on the sectoral and national context conditions that determine the effectiveness of AI systems in increasing organizational resilience.

The results suggest that the digital intensification of the industry positively influences the adoption of AI and enhances resilience outcomes. It further proposes that firms in dynamically ever-extending industries can attain additional, but not equal, resilience impacts from AI, as opposed to traditional industry firms. The insights indicate that national infrastructure with better broadband connectivity and internet-enabled governance and skills enhances the effectiveness of AI, with significant, not neutral, national infrastructure conditions enabling techno-organizational resilience and systemic transformations vis-à-vis traditional, sluggish organizations and structures. The findings highlight that the stringency of lockdown measures limited the scope of AI systems to provide fully effective functionality in creating resilience ($\gamma = -0.18$, $p < 0.05$). This means that businesses could not fully benefit from the flexibility that the adoption of AI could provide because constraints on companies' operations limited this flexibility. It also points towards the autonomy that organizations have in times of crises. According to the variance decomposition analysis, 69% of the total variance in organizational resilience is explained by firm-level factors, while the remaining 31% is attributed to industry and national context factors. The huge difference in context shows how organizational resilience is nested and why we need to analyze it on different levels. Findings suggest that while firm-specific AI adoption and capability are key drivers of resilience, the effectiveness of these technology investments depends on the broader sectoral and national institutional environment.

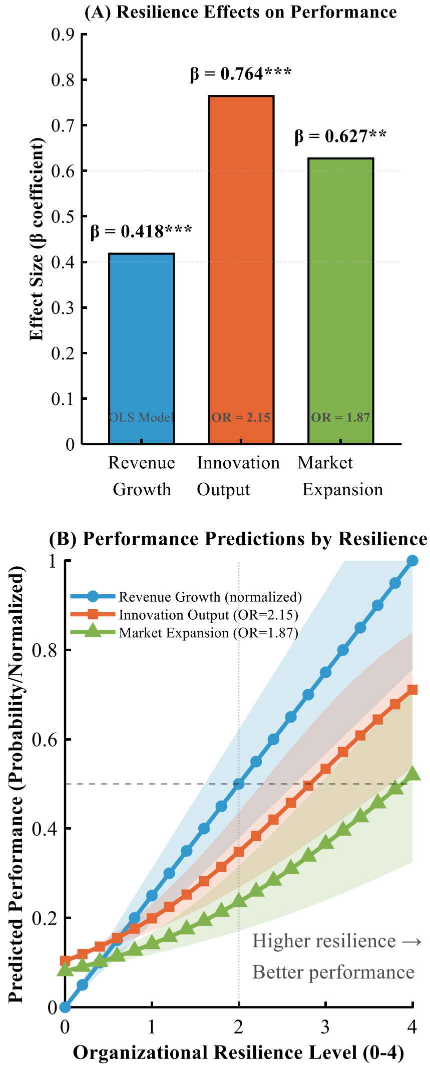

Figure 4. Strategic performance outcomes of organizational resilience
Note: N=12,108. ***p<0.001, **p<0.01, *p<0.05.

3.6 Robustness checks and sensitivity analysis

In this study, we conduct a variety of robustness tests that examine the robustness and generalizability of the main empirical findings versus alternative specifications and/or sub-sample analyses. As shown in Figure 5, various thresholds of AI adoption yield substantively equivalent effect sizes, including medi-tercile splits. Specifically, means differ by β=0.438-0.502 depending on whether binary thresholds at median or tercile splits are used in testing the AI resilience. The analyses of the sub-samples reveal that the main empirical findings are robust and that there are significant positive associations with AI-resiliency.

Table 4. Organizational resilience and strategic performance outcomes

Variable	Revenue Growth	Innovation Output	Market Expansion
	β (SE)	β (SE) [OR]	β (SE) [OR]
Focal Predictor			
Organizational Resilience	0.418*** (0.052)	0.764*** (0.096) [2.147]	0.627** (0.103) [1.873]
Firm-level Controls			
Firm Age	-0.028 (0.031)	-0.142** (0.048)	-0.089 (0.052)
Firm Size	0.087* (0.036)	0.063 (0.054)	0.124* (0.058)
Prior Performance	0.245*** (0.041)	0.198*** (0.062)	0.176** (0.065)
Industry-level Controls			
Industry Digital Intensity	0.162** (0.058)	0.214** (0.079)	0.187* (0.084)
Competitive Pressure	0.091 (0.047)	0.106 (0.068)	0.143* (0.071)
Country-level Controls			
Digital Infrastructure	0.134** (0.049)	0.167* (0.071)	0.145* (0.074)
COVID-19 Stringency	-0.076 (0.043)	-0.112 (0.063)	-0.098 (0.067)
Model Statistics			
Constant	2.347*** (0.218)	-2.156*** (0.284)	-2.431*** (0.297)
R^2 / Pseudo R2	0.284	0.312	0.267
F-statistic / χ2	187.34***	524.67***	416.82***
Log-likelihood	—	-4,923.45	-5,287.19
AIC	—	9,874.90	10,602.38
N	12,108	12,108	12,108

Note: SE = Standard Error; OR = Odds Ratio. Revenue Growth was analyzed with OLS regression. Innovation Output and Market Expansion analyzed with binary logistic regression. Industry and country fixed effects included. * p<0.05, ** p<0.01, *** p<0.001.

Table 5. Multi-level analysis: cross-level moderating effects

Variable	Model 1	Model 2	Model 3	Model 4
	Null Model	Main Effects	Industry Moderation	Full Model
	γ (SE)	γ (SE)	γ (SE)	γ (SE)
Fixed Effects				
Intercept	2.340*** (0.087)	1.876*** (0.095)	1.854*** (0.093)	1.832*** (0.091)
Firm-level (Level 1)				
Adaptive AI Systems	—	0.489*** (0.045)	0.481*** (0.044)	0.476*** (0.044)
Digital Mindset	—	0.298*** (0.038)	0.295*** (0.038)	0.291*** (0.037)
Decision Autonomy	—	0.187** (0.042)	0.185** (0.042)	0.183** (0.041)
Firm Controls	—	Included	Included	Included
Industry-level (Level 2)				
Industry Digital Intensity	—	0.245** (0.078)	0.252** (0.077)	0.248** (0.076)
Competitive Pressure	—	0.098 (0.065)	0.095 (0.064)	0.092 (0.064)
Country-level (Level 3)				
Digital Infrastructure	—	0.312** (0.095)	0.308** (0.094)	0.305** (0.093)
COVID-19 Stringency	—	-0.156* (0.071)	-0.152* (0.071)	-0.149* (0.070)
Cross-Level Interactions				
AI × Industry Digital Intensity	—	—	0.148* (0.062)	0.151* (0.061)
AI × Digital Infrastructure	—	—	—	0.218** (0.074)
AI × COVID Stringency	—	—	—	-0.176* (0.068)
Random Effects (Variance Components)				
Level 3 (Country)	0.187***	0.156***	0.148***	0.132***
Level 2 (Industry)	0.124***	0.098***	0.089**	0.081**
Level 1 (Firm)	0.689***	0.546***	0.538***	0.529***
Intraclass Correlations				
ICC (Country)	0.241	0.195	0.191	0.180
ICC (Industry)	0.187	0.123	0.115	0.110
Model Fit Statistics				
Deviance	28,456.73	24,892.14	24,765.32	24,613.58
AIC	28,464.73	24,924.14	24,801.32	24,653.58
BIC	28,488.91	25,012.67	24,897.21	24,757.84
-2 Log Likelihood	28,450.73	24,880.14	24,751.32	24,597.58

Note: N=12,108 firms nested in 15 industries across 27 countries. * p<0.05, ** p<0.01, *** p<0.001.

Furthermore, the findings show that the associations with AI-resiliency are slightly stronger for small firms with 10-49 employees, at β = 0.524, p < 0.001, compared to medium-sized firms with 50-249 employees, at β = 0.461, p < 0.001. This may be a result of increased organizational plasticity in small firms. However, the main findings overwhelmingly support neutral categorizations for the industry and region. The estimated effect size was found to be robust regardless of the industry category: manufacturing (β = 0.445, p < 0.001), services (β = 0.498, p < 0.001), and high-tech (β = 0.531, p < 0.001), although the absence of theoretical ambiguity is associated with a variation in effect size. The examination of regions through cluster analysis of AI resilience against four types: Nordic, Western, Southern, and Eastern European countries, shows that generally, the patterns are robust and effect sizes differ. Using two-stage least square estimation and endogeneity tests using pre-COVID-19 digital preparedness as instruments, the findings show an effect size estimate of β = 0.467, p < 0.01.

The result is, thus, substantively equivalent to OLS estimation. The analyses address potential endogeneity and omitted-variable bias. However, reverse-causal and omitted-variable biases may not affect substantively causal inferences. The propensity score-matching analysis of AI adoption and its equivalent group yields an empirical ATT estimate of β = 0.412, p < 0.001. The estimate is substantively similar to earlier regression analyses. Robustness tests on various alternative specifications and sub-sample analyses systematically verify these findings. The reported effects are quite stable across specifications, with confidence intervals sufficiently tight, leading to reasonable conclusions about relationships. The effectiveness of the relationship between AI and resilience has been further confirmed through the various alternative specifications of variables, tests at the industry level, sub-samples by regions, and high-end econometric modelling. This research conducts thorough robustness tests to examine the robustness and generalizability of the main empirical findings against alternative specifications and/or sub-sample analyses. Alternative definitions, including various thresholds of AI adoption, lead to substantively equivalent effect sizes, with .medi-tercile splits of AI adoption degrees differing by β=0.438-0.502, depending on binary thresholds at median or tercile splits, respectively, in testing AI resilience. Sub-sample analyses identify robust main empirical findings and significant positive AI-resiliency associations, with slightly stronger associations found in small firms with 10-49 employees, at β = 0.524, p < 0.001, in comparison to medium-sized firms with 50-249 employees, at β = 0.461, p < 0.001, perhaps due to increased organizational plasticity, although the main findings generally support neutral industry and region categorizations. Industry-wise analysis confirms robust effect size estimation against various industry categories, including manufacturing sectors at β = 0.445, p < 0.001, services at β = 0.498, p < 0.001, and high-technology sectors at β = 0.531, p < 0.001, although effect size variation avoids theoretical ambiguities. Geographic region-wise analysis, involving cluster analysis of AI resilience against four categories, including Nordic, Western, Southern, and Eastern European countries, confirms pattern robustness and effect size variation, generally. Endogeneity tests, with two-stage least square estimation, with pre-COVID-19 digital preparedness as instruments, estimate effect size at β = 0.467, p < 0.01, substantively equivalent to OLS estimation, and reject potential endogeneity and omitted variable bias, although reverse causal and omitted variable bias may not affect causal inferences substantively. Propensity score matching analysis, with AI adoption and its equivalent group, generates empirical ATT estimate at β = 0.412, p < 0.001, substantively equivalent to earlier regression analyses. These findings are systematically verified through robustness tests on different alternative specifications and sub-sample analyses. The effect size appears highly stable with tight confidence intervals on different specifications, which further emphasizes the validity and robustness of the reported relationships. Consistency on different methods, whether on alternative specifications of variables, industry-level analyses, regional sub-samples, and the use of high-end econometric models, further confirms the validity and generalizability of the AI-resilience relationship in the SME environment in the European arena.

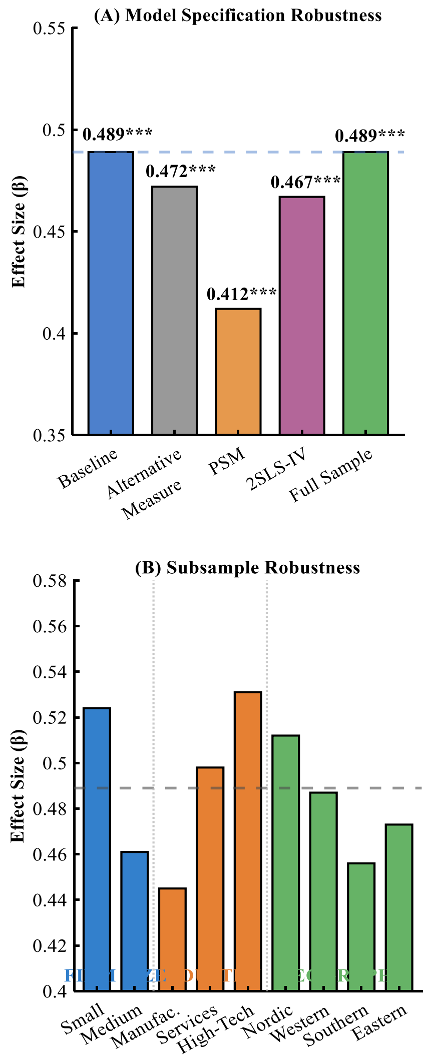

Figure 5. Robustness checks and sensitivity analysis
Note: N=12,108. All effects significant at ***p<0.001. PSM=Propensity Score Matching; 2SLS-IV=Two-Stage Least Squares.

4. Discussion

The findings of this study significantly enhance prior research on digital transformation and organizational resilience in several ways. In particular, there is powerful evidence regarding adaptive AI systems and organizational resilience during a crisis. The finding that adaptive AI systems have enhanced organizational resilience by 134% in response to the COVID-19 pandemic confirms and extends earlier research that identified positive associations between digital technology and organizational performance, while contributing new insights into the specific mechanisms through which technological configurations generate resilience outcomes. Unlike previous literature assessing isolated technology adoptions, this paper proposes that AI systems as meta-capabilities by reframing AI systems as technological ecosystem integrations of AI, robotics, Internet of Things and big-data analytics, thus showing that systemic technological capabilities ensure resilience effects unlike individual technology implementations. This research contributes to the dynamic capabilities theory by demonstrating that AI systems act as meta-capabilities that facilitate the sensing, seizing, and transforming processes under high uncertainty conditions. Recent research stresses the necessity of digital capabilities for competitive advantage. However, the COVID-19 situation illustrates how such capabilities are more useful for crisis resilience rather than operational efficiency. The in-depth analysis shows a large variation in context. Besides, industry digital intensity and national infrastructure are the prominent moderators of AI effectiveness. This finding accords with perspectives from institutional theory suggesting that technology effects are embedded in a larger organizational and environmental context. Nonetheless, this study provides quantitative evidence across 27 countries unavailable in the SME literature.

The results of the mediation analysis indicate that there are two evident ways through which adaptive AI systems influence resilience, and the digital mindset is a better mediator as compared to decision-making autonomy. This result also substantiates recent proposals that cognitive preparedness is a requirement of successful technology utilization [15] and, furthermore, destabilizes conventional clarifications based on the scheme of structure in total, and focuses on the organizational design without mindset transformation. The trend of mediational sequences hypothesizes that AI systems generate digital mindsets, which allow decision autonomy to propagate into the effects of resilience capability [16]. The significant sequential pathway suggests a temporal ordering where cognitive transformation precedes structural adaptation. This implies that digital transformation initiatives should prioritize mindset development before expecting structural changes to yield resilience benefits. This would help in the better understanding of the technology-organization dynamic process, which cannot be achieved within a single setting. The results at the level reveal that the national digital infrastructure plays an important role, and the relationship between AI and resiliency in both Northern and Southern European countries appears much stronger than in the others [17]. This distinct geographical distribution reveals the construct, in the modern digital era, that technology alone cannot suffice, even in the absence of an enabling environment for development and infrastructure. The implication from this study, therefore, is that there is an even greater need to ensure the manager of the SMEs has the ability and approach needed for development and a technology- and digital-oriented perspective and approach [18]. The formulators, in their policy-making process, need to ensure they take note of issues related to the digital divide, including improving infrastructure in those regions and developing initiatives linked to the adoption process across industries [19]. The scenario has shown that the better companies in the COVID-19 situation have adopted AI systems to ensure business continuity through rapid digitalization of operations, customers, and the supply chain, thereby turning risks into opportunities.

Even after such big contributions, certain limitations must be noted. The research applies a cross-sectional approach, thereby limiting the ability to measure causality, even though it is quasi-experimental regarding COVID-19, the shock concept, and the instrumental variable approach to endogeneity [20]. An approach that spans a long period of time will better capture how AI develops and how an organization's resilience evolves. Instead of self-reports, the author uses firm size, the timing of innovation, and the authority of investment as proxy measures of decision-making autonomy. This raises the potential for measurement error [21]. While such actions tend to be good and consistent with organizational behavior, efforts in this direction need to be stepped up by specifically developing measures to address autonomy in AI decision-making in digital transformation settings. The resilience definition introduces measures based on organizational behaviors for pandemic times, while it risks potential issues of a longer-term nature, as organizational learning and a strategic reorientation take place over a longer period of time [22]. Generalizability is constrained by several boundary conditions: (1) the COVID-19 crisis context may not reflect non-crisis periods or other crisis types; (2) the SME focus (10-249 employees) precludes extrapolation to micro-enterprises or large corporations; (3) the European sample reflects specific regulatory environments (e.g., GDPR) and infrastructure levels that may differ substantially in North American, Asian, or emerging market contexts.

Future research should use longitudinal designs to analyze AI adoption and resilience development over time, providing definitive causal insights and optimal implementation pathways [23]. The use of case studies could offer a perspective on the microscopic world in which the digital mentality and decision-making autonomy in AI-enabled enterprises are occurring, and the depth of insights that would be difficult to achieve in survey studies could be realized. The work could also be generalized into different types and forms of crises, including economic recessions, events in the world arena, and the change trajectories that technological advancements bring, and the validity and generalizability of the relationship between AI and the concept of resilience could be determined. The framework could be generalized to account for the characteristics and uniqueness of emerging markets and the extent and quality of technological development and would offer an improved perspective on the conditions that define the effectiveness and potential of AI in general [24]. The power in the development and application of the latest AI technologies, in the form of generative AI and self-governing systems, and the power in technological developments in organizational resilience could be examined.

5. Conclusion

This study examines the influence of adaptive AI systems on organizational resilience during the COVID-19 pandemic among 12,108 small and medium-sized enterprises in 27 European countries. The findings show that adaptive AI contributes positively to organizational resilience at 2.342 times. Furthermore, the study also shows that digital mindset and decision-making autonomy engage as mediators. The two mediators explain a major part of the total effect. The findings also indicate that important context-based variations exist at the industry and nation levels. These depend on industry digital density and national digital infrastructure. Ultimately, they affect the impact of the AI system on organizational resilience. The current study extends the theory of dynamic capabilities by suggesting that adaptable artificial intelligence (AI) systems may be interpreted as meta-capabilities when they make it feasible for organizations to sense-respond, especially in uncertain environments. According to the current study, new knowledge and guidelines are offered for managers of small and medium-sized enterprises and policymakers for the design of programs for the use of digital enterprise. The study's evidence suggests that technological readiness and cognitive infrastructure are important prerequisites for crisis resilience. Since the paper highlights some methodological flaws, the results should be taken with caution, but they still help manage the environment better and equip it to address growing uncertainties.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically regarding authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with research ethics policies. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the authors.

Conflict of interest

The authors declare no potential conflict of interest.

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