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AI-ENHANCED ORGANIZATIONAL RESILIENCE

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Purpose: The article identifies and analyzes a new theoretical construct — AI-enhanced organizational resilience. The study explains how employees utilize AI capabilities to support their own behavioral flexibility, thereby strengthening their organization's ability to cope with unpredictable threats.
Design/methodology/approach: A mixed-methods approach was applied, combining a literature review with empirical research. The research was conducted using an original survey questionnaire comprising 65 variables grouped into 19 categories, with a sample of n = 614 respondents. The results were analyzed using exploratory factor analysis (EFA) and linear regression.
Findings: A statistically significant construct of AI-enhanced resilience was identified, comprising two dimensions: behavioral flexibility and adaptability, as well as openness to collaboration with AI. The multidimensional nature of the studied phenomenon was confirmed, and key predictors were identified.
Research limitations/implications: The cross-sectional design limits our ability to infer causality, and we limited the sample to the Polish organizational context.
Practical implications: The results emphasize that organizations should invest in developing employee digital competencies and fostering an organizational culture that supports experimentation with new technologies.
Social implications: The study contributes to discussions about the future of work organization in the AI era and highlights the need for organizations to prepare their employees to collaborate with intelligent systems as part of socio-economic resilience.
Originality: This work introduces an innovative construct of AI-enhanced resilience and provides the first empirical contribution to understanding how individual AI-supported behaviors can strengthen organizational resilience to unpredictable threats.
Keywords: organizational resilience, artificial intelligence, adaptive behaviors.
Article category: Research paper.

1. Introduction

In the VUCA/BANI world, the ability of organizations to cope with events that are sudden, surprising, and highly destructive, yet simultaneously unclear or unknown, is becoming increasingly important. Put more simply, contemporary organizations must be able to quickly and effectively deal with the impact of sudden, unforeseen phenomena of an incompletely recognized nature. This sketches the role of organizational capabilities and action strategies that constitute organizational resilience (Salun, Zaslavska, 2024, p. 186). Within this article, resilience is understood as an organizational process that enables achieving outcomes in the form of resilient organizational actions and behaviors (Hillmann, Guenther, 2021, p. 8). This approach has its advantages, as it allows for the development of resilience theory as well as the assessment and improvement of this aspect of organizations. In this way, it is possible to consciously increase an organization's chances of success when confronting unknown and unpredictable scenarios of situational changes. The article discusses a specific organizational resource that, potentially, in the face of sudden exposure to unknown and strongly destructive factors, can constitute a source of resilient behaviors.

2. Organizational Resilience as Outcome and Process

The concept of organizational resilience began with assessing how organizations face difficulties that (1) threaten vital company interests, (2) leave little time to respond, and (3) are unexpected (Williams et al., 2017, p. 735). Resilience means the organization can respond adequately to these difficulties. This usually involves maintaining or improving efficiency, or quickly returning to normal (Sutcliffe, Vogus, 2003, p. 96; Williams et al., 2017, p. 740). Organizational resilience is thus a process leading to resilient reactions (Sutcliffe, Vogus, 2003 p. 96). Some views reduce resilience to just the reaction's outcome (Gibson, Tarrant, 2010, p. 9), but studying its sources is more common. Most definitions focus on the organization's capacity to absorb disruptions or on its ability to return to a previous state. Based on the classification developed by Hillman and Guenther (2021), six strategies for understanding and defining resilience can be characterized:

1. The behavioral approach, the oldest, focuses on specific behaviors of resilient organizations: Coutu (2002), Hamel and Välikangas (2003), Horne and Orr (1998). Ishak and Williams (2018) developed this approach into a two-dimensional model encompassing a typology of resilient behaviors.
2. The integrative approach combines resilient behaviors with organizational resources necessary for their occurrence. Resources are activated and combined in various ways, as noted by Lengnick-Hall, Beck (2005) and Sutcliffe, Vogus (2003), through processes defined as social mechanisms (Vogus, Sutcliffe, 2007).
3. The systems engineering approach emphasizes the role of proper organizational design as a hierarchical system and equipping it, through technology, coordination, and integration of subsystems, with the capacity for resilient response: Chewning et al. (2013), Erol, Sauser & Mansouri (2010), Patriarca et al. (2018).

4. The capabilities-based approach treats resilience as an organizational capability. It focuses on developing organizational response capacities, understood in terms of abilities, potential, or skills: Duchek (2020), Parker and Ameen (2018), Williams et al. (2017).
5. The typological approach proposes typologies and dimensions of organizational resilience, enabling the classification and comparison of organizations based on their resilience (Limnios et al., 2014).
6. The ecological approach combines various aspects of organizational activity in its understanding of ecology. It adapts earlier conceptualizations of the notion of resilience, developed in the natural sciences, to organizational considerations (Linnenluecke, Griffiths, 2012).

The concept of organizational resilience is clearer when we note what it is not. Resilience research does not overlap with crisis management, which studies crises—namely, their causes, dynamics, and consequences—not how organizations protect themselves from their impacts (Williams et al., 2017, p. 740). Resilience also differs from flexibility, agility, or adaptability. These concepts are related but not identical (Legnick-Hall et al., 2011). Resilience is not just about predicting the future. Some view prediction as one aspect of resilience (Duchek, 2020, p. 223), particularly in a strategic context (Hepfer, Lawrence, 2022, p. 15). Still, resilience mainly concerns coping with the unforeseen, which sets it apart. The distinction between prediction—attempting to forecast future events using available information—and resilience—coping with unforeseen phenomena—is necessary due to the fallibility of prediction (Vogus, Sutcliffe, 2007, p. 3419).

3. Modeling Resilience

This research uses the integrative approach (number 2 above). Resilience is seen as either the ability to return to pre-disruption operations or as a way to create and exploit new opportunities (Lengnick-Hall et al., 2011, p. 245). Lengnick-Hall sees this capacity arising from the combined knowledge, skills, and abilities of key employees (2011, p. 246). The first definition stresses quickly fixing the disruption effects. The second view sees difficulties as an opportunity to utilize resources and skills more effectively. Each definition points to different abilities as sources of resilience. Gittell et al. (2006) emphasize the importance of returning to normal quickly, focusing on both financial and relational resources. Richtnér and Löfsten (2014) stress transformation and the ability to spot new opportunities. They focus on organizational creativity as a vital source of resilience, based on the following resources (Richtnér, Löfsten, 2014, pp. 140-141):

1. Structural - structure, vision, and action plans shared by employees, financial resources, distribution of power, and core values.
2. Cognitive - skills, knowledge, and competencies, access to expert knowledge, experienced mentors, and experts.
3. Relational - external partners and collaborators, such as subcontractors, consultants, clients, or policymakers.
4. Emotional - friendship, support, trust, respect, camaraderie.

These resources create potential that allows organizations to generate solutions characterized by a significant level of creativity and, consequently, effectiveness in coping with difficulties. Organizations achieve the outcome of organizational resilience by engaging the above resources in action. The models presented by Hillman and Guenther (2021) and Hepfer and Lawrence (2022) share a similar vision of organizational resilience. Hillman and Guenther, summarizing their original integrative model, defined organizational resilience as *the ability of an organization to maintain functions and recover fast from adversity by mobilizing and accessing the resources needed. An organization's resilient behaviour, resilience resources and resilience capabilities enable and determine organizational resilience. The result of an organization's response to adversity is growth and learning* (2021, p. 31). Meanwhile, Hepfer and Lawrence state: *(o)ur review of research on organizational resilience suggests a nested, recursive model that connects the foundations, dynamics and outcomes of organizational resilience through processes of application, transformation and learning* (2022, p. 17).

In both models, the threat or difficulty is identified and interpreted, and then the process of constructing a response begins, utilizing all available organizational resources. Its structure and dynamics depend on how the threat was understood - how its structure, dynamics, and potential impact on the organization were interpreted, as well as on resource availability. The organization's response mitigates the negative factor and alters the consequences of its occurrence. The effectiveness of neutralizing potentially dangerous or undesirable impacts constitutes organizational resilience. The cyclical nature of the process allows for its improvement through organizational learning. Improvement encompasses the recursive relationship between organizational resources and managerial cognitive capabilities, as well as processes of shaping organizational response and expanding their repertoire.

4. The Role of AI in Developing Organizational Resilience

Based on the above-cited literature review results, organizational resilience can be defined as the outcome of a process of transforming organizational resources into actions aimed at neutralizing difficulties or threats affecting the organization, or changing their nature to a favorable one. The effectiveness of these actions is difficult to determine ex ante, but remains directly related to the level of organizational capability development. As demonstrated in the earlier part of the study, key capabilities conditioning organizational resilience include:

1. Cognitive capabilities of managerial staff, including the ability to interpret events, phenomena, processes, and trends in the environment. These capabilities are conditioned by both knowledge and experience, as well as the ability to work effectively in the face of information overload.
2. Organizational cognitive resources in the form of knowledge records and the employment of experts.
3. Relational resources in the form of people possessing knowledge, experience, and other resources.
4. Creative capabilities - allowing the creation of original responses to threats. Creativity constitutes a key source of organizational resilience (Richtnér, Löfsten, 2014; Weick, 1993).
5. Decision-making capabilities - necessary in the face of time pressure characteristic of crisis situations.

The cognitive nature of these resources, the role of information and decisions in their transformation into action, as well as the conditions for using networks of relationships to acquire needed resources, draw attention to, in each case, the role of information, informatics, and communication technologies (ICT - Information and Communication Technology, or increasingly DT - Digital Technology). In the case of resilience as a means to quickly restore the organization's state before the occurrence of a disruptive factor, communication plays an important role (Chewing et al., 2013; Zaskórski, Woźniak, 2024). Seeking innovative responses requires the engagement of creative processes, as the resilient organizational state in this case is distinct from those in previous instances. Comprehensive support for resilience processes is provided by dynamically developing artificial intelligence (AI). This technology serves as a means for comprehensive improvement of information processing capabilities (Li, Li, He, 2025, p. 5), and consequently positively affects generally understood organizational performance (Yu et al., 2024, p. 3). In terms of resilience:

1. AI allows for effective environmental monitoring. The capabilities of current data processing enable the monitoring of trends in the environment and the estimation of the risk of phenomena threatening the organization based on them (Li, Li, He, 2025, p. 5).
2. Generative AI can support the creative process by nature of creating potential organizational behaviors, that is, the process of transforming organizational cognitive resources (Kmiecik et al., 2024).
3. AI's analytical and predictive capabilities enable the support of decision-making processes aimed at selecting and implementing the developed solution most effectively (Badmus et al., 2024).
4. Organizational learning is a component of organizational resilience (Hepfer, Lawrence, 2022, p. 8), which can also be effectively supported by AI.

5. Empirical Research Design

The empirical research design incorporated the following conclusions from the literature review:

1. The area of organizational resilience is not clearly and strictly defined. It is a category that encompasses a wide range of diverse concepts and research areas (Williams et al., 2017, p. 743).
2. The core of resilience is the ability to improvise and respond effectively to unexpected events.
3. Resources are cognitive, and AI is currently the organizational core of transforming resources of this type.
4. Investments in technological innovations increase organizational resilience (Jiang et al., 2024, p. 2).

It may happen that the threat arises from an improper interpretation of the environment. Therefore, cultivating organizational routines in the interpretation of situations, implementation of solutions, and decision-making may hinder the ability to find an effective response. It would be a mistake to rely on organizational knowledge, as it formed the basis of previous interpretations, decisions, and actions. Another argument for abandoning existing decision-making processes and resources is the time pressure accompanying threats. Organizational decisions may not only be erroneous but also delayed. Therefore, it was assumed that the study would concern individual responses to threats, undertaken to protect the organization, but against organizational routines and procedures. This provides an opportunity to identify responses to unexpected threats that extend far beyond predicted scenarios of situation development. Thus, resilient behavior may involve ignoring both routines and procedures as well as organizational shared notions regarding the acceptable scope of actions. However, they are undertaken in the organization's interest, which allows them to be classified as Pro-Social Rule Breaking (PSRB) behaviors (Miao, Chen, Yao, 2024, p. 1).

The rejected knowledge, routines, and organizational procedures are worth replacing with other cognitive resources - those that are more quickly available and facilitate a different perception of the situation than those cultivated within the organization. This is enabled by the development of mobile, cloud, and AI technologies. A competent person can significantly support their decision-making process by using their assistance.

In the discussed context, among digital technologies, artificial intelligence gains particular significance (Zheng et al., 2017, p. 155), which, unlike traditional ICT tools, not only processes information but also supports creative thinking and decision-making. AI provides exceptionally effective support for decision-making processes under time pressure, which aligns with the specificity of crisis situations that require resilient responses.

These unique properties of AI, combined with individual employee initiative, create a new type of organizational potential, which has been adopted as an area of empirical research. This studied potential can be termed AI-enhanced resilience.

6. Research Method

The empirical research concerns exploring the structure of the network of organizational resources that condition the occurrence and intensity of resilient action. The research aims to identify the determinants influencing the level of AI-enhanced resilience, which can be understood as a component of organizational resilience, characterized by an employee's tendency to take independent action utilizing AI support. Therefore, the dependent variable of the research consists of two items:

1. Behavioral flexibility and adaptability, understood as readiness to take action for the good of the organization, even in situations of risk where this activity may be interpreted as breaking applicable rules.
2. Openness to collaboration with AI, understood as readiness to consider AI as a useful partner offering useful support in implementing cognitive processes.
3. The analysis of survey results consisted of two phases, whose content determines the research tool used:
4. Exploratory Factor Analysis (EFA) - allowing verification of whether theoretically selected variables actually create a factor (Grabowski, 2014, p. 251).

Linear regression - allowing examination of relationships between the explained variable - dependent, and a set of explanatory variables - independent (Biecek, 2013, p. 1; Hair et al., 2019, p. 265). Results were refined using the Akaike criterion (Akaike Information Criterion - AIC). This criterion aims to minimize the number of explanatory variables (Yamashita et al., 2007, pp. 2395-2396), which enables the identification of key explanatory variables influencing the level of AI-enhanced resilience, represented by two factors that group a total of 14 dependent variables (explained). Linear regression was applied twice, examining the influence of substantive variables and the influence of demographic variables separately.

The research was conducted using an original online survey in February 2025. It was carried out by an external research company. The author adopted the condition for including responses in the research set was meeting two requirements: current professional activity performed at a dimension of at least ¾ full-time equivalent and length of service at the current place of employment of no less than two years. Imposing these limitations resulted from our effort to obtain responses from people whose experiences in organizational participation are current and have been shaped under conditions of continuity for at least two years. Among the 1000 responses delivered by the company conducting the research, 614 met the above criteria.

Respondents were individuals of diverse genders, ages, and occupations, employed in various industries, at different positions, and in organizations of varying sizes. The following list presents in detail the structure of the studied sample:

- Respondent gender: female: 370 (60,3%); male: 244 (39,7%).
- Age (categories): up to 30 years: 114 (18,6%); 31-40 years: 213 (34,7%); 41-50 years: 168 (27,4%); 51-60 years: 90 (14,7%); over 60 years: 29 (4,7%).
- Education: higher than master's: 73 (11,9%); master's: 243 (39,6%); bachelor's, engineering: 68 (11,1%); secondary: 199 (32,4%); vocational: 31 (5,0%).
- Position: board member: 18 (2,9%); managerial: 141 (23,0%); independent/specialist: 223 (36,3%); executive: 232 (37,8%).
- Length of service at current place of employment: from 2 to 5 years: 223 (36,3%); from 5 to 10 years: 214 (34,9%); over 10 years: 177 (28,8%).
- Industry: manufacturing: 160 (26,1%); market services: 283 (46,1%); public services: 117 (19,1%); other: 54 (8,8%).
- Organization size: up to 9 people: 97 (15,8%); between 10 and 49 people: 171 (27,9%); between 50 and 249 people: 178 (29,0%); over 250 people: 168 (27,4%).
- Organization location: city over 300 thousand inhabitants: 222 (36,2%); city 100-300 thousand inhabitants: 136 (22,1%); city 20-100 thousand inhabitants: 143 (23,3%); city below 20 thousand inhabitants: 62 (10,1%); rural area: 51 (8,3%).

The principal part of the survey consisted of 65 questions divided into nineteen categories. Some of these variables (14 in total, categorized into 4 categories) were incorporated into the factors and are presented in Table 2. The remaining categories, along with the number of variables assigned to them, are presented in Table 3. Respondents provided answers by selecting one option on a five-point Likert scale. In the process of processing results, the following weights were assigned to individual response options: definitely not: -2; rather not: -1; hard to say: 0; rather yes: +1; definitely yes: +2.

The 614 responses meeting the adopted conditions are sufficient for conducting the planned research. In the case of linear regression, the minimum sufficient ratio is 10:1 (Austin, Steyerberg, 2015, p. 632). In this research, it is nearly 12:1. Moreover, the quality of the research set is significantly enhanced by the inclusion of criteria for minimum length of service and current employment (Memon et al., 2020, p. xiv).

7. Results

At the literature review stage, a series of factors were constructed that could serve to build the research model; however, some of them obtained negative results in empirical assessment using Cronbach's alpha reliability coefficient or factor verification using EFA. Factors whose reliability was confirmed empirically are presented in Table 1. Table 2 presents the set of parameters used in assessing factor reliability.

Table 1.
Factor names and indicators

Factor name	Indicators
dependent variable items	
Behavioral flexibility and adaptability	(1) readiness to break procedures when in the employee's opinion it is worth doing; (2) readiness to break procedures for the good of the organization; (3) readiness to break procedures for the good of the organization - even in face of misunderstanding from superiors; (4) experimenting with application of new methods and tools even against rules
Openness to collaboration with AI	(1) readiness to accept AI as a partner in task implementation; (2) acceptance of AI's influence on work flow; (3) readiness to accept plans prepared by AI
independent variable items	
Organizational innovation in the digital sphere	(1) striving for the widest possible application of DT in the organization; (2) continuous search and testing of digital tools; (3) existence of plans regarding AI application development; (4) growth of digital component in offered products and services
Personal digital competencies of employee	(1) programming skills; (2) ability to train AI models; (3) ability to create websites

Source: own elaboration.

Table 2.
Selected parameters for assessing factor reliability

Factor name	Cronbach's alpha	Range of factor loadings	Explained variance	RMSEA	Tucker-Lewis Index (TLI)
Behavioral flexibility and adaptability	0,85	0,72-0,85	60%	0,032	0,997
Openness to collaboration with AI	0,87	0,82-0,86	69%	0,000	-
Innovation in the digital sphere	0,84	0,70-0,81	58%	0,113	0,953
Personal digital competencies of employee	0,81	0,67-0,86	59%	0,000	-

Source: own elaboration.

Only in the case of one variable (concerning the ability to create websites), the factor loading was 0,67 and was lower than the recommended 0,7; however, due to the substantive value of the variable, it was retained in the factor structure. All factors achieved low RMSR values (< 0,03), which confirms good model fit. The highest correlation coefficient value between the factors is 0,512, indicating no problems with multicollinearity.

The dependent variable was the sum of two factors: (1) behavioral flexibility and adaptability, and (2) openness to collaboration with AI. Its predictors are two independent factors characterized above: organizational innovation in the digital sphere and personal digital competencies of the employee, as well as a series of fifty-one individual variables representing selected issues considered as potentially influencing the level of AI-enhanced resilience. Aspects of the organizational situation, as well as those concerning the employee, are represented by individual variables in Table 3. As can be seen, some aspects were assigned more than one variable. However, as determined empirically, they do not form reliable factors.

Table 3.
Selected aspects of the organizational situation, concerning the employee, along with the number of assigned individual independent variables

Group	No.	Aspect	Number of variables
Aspects of organizational situation	1.	formalization	6
	2.	IT infrastructure	1
	3.	AI use in practice	1
	4.	AI implementation plans	1
	5.	knowledge sharing practices in organization	9
	6.	employee preferences regarding work organization forms	3
	7.	organization's advancement in IT	1
	8.	leadership	1
Aspects concerning the employee	9.	basic digital competencies of employee	5
	10.	employee competencies regarding IT equipment	1
	11.	employee competency development practices in IT field	2
	12.	sources of employee digital competencies	5
	13.	self-assessment of one's digital competency level	3
	14.	employee attitude toward digitalization	10
	15.	employee attitude toward digital threats	2

Source: own elaboration.

The model prepared in this way showed a high quality of fit to the data. The model is globally statistically significant ($F(23, 590) = 34{,}930$, $p < 0{,}001$) and characterized by a high coefficient of determination ($R^2 = 0{,}577$), which indicates that it explains 57,766% of the variance in AI-enhanced organizational resilience. The value of the adjusted coefficient of determination (adjusted $R^2 = 0{,}560$) confirms the model's stability after accounting for the number of predictors. The AIC variable selection procedure reduced the initial set of 53 predictors to 24 most significant for the model.

Table 4.
Significant predictors of AI-enhanced organizational resilience from the group of substantive variables

Group	No.	Predictor	Aspect	B	p
Predictors concerning organizational situation	1.	factor: organizational innovation in the digital sphere	-	-0,190	0,043 *
	2.	high degree of work proceduralization	formalization	-0,103	0,049 *
	3.	team meetings occur according to schedule	formalization	-0,123	0,005 **
	4.	internal cooperation occurs via digital tools	knowledge sharing practices in organization	-0,139	0,012 *
	5.	using support of IT-proficient colleagues	knowledge sharing practices in organization	0,125	0,008 **
	6.	implementation plans for AI and machine learning systems	AI implementation plans	0,218	< 0,001 ***
	7.	organization is a digitalization leader in its field/industry	organization's advancement in IT	0,168	0,002 **
Predictors concerning the employee	8.	factor: personal digital competencies of employee	-	0,309	< 0,001 ***
	9.	belief that one should strive for the most far-reaching digitalization of work	employee attitude toward digitalization	0,139	0,017 *
	10.	own ideas regarding development of work digitalization	employee attitude toward digitalization	0,172	0,001 **
	11.	belief that concerns about AI are exaggerated	employee attitude toward digitalization	0,140	0,005 **
	12.	concern about security of digital records	employee attitude toward digital threats	-0,130	0,010 **
	13.	image as an IT enthusiast	self-assessment of one's digital competency level	0,129	0,011 *
	14.	belief in colleagues' superiority in digital competencies	self-assessment of one's digital competency level	0,092	0,038 *
	15.	plans for professional involvement with IT industry	employee competency development practices in IT field	0,116	0,018 *

Notes: B - unstandardized regression coefficient; p - significance level: ***p < ,001, **p < ,01, *p < ,05.

Source: own elaboration.

In the next step, the collected demographic variables were used as predictors of the dependent variable. Their list, values, and distributions are presented in the earlier part of the article. To examine their influence, linear regression was used again. The obtained model proved to be statistically significant ($F(10, 603) = 5{,}653$, $p < 0{,}001$), explaining 8,572% of the variance in AI- enhanced organizational resilience. Significant variables are presented in Table 5.

Table 5.
Significant predictors of AI-enhanced organizational resilience from the group of demographic variables

No.	Predictor	B	p
1.	gender: female	-1,291	0,008**
2.	position	1,472	< ,001***
3.	industry: manufacturing	1,730	0,049*
4.	industry: market services	1,611	0,053

Notes: B - unstandardized regression coefficient; p - significance level: ***p < ,001, **p < ,01, *p < ,05, p < ,01; The category "market services" at the borderline of significance (p = 0,053) includes trade, transport, and IT services.

Source: own elaboration.

8. Discussion

Two elements stand out in the research results. First, the model explains 57.7% of the variance in AI-enhanced resilience and shows high stability, indicating reliable and credible results. Second, the findings empirically confirm that organizational resilience is multidimensional: eight of the 15 analyzed aspects significantly affect resilience. Therefore, organizations aiming to strengthen crisis resilience should invest holistically in competencies, culture, structures, and technologies.

The research defines resilience in a distinct way, focusing on individual actions that may diverge from established procedures. In this context, decision-making involves collaboration with AI rather than consultation with superiors, colleagues, or formal regulations, promoting faster and often substantively valuable outcomes. This approach aligns with approaches that emphasize the role of creative organizational threads and also relates to the realities of the VUCA/BANI world, where the possibility of sudden and dangerous phenomena occurring completely outside considered scenarios of future development exists. It was precisely this vision of resilience that was operationalized as a dependent variable, and the conducted analysis allowed for the identification of factors that increase the chances of this form of organizational resilience occurring.

The compilation of factors influencing the level of the dependent variable in a significant and positive way includes both organizational and individual factors. Individual factors comprise an image of a high-class specialist (Table 4, items 8 and 15) in the field of DT. Personal digital competencies of the employee (Table 4, item 8) constitute the strongest predictor of AI-enhanced organizational resilience ($B = 0,309$, $p < 0,001$). This statistically significant effect, with a high level of explained variance ($R^2 = 0,577$), confirms the fundamental role of individual capabilities in building organizational resilience in the digital era. Competencies such as programming skills, ability to train AI models, or create websites form a foundation upon which an organization can build its adaptive capacity. The level of competencies is also influenced by the dynamics of knowledge processes, as this specialist works in an environment with other high-level IT specialists, as indicated by item 14 in Table 4 ($B = 0,092$, $p < 0,05$).

High personal competencies and even higher ones, those of colleagues, go hand in hand with an enthusiastic attitude toward digitalization, as expressed in employees' attitudes and behaviors (Table 4, items 9, 10, 11, 13). The belief in the need for maximum digitalization of work (Table 4, item 9: $B = 0,139$, $p < 0,05$) and own ideas regarding the development of digitalization (Table 4, item 10: $B = 0,172$, $p = 0,001$) show that AI-enhanced resilience is not solely a function of technical skills, but also of a proactive attitude and readiness to initiate changes.

The model also confirmed the significance of concrete AI implementation plans as a predictor of resilience (Table 4, item 6: $B = 0{,}218$, $p < 0{,}001$). This suggests that mere openness to technology is insufficient; concrete, planned implementation actions are necessary. Similarly, the organization's position as a digitalization leader in the industry (Table 4, item 7: $B = 0{,}168$, $p < 0{,}01$) proved to be a significant predictor, suggesting that being at the forefront of digital transformation brings measurable advantage in terms of organizational resilience.

The second component of the dependent variable is readiness to break applicable rules. It turns out that readiness for such behavior is closely linked to a lack of concern about data record security (Table 4, item 12, with a negative regression coefficient $B = -0{,}130$, $p = 0{,}01$) and trust in AI (Table 4, item 11: $B = 0{,}140$, $p < 0{,}01$). Such a relationship between an attitude of indifference to particular data security issues and readiness to undertake rule-breaking behaviors causes the studied component of organizational resilience to be considered a high-risk resource.

Among the predictors related to the organizational situation, substantive factors have a positive influence on the value of the dependent variable, similar to those related to the person. This is superiority in DT over other organizations operating in the same industry (Table 4, item 7) and striving to maintain, and perhaps strengthen, this superiority, expressed by the presence of plans to implement systems based on AI and machine learning (Table 4, item 6).

A certain organizational approach negatively affects the value of the dependent variable. The inhibiting impact of highly formalized work organization (Table 4, items 2 and 3, with negative regression coefficients) on actions exceeding applicable regulations is consistent with intuition.

Intriguing, however, is the negative regression coefficient for organizational innovation in the digital sphere ($B = -0{,}190$, $p = 0{,}043$). This seemingly paradoxical result can be explained in several ways:

1. A statistical suppressor effect is possible. Digital innovation may act as a suppressor variable, controlling variance shared with personal digital competencies and revealing the true relationship between individual capabilities and organizational resilience. Given the high regression coefficient for employee competencies ($B = 0{,}309$), intensive organizational innovation may indicate a phase of digital transformation in which the organization has not yet fully absorbed the introduced changes.
2. Organizations that intensively innovate in the digital sphere may experience temporary destabilization (Cyfert et al., 2025). Continuous testing of new tools and searching for the latest solutions may lead to a transient weakening of operational stability. Employees may be overwhelmed with changes, and organizational routines may be disrupted.

3. Organizational innovation may not only disrupt routines but also change their architecture. This means that in innovative organizations, a much wider range of behaviors fits within accepted organizational norms, not meeting the criteria for deviation. Colloquially speaking, in innovative organizations, employees "are allowed more".
4. This relationship may be nonlinear or moderated by other variables. This hypothesis requires verification in future research using nonlinear models (e.g., quadratic regression) or analysis of interaction effects. Longitudinal studies would have great value in explaining the dynamics of the relationship between innovation and resilience.

On the basis of empirical material collected in the presented research procedure, it can be stated that the more clearly marked the form of work organization is, the more strongly it contributes to limiting deviant behaviors. Regardless of whether it is directed at inspiring innovation or maintaining work processes within the framework of procedures and regulations, it has the same effect.

Demographic analysis reveals an additional finding: these variables, while explaining less than 9% of the variability in resilience, have a statistically significant effect. Women show less inclination toward the behaviors under study, while a tendency for AI-supported, non-regulation-conforming behaviors increases with organizational rank. Such behaviors are most prevalent in manufacturing, trade, transport, and IT services.

9. Conclusion

Perceiving readiness to break regulations without coordinating actions with superiors or colleagues, while only using AI assistance as an organizational resource, may raise justified doubts. However, three arguments can be indicated for such perception:

1. Resilience is a response to surprising and atypical situations. Describing today's world using the acronym VUCA/BANI, i.e., volatility, uncertainty, complexity, ambiguity, and brittleness, anxiety, non-linearity, incomprehensibility, does not testify to the effectiveness of forecasting tools used in business, nor to the lack of problems with controlling selected processes. It testifies to something quite opposite.
2. Actions classified within the studied category lie outside the formalized organization. Rules and hierarchical dependencies are broken, as are processes of social knowledge sharing, customs of action, and decision-making.

3. When, due to the specificity of the situation, all rules that allowed the organization to function fail, breaking them may prove to be the only chance for survival. All the more so, as this is not a random action. Its direction takes into account the value of the organization's goods, utilizing employee competencies and AI capabilities. Therefore, it is the realization of values in a new way, possessing the highly desirable quality of creativity (Panasiewicz 2021; Richtnér, Löfsten, 2014).

The research demonstrated that AI-enhanced resilience exists, as indicated by the statistical significance of the developed models, and is a complex, multidimensional construct. The previously discussed research results indicate both factors that contribute to the development of this specific organizational potential and factors that limit its level. On the one hand, thanks to this, it is possible to choose the direction of purposeful and effective influence at this level, depending on the degree of acceptance of the arguments cited above. On the other hand, a significant factor in the development of the studied potential is organizational digitalization and the development of employees' and teams' digital competencies. Currently, there is no alternative to the development of organizational digitalization. Therefore, one must reckon with the fact that progress in this area may inspire behaviors of a PSRB nature.

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