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FUZZY COGNITIVE MAPS FOR HIGH-TECH COMPANIES' RESILIENCE MODELING

Background. ***Relevance. Modern high-tech companies are dealing with more uncertainty and a range of complex threats, such as cyberattacks, infrastructure disruptions, and personnel challenges. Building resilience in these businesses is now essential for the national economy. Objective. This study aims to develop a cognitive model for assessing the resilience of high-tech companies under complex threats based on fuzzy cognitive maps.***

Methods. ***The fuzzy cognitive map (FCM) method combined with fuzzy DEMATEL was used to determine factor weight coefficients. An expert survey of 10 top managers was conducted to assess the relationships between factors. The agreement among experts was assessed using Kendall's coefficient of concordance (W = 0.864, p < 0.01). Impulse modeling was applied to analyze system dynamics.***

Results. ***The resulting FCM, with weights determined through Fuzzy DEMATEL, identified cyber threats as the most critical negative factor (–0.32) and physical infrastructure as the most significant positive factor (+0.28) influencing overall company resilience.***

Conclusions. ***The proposed model shows how different factors influence a company's resilience and helps managers set clear priorities. In practice, it can be used to model crisis scenarios and guide better resource allocation to strengthen business resilience.***

Keywords: ***fuzzy cognitive map; fuzzy DEMATEL; enterprise resilience; impulse modeling.***

Background

The events of the past decade, including the COVID-19 pandemic and various military conflicts, have highlighted the vital role of organizational resilience as the ability to adapt to extreme conditions while maintaining functionality and competitiveness (Dahmen, 2023). This issue is particularly acute for Ukrainian businesses, which have operated under constant security challenges since 2014 and, since 2022, under martial law (Opatska, Gajić, & Kašćelan, 2024).

In general, the modern business environment is characterized by unprecedented turbulence and uncertainty. High-tech companies, including those in the IT industry, start-ups, and Research and Development (R&D) firms, face complex threats that simultaneously affect different aspects of their operations: cybersecurity, physical infrastructure, human resources, and financial stability (Duchek, 2020; Koporcic et al., 2025).

These complex threats rarely happen on their own. They often interact and make each other worse, which traditional risk assessment methods have trouble capturing. For example, a cyberattack can harm information systems and also disrupt operations, lower staff morale, shake customer trust, and hurt financial stability. Infrastructure failures can reveal security gaps and use up funds needed for recovery. Because these risks are so connected, we need assessment tools that show how they influence each other, not just treat them as separate problems. This necessitates cognitive approaches that account for nonlinear links, feedback loops, and cascading effects in the "enterprise-environment" system (Papageorgiou et al., 2020).

The purpose of this study is to develop and validate an integrated fuzzy cognitive map model for assessing organizational resilience of high-tech companies operating under complex threat environments, and to identify critical resilience factors to inform strategic management decisions.

Literature eview. Fuzzy cognitive maps (FCMs) were proposed by Bart Kosko in 1986 as an extension of Axelrod's cognitive maps using fuzzy logic (Kosko, 1986). FCMs are directed graphs that model causal relations between system concepts, with weights in the range [–1, 1], where the sign indicates direction (positive/negative) and the magnitude indicates strength (Kosko, 1992).

Applications of FCMs in economics and management have expanded since the 2000s. Xirogiannis, Glykas and Staikouras (2010) demonstrated the use of hierarchical FCMs for strategic planning in banking. Glykas, Xirogiannis, and Staikouras (2012) extended this to dynamic Key Performance Indicators modeling. Recent work emphasizes hybrid approaches. Poczeta, Papageorgiou and Gerogiannis (2020) proposed nested FCMs with genetic algorithms, while Papageorgiou et al. (2020) developed an aggregation method using ordered weighted averaging operators for sustainable development planning. Kokkinos et al. (2018) applied FCMs to assess the socio-economic impacts of industrial projects. In Ukraine, cognitive modeling in economics has been developed by scholars at Taras Shevchenko National University of Kyiv (e.g., Bazhenova, & Bazhenova, 2016).

Decision Making Trial and Evaluation Laboratory (DEMATEL) was created in the 1970s to analyze complex causal systems. Wu and Lee (2007) introduced fuzzy DEMATEL for managerial competencies, highlighting the advantages of fuzzy expert processing. Chang, Chang and Wu (2011) integrated fuzzy DEMATEL with the Analytical Network Process for supplier selection. Li et al. (2011) adapted it to identify critical success factors in emergency management. Zhou, Huang and Zhang (2023) used fuzzy DEMATEL with Triangular Fuzzy Numbers (TFN) for urban safety.

Organizational resilience has advanced substantially over the last decade. Duchek (2020) conceptualizes resilience as a meta-capability that encompasses anticipation, coping, and adaptation. Zhang, Dou and Wang (2025) empirically link resilience and sustainability for Chinese firms. Dahmen (2023) posits resilience as a core property of enterprise risk management in the face of black swans. Settembre-Blundo et al. (2021) propose a multidimensional risk system that integrates sustainability. Opatska, Gajić and Kašćelan (2024) provide wartime crisis‑management insights from Ukraine.

Building on these methodological foundations, the following section describes our integrated approach combining FCM construction, fuzzy DEMATEL weighting, and impulse simulation.

Methods

Fuzzy Cognitive Map Construction. An FCM is formally described as a pair <K, W>, where K = {K_1, K_2, ..., K_n} is a set of concepts (factors), W = ||w_{ij}|| is a matrix of connection weights between them. The weight $w_{ij} \in [-1; 1]$ characterizes the strength and direction of influence of concept Kj on concept K_i:

- wij > 0 – positive influence (increase in Kj causes growth in K_i);
- wij < 0 – negative influence (increase in Kj leads to decrease in K_i);
- wij = 0 – absence of direct connection.

Model Factor Determination. Factor selection is based on the following research:

1. Theoretical analysis – literature review (Duchek, 2020; Koporcic et al., 2025; Opatska, Gajić, & Kašćelan, 2024) on organizational resilience revealed the 5 most frequently mentioned factors;
2. Preliminary pilot study – interviews with 10 top managers of Ukrainian high-tech companies confirmed the relevance of these factors.

Based on literature analysis and preliminary expert interviews, 5 key factors were identified:

1. Cyber threats (K_1) – integral indicator of cybernetic and information threats.
2. Physical infrastructure (K_2) – state of material and technical base, energy supply.
3. Financial resources (K_3) – financial stability, liquidity, access to capital.
4. Human capital (K_4) – availability of qualified personnel, team competencies.
5. Managerial flexibility (K_5) – management adaptability, decision-making speed.

The resulting concept – Company Resilience (R) – is an integral resilience indicator.

Fuzzy DEMATEL Method. To construct a meaningful FCM, it is necessary to determine the weight of the causal links between factors. While these can be estimated directly by experts, such an approach may fail to capture the deeper structure of the system. To address this, this study employs the Fuzzy Decision-Making Trial and Evaluation Laboratory (DEMATEL) method. This research method serves two main purposes. First, it provides a structured process for aggregating the subjective judgments of multiple experts. By using fuzzy logic, and specifically Triangular Fuzzy Numbers (TFNs), the model can handle the uncertainty and vagueness in human linguistic assessments, offering a more robust analysis than methods relying on crisp numerical inputs. Second, DEMATEL measures how much each factor affects the system and how much it is affected by others. By comparing these results, it sorts factors into two important groups: 'cause' factors, which drive changes in the system, and 'effect' factors, which are shaped by other variables. (Li et al., 2011; Chang, Chang, & Wu, 2011):

Stage 1. Expert evaluation in linguistic form with conversion to triangular fuzzy numbers (TFN) (Table 1).

TFN Parameters Explanation. Each linguistic term is converted to a triangular fuzzy number (TFN) represented as (l, m, u), where:

- l (left) – the lower bound representing the minimum possible value;
- m (middle) – the most likely value or peak of the membership function;
- u (upper) – the upper bound representing the maximum possible value.

For example, "Strong influence" = (0.5, 0.75, 1.0) means:

- The influence is at least 0.5 (minimum certainty);
- Most likely 0.75 (highest confidence);
- At most 1.0 (maximum possibility).

Table 1

Linguistic term values

Linguistic term	TFN (l, m, u)
No influence	(0.0; 0.0; 0.25)
Weak influence	(0.0; 0.25; 0.5)
Medium influence	(0.25; 0.5; 0.75)
Strong influence	(0.5; 0.75; 1.0)
Very strong influence	(0.75; 1.0; 1.0)

Source: adapted from Li et al. (2011) and Zhou, Huang and Zhang (2023).

This triangular representation captures both the expert's assessment and the inherent uncertainty in their judgment, allowing for more subtle modeling than crisp values.

Stage 2. Aggregation of expert assessments:

$$\tilde{x}_{ij} = (1/k) \oplus (\tilde{x}_{ij}^1 \oplus \tilde{x}_{ij}^2 \oplus \ldots \oplus \tilde{x}_{ij}^k)$$

Stage 3. Defuzzification using the center of gravity method:

$$x_{ij} = (l + m + u) / 3$$

Stage 4. Normalization of the direct influence matrix:

$$N = X / max(\Sigma_j |x_{ij}|)$$

Stage 5. Calculation of total influence matrix:

$$T = N(I - N)^{-1}$$

Stage 6. Determination of centrality indicators:

- $D_i = \Sigma_j t_{ij}$ (sum of outgoing influences)
- $R_i = \Sigma_i t_{ij}$ (sum of incoming influences)
- (D - R) > 0 - cause factor
- (D - R) < 0 - effect factor

Impulse Modeling. While the FCM connection matrix provides a static map of the system's structure, the true value of the model lies in its ability to simulate dynamic behavior. Impulse modeling is the primary technique for conducting such dynamic analysis with FCMs. It allows researchers and managers to perform "what-if" scenario planning by simulating how a change to one or more factors propagates throughout the entire system over time. So the impulse method was used to analyze system dynamics (Kosko, 1993):

$$K_i(t + 1) = f(\Sigma_j w_{ij} \cdot K_j(t) + \Delta K_i)$$

where f is the activation function (sigmoid), ΔK_i is the impulse in concept i.

Transitive closure matrix:

$$M = E + W + W^2 + \ldots + W^m$$

where m is the number of iterations until stabilization.

Threshold Reduction. To improve interpretability, θ-reduction was applied: connections with $|t_{ij}| < \theta$ are removed. The threshold value θ = 0.10 was used for the study.

Expert Survey Procedure. Ten experts were carefully selected based on specific criteria, ensuring relevant expertise: minimum 5 years of senior management experience in Ukrainian high-tech companies (IT services, software development, or R&D firms); direct responsibility for crisis management or business continuity during the 2014–2024 period; and company headcount exceeding 50 employees to ensure organizational complexity. The final expert panel comprised 2 CEOs, 1 Chief Operating Officer, 1 Chief Information Security Officer, 2 Chief Technology Officers, 3 Senior Delivery Managers, and 1 crisis management consultant.

The assessment utilized a structured questionnaire with two components. Part A requested pairwise comparison of all five factors' mutual influences using the linguistic scale shown in Table 1 (No influence, Weak influence, Medium influence, Strong influence, Very strong influence). Experts evaluated 25 factor pairs (5x5 matrix), assessing "How strongly does factor X influence factor Y?" for each pair. Part B requested a ranking of the five factors by their overall importance for organizational resilience.

Data collection followed a modified three-round Delphi protocol to achieve consensus. Round №1 involved individual expert assessments. Round №2 presented aggregated Round №1 results to experts with outliers highlighted, allowing reassessment. Round №3 achieved consensus with a coefficient of concordance W = 0.864 ($p < 0.01$), exceeding the 0.70 threshold for acceptable agreement.

Expert Assessment Consistency Verification. The consistency of assessments from 10 experts was verified using Kendall's coefficient of concordance. Experts ranked 5 factors by their impact strength on company resilience.

Calculation of concordance coefficient:

$$W = \frac{12S}{m^2(n^3-n)},$$

where m = 10 (number of experts); n = 5 (number of factors); S = 864 (sum of squared deviations of ranks from the mean)

$$W = \frac{12*864}{10^2(5^3-5)} = 0.864.$$

The high level of concordance (86.4%) confirms the reliability of expert assessments and consensus regarding the dominant role of cyber threats (K_1) as the most critical factor affecting high-tech company resilience.

Results

The analysis of expert assessments using the Fuzzy DEMATEL method produced a weighted fuzzy cognitive map of the high-tech company resilience system. The final normalized weight coefficients, which quantify the direct influence of each of the five key factors on the integral concept of "Company resilience" (R), are presented in Table 2. Most notably, Cyber threats (K1) emerged as the most critical factor, exerting a strong negative influence with a weight of –0.32. This indicates that an increase in the level of cyber threats directly and significantly degrades a company's overall resilience.

On the other hand, Physical infrastructure (K2) and Financial resources (K3) were the top positive contributors, with influence weights of +0.28 and +0.24. This shows that having strong physical assets and stable finances is essential for a company to handle disruptions. Human capital (K4) and Managerial flexibility (K5) also have positive effects, but their influence is smaller, at +0.20 and +0.16.

Weight Coefficient Matrix. After processing expert assessments using fuzzy DEMATEL, a normalized influence matrix was obtained (Table 2):

Table 2

Normalized weight coefficients of factor influence on resilience

Factor	Weight coefficient	Impact type	Rank
Cyber threats (K_1)	–0.32	negative	1
Physical infrastructure (K_2)	+0.28	positive	2
Financial resources (K_3)	+0.24	positive	3
Human capital (K_4)	+0.20	positive	4
Managerial flexibility (K_5)	+0.16	positive	5

Note: $\Sigma|w_i|$ = 1.20 after normalization. The largest factor contribution is 0.32, and all factors together give 1.20 units of influence.
Source: authors' calculations based on expert survey data (n=10 experts).

Factor Classification. To better understand how different factors influence each other in this system, we used the total influence matrix from the DEMATEL analysis to calculate centrality indicators for each factor, as shown in Table 3. This approach helps us sort the factors into net 'causes' (drivers) or net 'effects' (outcomes). The findings show a clear pattern. Cyber threats (K1) stands out as the main driving factor, with the highest positive (D – R) value of +1.60. Physical infrastructure (K2) and Financial resources (K3) also act as cause factors, with (D – R) values of +0.34 and +0.33. These results suggest that both external threats and internal resources are the key drivers shaping the company's resilience.

Table 3

Factor centrality indicators

Factor	D	R	D – R	D + R	Type
K_1	2.45	0.85	+1.60	3.30	Cause
K_2	2.12	1.78	+0.34	3.90	Cause
K_3	1.98	1.65	+0.33	3.63	Cause
K_4	1.23	2.34	–1.11	3.57	Effect
K_5	1.15	2.31	–1.16	3.46	Effect

Source: authors' calculations using the total influence matrix.

In contrast, Human capital (K4) and Managerial flexibility (K5) were identified as strong effect factors, with negative (D – R) values of –1.11 and –1.16, respectively. This suggests that while these capabilities support resilience, they mostly result from the company's resources and the challenges it faces.

Impulse Modeling Results. To better understand the dynamic behavior of this structured system, a series of impulse modeling experiments was conducted to simulate the impact of various shocks and interventions on overall resilience. A series of experiments with impulses $\Delta K_i = \pm 0.2$ was conducted for each factor, and the results are summarized in Table 4. The simulations show that Cyber threats have the strongest impact. Scenario S1 shows that an isolated 20% increase in the intensity of cyber threats leads to a significant 15.6% decline in overall resilience. In contrast, Scenario S4 shows that reducing these threats increases resilience by 14.8%. Strengthening infrastructure (S2) and Finances (S3) also helps, raising resilience by 14.2% and 11.8%.

Scenario S5 was created to explore whether combining several management actions could have a stronger effect. It includes three steps: reducing Cyber threat exposure by $\Delta K_1 = -0.1$ through enhanced security measures, improving Infrastructure by $\Delta K_2 = +0.1$ with more diversification and backup systems, and strengthening Finances by $\Delta K_3 = +0.1$ by building reserves. Each action uses a magnitude of 0.1, which is half the size used in single-factor scenarios, to reflect realistic improvements that managers can achieve together with typical resources. These three factors were selected because they represent the three highest-magnitude causal drivers (D-R > 0) that management can directly influence, making them the logical focus for an integrated resilience strategy.

Table 4

Impact of impulses on integral resilience

Scenario	Impulse	ΔR	Interpretation
S1	$\Delta K_1 = +0.2$	–0.156	Increased cyberattacks reduce resilience by 15.6%
S2	$\Delta K_2 = +0.2$	+0.142	Infrastructure improvement increases resilience by 14.2%
S3	$\Delta K_3 = +0.2$	+0.118	Financial resource growth increases resilience by 11.8%
S4	$\Delta K_1 = -0.2$	+0.148	Reduced cyber threats increase resilience by 14.8%
S5	Combined*	+0.245	Comprehensive improvement increases resilience by 24.5%

Combined scenario: $\Delta K_1 = -0.1$, $\Delta K_2 = +0.1$, $\Delta K_3 = +0.1$.

Source: Authors' impulse modeling simulations.

Sensitivity Analysis. The sensitivity analysis further reinforced the dominant role of Cyber threats (K1). Variations of ±10% in its connection weight resulted in an 18–22% change in the resilience outcome (ΔR) in relevant scenarios, confirming it as the most sensitive and critical parameter in the model.

Discussion and conclusions

The obtained results confirm the critical role of cybersecurity in enhancing the resilience of high-tech companies under current conditions. The dominance of the "Cyber threats" factor (|w| = 0.32) aligns with data from Opatska, Gajić and Kašćelan (2024), which indicates that 78% of Ukrainian IT companies consider cyberattacks the greatest threat during martial law.

The identification of "Human capital" and "Managerial flexibility" as effect factors (D – R < 0) corresponds to Duchek's (2020) theoretical model, according to which adaptive capabilities are formed under the influence of the enterprise's resource base.

The multiplicative effect of cyber threats, revealed through impulse modeling, confirms the need for a systematic approach to ensuring resilience, as described in works by Dahmen (2023) and Settembre-Blundo et al. (2021).

A comparison with classical risk assessment approaches highlights several advantages of using fuzzy cognitive maps:

1. Accounting for nonlinear relationships and feedback loops.
2. Ability to work with qualitative expert assessments.
3. Dynamic scenario modeling.

This research has several limitations that future work should address. First, the expert sample size (n=10) represents a constraint, though the high concordance coefficient (W = 0.864) suggests this sample achieved reliable consensus. Future research could expand to 20–30 experts across multiple countries to test model generalizability beyond the Ukrainian context.

Second, focusing only on the IT sector means the findings may not apply to other industries. Companies in manufacturing, logistics, or financial services have different risks and resources. A promising approach would be hierarchical fuzzy cognitive maps (Xirogiannis, Glykas & Staikouras, 2010) with sector-specific sub-models nested within a general resilience framework.

Third, the model uses fixed weight coefficients, but real-world relationships between factors can change over time. To improve this, future research should collect data over longer periods and regularly update expert assessments. Adaptive algorithms could then adjust the weights as new data arrives. Machine learning methods, such as recurrent neural networks, could help the model learn how these weights change during different crises.

Finally, the model has not yet been tested with large-scale quantitative data. Future research should collect objective resilience metrics (system downtime, financial impact, recovery time) from 50+ companies over multiple crisis events to validate model predictions against actual outcomes.

The results directly address the study's main goal. An integrated FCM model for assessing resilience was developed and validated, key factors were identified using quantitative analysis, and practical management strategies were outlined. The model also uncovered patterns that are not immediately obvious. For example, when interventions were combined, the improvement was 24.5%, which is greater than what would be expected if the effects were simply added together. This shows the model's value goes beyond just identifying important factors.

Key Scientific Results:

1. Adapted fuzzy DEMATEL methodology for determining FCM weight coefficients in the context of organizational resilience.
2. Empirically confirmed the dominant role of cyber threats (-0.32) in forming high-tech company vulnerability.
3. Revealed the structure of cause-and-effect relationships: infrastructure and resource factors act as drivers, while organizational capabilities are results.

Practical Implications:

The model can be used for:

- prioritizing investments in resilience enhancement;
- scenario planning of anti-crisis measures;
- optimizing resource allocation between protection areas;
- real-time resilience dynamics monitoring.

Management Recommendations:

1. Cybersecurity – priority #1: investments in Security Operations Center (SOC), critical systems backup, personnel training.
2. Infrastructure independence: autonomous energy sources, communication channel duplication.
3. Financial cushion: 3–6 months operational expense reserves.
4. Personnel policy: retention programs, cross-functional training.
5. Agile management: decision decentralization, scenario planning.

Further Research Directions:

- model expansion with additional factors (reputation, ecosystem connections);
- dynamic adaptation of weight coefficients based on machine learning;
- validation on empirical data from various industries;
- integration with business analytics systems for real-time monitoring.

This research offers a key step forward by turning proactive resilience management into a practical process using predictive scenario modeling. Traditional resilience methods are mostly reactive; organizations deal with crises after they happen and learn from those tough experiences. The fuzzy cognitive map framework introduced here helps organizations prepare in advance by measuring possible future outcomes before they occur. Managers can test different strategies, such as investing in cybersecurity, upgrading infrastructure, or setting financial reserves, to see how these choices might improve resilience. This approach supports resource decisions based on evidence rather than intuition.

For Ukrainian businesses operating under permanent crisis conditions, and for more organizations around the world facing growing challenges, moving from reactive to proactive resilience management is not just helpful - it is existential. The model provides a practical tool for the transition, bridging academic theory and operational practice.

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НЕЧІТКІ КОГНІТИВНІ КАРТИ СТІЙКОСТІ ВИСОКОТЕХНОЛОГІЧНИХ КОМПАНІЙ

В с т у п . ***Актуальність. Сучасні високотехнологічні компанії стикаються зі зростаючою невизначеністю та комплексними загрозами, такими як кібератаки, руйнування інфраструктури та кадрові виклики. Забезпечення стійкості зазначених підприємств стає критично важливим завданням для національної економіки. Мета статті – розробити когнітивну модель оцінювання стійкості високотехнологічних компаній в умовах комплексних загроз на основі нечітких когнітивних карт.***

М е т о д и . ***Використано метод нечітких когнітивних карт (НКК) у поєднанні з fuzzy DEMATEL для визначення вагових коефіцієнтів факторів. Проведено експертне опитування 10 топменеджерів для оцінювання взаємозв'язків між факторами. Узгодженість експертних оцінок перевірено за допомогою коефіцієнта конкордації Кендала (W = 0,864, p < 0,01). Застосовано імпульсне моделювання для аналізу динаміки системи.***

Р е з у л ь т а т и . ***Отримана нечітка когнітивна карта (FCM), із вагами, визначеними за методом Fuzzy DEMATEL, виявила кіберзагрози як найкритичніший негативний фактор (–0.32), а фізичну інфраструктуру – як ключовий позитивний фактор (+0.28), що впливає на загальну стійкість компанії.***

В и с н о в к и . ***Запропонована модель демонструє, як різні фактори впливають на стійкість компанії, та допомагає менеджерам визначити чіткі пріоритети. На практиці модель може використовуватися для моделювання кризових сценаріїв та оптимізації розподілу ресурсів для підвищення резильєнтності бізнесу.***

К л ю ч о в і с л о в а : ***нечітка когнітивна карта, нечіткий DEMATEL, стійкість підприємства, імпульсне моделювання.***

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