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Cognitive AI-Based Data Envelopment Analysis for Modeling Economic Collapse and Adaptive Responses in Modern Warfare

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Abstract

Modern warfare exerts profound and heterogeneous impacts on national and sectoral economies, often triggering complex patterns of collapse or adaptation that traditional efficiency analysis fails to capture. This study introduces a cognitive Artificial Intelligence (AI)-based Data Envelopment Analysis (DEA) framework to evaluate economic resilience under extreme stress by integrating classical DEA, cognitive behavioral indicators, and AI-based pattern recognition. The proposed methodology adjusts conventional efficiency scores using a cognitive coefficient derived from decision-making quality, risk perception, and adaptive policy responses, and applies AI-driven clustering and temporal trajectory analysis to identify latent structures of resilience and collapse. The framework was applied to a sample of simulated economic units, revealing that technically efficient economies may nonetheless be vulnerable if cognitive adaptability is low, whereas moderately efficient economies with high behavioral resilience can maintain stability under conflict. AI-based clustering effectively distinguished adaptive and collapse-prone units, while temporal and Markov chain analyses provided predictive insights into the dynamics of recovery and failure. These findings demonstrate that behavioral and cognitive factors are critical determinants of economic adaptation, extending the explanatory power of traditional DEA. The results offer practical guidance for policymakers aiming to enhance resilience, prioritize adaptive capacity, and design preemptive interventions in conflict-affected contexts. By integrating technical efficiency with cognitive adaptability and predictive modeling, this framework represents a novel, multidimensional tool for understanding and managing economic resilience under modern warfare.

Keywords: Adaptive capacity, Cognitive data envelopment analysis, Economic resilience, Machine learning, Modern warfare.

1 | Introduction

Modern armed conflicts exert profound and multifaceted impacts on national and regional economies, extending far beyond immediate physical destruction to include persistent disruptions in production,

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employment, investment, and fiscal stability [1]. Empirical evidence indicates that wartime economies often experience substantial declines in GDP and consumption, while investment and trade flows are sharply curtailed, leading to long-term economic stagnation in many affected regions [2]. For instance, historical analyses of post-World War II conflicts reveal average GDP contractions of 10–15% during war periods, with lasting reductions in economic activity for decades after the cessation of hostilities [3]. Recent evidence from the Russo-Ukrainian conflict further illustrates significant declines in entrepreneurial activity, firm formation, and regional productivity, highlighting the multifactorial economic consequences of contemporary conflicts [4]. Regional studies, such as those examining the former Yugoslavia, show that certain subnational areas can experience permanent per capita GDP losses exceeding 30–40%, suggesting that conflict-induced shocks are highly heterogeneous and context-dependent [5]. Macro-level analyses also reveal that post-conflict GDP per capita may remain 20–30% below potential for extended periods, emphasizing the structural severity of wartime economic shocks [6]. Collectively, these results indicate that modern conflicts impose systemic pressures on economies, affecting both macroeconomic indicators and the micro-level mechanisms through which resources are allocated and decisions are made [7].

Despite robust documentation of the aggregate economic impacts of war, there remains a critical gap in understanding the decision-making mechanisms that determine whether an economy adapts successfully or collapses under conflict conditions [8]. Conventional macroeconomic models and impact assessments primarily focus on observable outcomes, often assuming rational actors operating under stable conditions and complete information [9]. However, behavioral economics and cognitive science research consistently demonstrate that decision-making under stress deviates from classical rationality, influenced by heuristics, biases, loss aversion, and risk perceptions, particularly in environments characterized by uncertainty and high stakes [10]. Empirical studies further indicate that conflict-induced stress exacerbates these deviations, with policymakers, managers, and firms often adopting conservative or risk-averse strategies that may be adaptive in the short term but suboptimal for long-term efficiency [11]. For example, research on organizational behavior during martial law conditions demonstrates that cognitive stress alters decision priorities, favoring survival-oriented choices over efficiency-maximizing strategies [12]. These insights underscore the need for analytical frameworks that integrate cognitive and behavioral dimensions into economic performance analysis, especially under extreme uncertainty [13].

Data Envelopment Analysis (DEA) has emerged as a robust non-parametric method for evaluating the relative efficiency of Decision-Making Units (DMUs) across multiple inputs and outputs [14]. Since its introduction by Charnes, Cooper, and Rhodes, DEA has been widely applied to assess performance in banking, healthcare, public sector operations, and national economic efficiency [15]. DEA enables benchmarking against a constructed efficiency frontier, identifying best practices and quantifying inefficiencies relative to peer units [16]. However, traditional DEA models are limited in capturing cognitive and behavioral dynamics, as they treat DMUs as black boxes and focus solely on observable input-output relationships [17]. This limitation is especially salient in conflict contexts, where similar input-output performance may mask divergent decision strategies that influence resilience or collapse [18]. Extensions of DEA, including stochastic and network models, have improved flexibility, yet the integration of behavioral and cognitive indicators remains largely unexplored [19]. Consequently, while DEA provides precise measurements of relative efficiency, it cannot inherently explain why certain economies adapt while others fail under wartime pressures [20].

Advances in Artificial Intelligence (AI) and Machine Learning (ML) offer complementary tools to overcome the limitations of traditional DEA [21]. AI techniques, including deep learning, reinforcement learning, and clustering algorithms, can model complex, nonlinear relationships and adaptive behavior that are difficult to capture with conventional econometric or DEA approaches [22]. Within economic research, AI has been applied to forecast trends, simulate adaptive decision-making, and identify latent patterns in large-scale datasets [23]. Importantly, AI can infer cognitive and behavioral patterns from observable economic responses, thereby bridging the gap between technical efficiency and decision-making processes [24]. Despite these advances, few studies have integrated AI with DEA to assess economic resilience under extreme uncertainty, and virtually none have operationalized cognitive-behavioral indicators within an efficiency benchmarking framework. This gap highlights the need for hybrid approaches that combine the strengths of DEA and AI while explicitly accounting for the behavioral strategies that shape adaptive or maladaptive responses to conflict.

Conventional economic performance metrics often assume stable environments and rational expectations, whereas conflict introduces extreme volatility, information asymmetry, and stress-induced behavioral changes [25]. Decision-making under such conditions involves trade-offs between risk, uncertainty, and cognitive load, which influence resource allocation, investment decisions, and policy choices [26]. Without incorporating cognitive and behavioral dimensions, analyses risk misclassifying adaptive strategies as inefficiencies or failing to anticipate pathways to economic collapse [27]. Furthermore, heterogeneity in conflict impacts across countries, regions, and sectors demonstrates that resilience is not solely a function of resources or efficiency but also of decision-making quality and adaptability [28]. Studies of firm-level responses during recent conflicts show that clusters of organizations exhibit distinct adaptive behaviors, emphasizing the importance of cognitive and strategic decision-making in shaping outcomes [29].

To address these gaps, we propose Cognitive AI-Based DEA, a novel framework that integrates cognitive-behavioral indicators and AI techniques into the DEA efficiency frontier to analyze economic collapse and adaptation during modern warfare. This approach conceptualizes economic agents, governments, firms, or sectors—not as passive resource allocators but as cognitive actors whose strategies evolve under stress and uncertainty. By embedding cognitive metrics and machine-learning-derived behavioral patterns into the DEA, the model distinguishes adaptive efficiency from traditional technical efficiency, capturing both resource optimization and the quality of decision-making under conflict shocks. AI algorithms enable the identification of latent decision patterns, the clustering of economies or sectors by adaptive capacity, and the simulation of potential pathways of resilience or collapse [30]. In doing so, cognitive AI-based DEA offers a unified framework for benchmarking performance, predicting responses to shocks, and guiding evidence-based policy design.

This study addresses three critical limitations in the existing literature. First, it operationalizes cognitive decision-making processes within a formal performance measurement framework, bridging behavioral economics and DEA. Second, it leverages AI's ability to model complex adaptive behaviors under uncertainty, extending the explanatory power of traditional efficiency analysis. Third, it provides a comprehensive tool for cross-country and cross-sector comparative analysis, enabling the identification of factors that promote economic resilience under conflict conditions. By integrating these dimensions, the proposed framework supports policymakers and international organizations in designing interventions that enhance economic adaptability, reduce vulnerability to collapse, and facilitate post-conflict recovery.

In sum, the cognitive AI-based DEA framework advances methodological, theoretical, and practical understanding of economic performance under modern warfare. It moves beyond static efficiency measurements to capture the interplay between cognitive decision strategies, resource allocation, and adaptive outcomes. By doing so, it provides scholars and policymakers with a rigorous tool to anticipate economic responses to conflict, identify pathways to resilience, and inform strategic interventions that mitigate collapse.

2 | Methodology

This study proposes a novel Cognitive AI-based DEA framework to evaluate economic collapse and adaptive efficiency under conditions of modern warfare. The methodology integrates classical DEA, cognitive behavioral indicators, and AI-based clustering and pattern recognition to model the decision-making processes of economies or sectors under extreme uncertainty. The framework consists of three core components: 1) classical DEA efficiency measurement, 2) cognitive behavioral adjustment, and 3) AI-based pattern recognition and adaptive efficiency analysis. Each component is formalized mathematically and described below.

2.1 | Classical Data Envelopment Analysis Framework

Let n denote the number of DMUs, representing countries, sectors, or firms, indexed by i=1,…,n. Each DMU consumes mmm inputs x_{ij} (j=1,…,m) to produce sss outputs y_{ik} (k=1,…,s). The input-oriented CCR [31] DEA model is defined as [30]:

$$\min_{\theta,\lambda} \theta_i,$$

$$\text{s.t.} \quad \sum_{j=1}^{n} \lambda_j x_{jk} \le \theta_i x_{ik}, \qquad k = 1, \dots, m,$$

$$\sum_{j=1}^{n} \lambda_j y_{jk} \ge y_{ik}, \qquad k = 1, \dots, s,$$

$$\lambda_j \ge 0, \quad j = 1, \dots, n,$$

where θ_i is the efficiency score of DMU i $(0 < \theta_i \le 1)$, and λ_j are intensity variables. $\theta_i = 1$ denotes a fully efficient unit, while $\theta_i < 1$ indicates inefficiency.

The CCR model assumes Constant Returns to Scale (CRS). To account for Variable Returns to Scale (VRS), the BCC model [32] adds the convexity constraint:

$$\sum_{j=1}^{n} \lambda_j = 1.$$

The classical DEA framework provides a baseline efficiency measurement, but does not consider the cognitive-behavioral responses of DMUs under wartime conditions.

2.2 | Cognitive Behavioral Adjustment

To incorporate the impact of decision-making behavior under stress, we introduce a cognitive behavior coefficient $\emptyset_i$ for each DMU. This coefficient captures deviations from purely rational efficiency due to cognitive, emotional, or stress-induced factors, derived from behavioral indicators such as risk perception, loss aversion, and adaptive policy responses:

$$\emptyset_i = f(B_i),$$

where $B_i = [b_{i1}, b_{i2}, \dots, b_{ip}]$ is a vector of ppp behavioral indicators for DMU i, and $f(\cdot)$ is a normalization function mapping behavioral measures to the interval [0,1]. A higher $\emptyset_i$ indicates rational and adaptive behavior, while lower values correspond to suboptimal or maladaptive behavior under stress. We then define the cognitively adjusted efficiency θ_i^c as:

$$\theta_i^c = \theta_i \cdot \emptyset_i,$$

where θ_i is the classical DEA efficiency score, and θ_i^c integrates both technical efficiency and cognitive resilience. This formulation allows DMUs that demonstrate strong adaptive decision-making to achieve higher adjusted scores even under resource constraints.

2.3 | Artificial Intelligence-Based Pattern Recognition and Clustering

To identify latent patterns of adaptation and collapse, we apply unsupervised machine learning techniques to the set of cognitively adjusted efficiency scores $\{\theta_1^c, \dots, \theta_n^c\}$ and the behavioral indicator matrix $B \in \mathbb{R}^{n \times p}$.

I. Dimensionality reduction

First, we apply Principal Component Analysis (PCA) to reduce high-dimensional behavioral data to q principal components Z:

$$Z = BW, W \in \mathbb{R}^{p\times q},$$

where W contains the eigenvectors corresponding to the top q eigenvalues of the covariance matrix of B. This step ensures computational tractability and highlights dominant cognitive behavior patterns.

II. Clustering

Next, we perform k-means clustering on the reduced feature matrix $X = [\theta_c, Z]$ to classify DMUs into adaptive and collapse-prone clusters. The k-means objective is:

$$\min_{\{C_k\}_{k=1}^{K}} \sum_{k=1}^{K} \sum_{i\in C_k} \|x_i - \mu_k\|^2,$$

where C_k is cluster k, μ_k is the cluster centroid, and x_i is the feature vector of DMU i. The optimal number of clusters K is determined using the Silhouette coefficient or the Gap statistic, ensuring meaningful separation between adaptive and collapse-prone groups.

III. Path analysis

Finally, we evaluate transition trajectories of DMUs under conflict by analyzing temporal sequences of $\theta_i^c(t)$ over time t. Using Markov chain modeling, we define the probability P_{ij} of transition from state i to state j:

$$P_{ij} = \frac{\text{Number of DMUs transitioning from state i to j}}{\text{Total DMUs in state i}}.$$

allowing us to identify likely pathways to adaptation or collapse under war conditions.

IV. Integrated framework

The full Cognitive AI-Based DEA framework integrates the components above as follows:

Step 1. Compute classical DEA efficiency θi using inputs xij and outputs yik,

Step 2. Compute the cognitive behavioral coefficient $\emptyset_i = f(B_i)$,

Step 3. Calculate cognitively adjusted efficiency $\theta_i^c = \theta_i \cdot \emptyset_i$,

Step 4. Perform PCA on behavioral indicators and combine with θ_i^c for feature matrix X,

Step 5. Apply k-means clustering to classify DMUs into adaptive and collapse-prone groups,

Step 6. Analyze transition trajectories using temporal sequences of $\theta_i^c(t)$ and Markov chain modeling.

This integrated approach simultaneously evaluates technical efficiency, cognitive adaptation, and latent behavioral patterns, providing a comprehensive tool for analyzing economic resilience under modern warfare.

V. Data and implementation

The methodology is implemented using MATLAB and Python (scikit-learn). Input-output data (x_{ij}, y_{ik}) are derived from macroeconomic statistics, sectoral production data, and trade flows. Behavioral indicators (B_i) are constructed from observable proxies such as fiscal policy responsiveness, military expenditure adaptation, risk perception indices, and governance metrics. Temporal analysis uses annual data spanning multiple conflict events to capture dynamic adaptation processes.

3 | Results

This section presents a comprehensive analysis of economic adaptation and collapse under modern warfare using the proposed Cognitive AI-based DEA framework. The analysis is performed on a sample of 30 DMUs representing countries or economic sectors under simulated wartime conditions. The results are reported in four sequential stages: 1) classical DEA efficiency, 2) cognitively adjusted efficiency, 3) AI-based clustering of DMUs, and 4) temporal trajectory analysis.

3.1 | Classical Data Envelopment Analysis Efficiency

The classical CCR DEA model was first applied to measure technical efficiency based on three inputs (labor, capital, natural resources) and three outputs (GDP, exports, industrial production).

Table 1. Classical DEA Efficiency Scores of DMUs.

DMU	Input Sum	Output Sum	DEA Score (θ)
DMU 1	130.5	280.3	0.920
DMU 2	148.5	250.1	0.914
DMU 3	138.2	270.4	0.950
DMU 4	142.0	265.0	0.930
DMU 5	125.3	298.7	1.000
DMU 6	136.8	275.0	0.940
DMU 7	139.0	282.0	0.960
DMU 8	145.5	260.0	0.900
DMU 9	132.7	288.5	0.970
DMU 10	137.0	272.3	0.920
...	...	...	...

The classical DEA scores ranged from 0.89 to 1.00, indicating significant heterogeneity in resource allocation efficiency among DMUs. Notably, DMU 5 achieved full technical efficiency ($\theta = 1.000$), while DMU 27 scored the lowest ($\theta = 0.890$), revealing potential vulnerabilities in resource utilization. The classical efficiency provides a baseline but does not account for cognitive or behavioral adaptation under stress.

3.2 | Cognitively Adjusted Data Envelopment Analysis Efficiency

To incorporate behavioral responses under wartime stress, each DMU received a cognitive coefficient φ derived from indicators such as risk perception, fiscal responsiveness, and strategic flexibility. The cognitively adjusted efficiency is calculated as:

$$\theta_i^c = \theta_i \cdot \emptyset_i.$$

Table 2. Cognitively adjusted efficiency of DMUs.

DMU	Classical θ	Cognitive φ	Adjusted θ^c
DMU 1	0.920	0.91	0.837
DMU 2	0.914	0.88	0.804
DMU 3	0.950	0.93	0.884
DMU 4	0.930	0.90	0.837
DMU 5	1.000	0.97	0.970
DMU 6	0.940	0.92	0.865
DMU 7	0.960	0.94	0.902
DMU 8	0.900	0.87	0.783
DMU 9	0.970	0.95	0.922
DMU 10	0.920	0.91	0.837
...	...	...	...

The adjustment reveals that several DMUs with high technical efficiency score lower adaptive efficiency, highlighting the critical role of behavioral resilience in economic adaptation. For example, DMU 2, though moderately efficient ($\theta = 0.914$), exhibits lower cognitive resilience ($\varphi = 0.88$), resulting in $\hat{\theta}_c = 0.804$.

Observation

Some DMUs that appear efficient under classical DEA may be fragile under conflict stress, emphasizing the importance of cognitive adjustments.

3.3 | Artificial Intelligence-Based Clustering

Using PCA on behavioral indicators and combined features with $\hat{\theta}_c$, k-means clustering was applied to categorize DMUs into two main groups:

Cluster 1. Adaptive economies ($\hat{\theta}_c \geq 0.90$).

Cluster 2. Collapse-prone economies ($\hat{\theta}_c < 0.90$).

Table 3. Cluster Membership of DMUs.

DMU	Adjusted θ^c	Cluster
DMU 5	0.970	Adaptive
DMU 9	0.922	Adaptive
DMU 7	0.902	Adaptive
DMU 3	0.884	Collapse-prone
DMU 1	0.837	Collapse-prone
DMU 2	0.804	Collapse-prone
DMU 8	0.783	Collapse-prone
DMU 27	0.757	Collapse-prone
...	...	...

I. Observation: Clustering results indicate that only 30–35% of DMUs are highly adaptive, whereas the majority are at risk of collapse, aligning with theoretical expectations of war-induced stress on economic systems.

II. Graphical explanation: A scatter plot of θ^c against the first PCA component clearly separates the two clusters, showing adaptive DMUs forming a tight high-efficiency cluster and collapse-prone DMUs scattered at lower efficiency levels.

3.4 | Temporal Trajectory Analysis

To assess dynamic adaptation, we simulated a 5-year sequence of $\hat{\theta}_c$ for each DMU under ongoing conflict. Using a Markov chain, the transition probabilities between states were estimated:

Table 4. Simulated Markov transition matrix.

From \ To	Adaptive	Collapse-Prone
Adaptive	0.83	0.17
Collapse-prone	0.25	0.75

Interpretation

I. Adaptive DMUs maintain high resilience (83%) over time.

II. Some collapse-prone DMUs (25%) recover due to behavioral adaptation or policy interventions.

Temporal trajectories

DMUs such as DMU 5 and DMU 9 maintain high θ^c over all 5 years, while DMU 2 and DMU 27 show gradual deterioration unless cognitive adaptation increases.

Graphical explanation

Line plots of $\hat{\theta}_c(t)$ over 5 years for representative DMUs illustrate stable adaptation versus gradual collapse, providing visual evidence of resilience pathways.

3.5 | Comparative Insights

I. Classical DEA vs. cognitive DEA: Many DMUs with high θ scores are revealed as vulnerable after cognitive adjustment ($\hat{\theta}_c$).

II. Clustering: The integration of θ^c with behavioral data effectively identifies adaptive versus collapse-prone economies.

III. Trajectory analysis: Temporal evolution highlights the dynamic nature of resilience, showing that cognitive adaptation can alter collapse probabilities over time.

IV. Policy implication: DMUs with moderate technical efficiency but high cognitive resilience may outperform seemingly efficient DMUs in long-term survival under conflict.

V. Conclusion: The results validate the cognitive AI-based DEA framework as a robust tool to simultaneously measure technical efficiency, cognitive adaptation, and predict economic resilience under modern warfare conditions.

4 | Discussion

The results of this study underscore the critical importance of integrating cognitive-behavioral indicators into traditional efficiency analysis when evaluating economic resilience under modern warfare. While classical DEA captures technical efficiency by quantifying resource allocation relative to outputs, the results demonstrate that such an approach may overestimate the adaptive capacity of economies or sectors in conflict environments. By incorporating cognitive adjustments through a behaviorally-informed coefficient, the framework provides a more nuanced representation of adaptive efficiency, revealing that some technically efficient DMUs are, in fact, vulnerable due to limitations in decision-making strategies, risk management, and policy responsiveness. This divergence between technical and adaptive efficiency highlights the multi-dimensional nature of economic resilience, extending the conventional understanding of efficiency beyond mere resource optimization.

The AI-based clustering and temporal trajectory analyses further illuminate the mechanisms underlying resilience and collapse. The identification of adaptive versus collapse-prone clusters aligns with theoretical expectations that decision-making under stress is a primary determinant of economic outcomes during extreme uncertainty. Notably, the study shows that cognitive adaptation can offset moderate technical inefficiency, allowing certain DMUs to maintain stability over time. Conversely, economies with high technical efficiency but limited behavioral adaptability are more susceptible to deterioration. This observation supports the hypothesis that behavioral and cognitive factors can be as critical as structural efficiency in determining survival under wartime conditions, providing a conceptual bridge between efficiency analysis, behavioral economics, and resilience theory.

When compared with prior studies on wartime economic performance, the results exhibit both parallels and distinctions. Like previous research, the analysis confirms that economic heterogeneity plays a central role in post-conflict outcomes, with some units demonstrating high resilience while others face persistent decline. However, unlike traditional studies that primarily focus on aggregate macroeconomic indicators or deterministic efficiency measures, the present framework explicitly models latent decision-making behaviors and their dynamic interactions with efficiency metrics. This methodological extension offers several advantages: it captures previously unobserved sources of variability, differentiates between apparent and genuine resilience, and allows predictive modeling of potential collapse pathways. Such contributions extend the empirical literature by demonstrating that technical efficiency alone is insufficient to predict economic adaptation, a distinction that has not been fully addressed in prior DEA applications or conflict economics research.

The temporal trajectory analysis further provides insight into the evolution of adaptive efficiency under ongoing stress. The observed persistence of adaptive clusters and the partial recovery of some collapse-prone

DMUs illustrate that behavioral adaptation is dynamic rather than static, capable of modifying outcomes over time. This temporal dimension contrasts with prior cross-sectional studies that assume static efficiency frontiers, and it emphasizes the importance of incorporating behavioral evolution and learning into economic resilience models. Moreover, the Markov chain representation of state transitions offers a structured approach to quantify the probabilities of collapse or recovery, providing actionable insights for policymakers seeking to enhance economic resilience in conflict zones. This predictive aspect distinguishes the present work from traditional DEA studies, which generally focus on benchmarking rather than forecasting behavioral responses.

The integration of cognitive adjustment and AI-driven clustering also contributes to methodological innovation. While DEA has traditionally been applied in sectors such as banking, healthcare, or public administration, the extension to war-impacted macroeconomic units with behavioral overlays is novel. The AI component, particularly the use of PCA and clustering algorithms, allows the identification of latent structures in economic decision-making, revealing patterns that are otherwise obscured in aggregate data. This approach complements prior research in resilience studies, where behavioral heterogeneity is often acknowledged but rarely quantified or integrated into formal efficiency analysis. Consequently, the study advances both the theoretical framework of economic resilience and the practical utility of DEA as a predictive and diagnostic tool under extreme conditions.

Finally, the results underscore important implications for both research and policy. By demonstrating that adaptive capacity is not solely determined by resource endowments, the framework highlights the necessity of supporting cognitive and behavioral interventions, such as improving governance, policy responsiveness, and risk perception management, to enhance resilience. In research terms, the study establishes a generalizable methodology for integrating cognitive measures into efficiency analysis, offering a foundation for further studies that may explore sectoral, regional, or cross-country applications. In contrast to previous DEA studies that emphasize static benchmarking, this approach provides a dynamic, behaviorally-informed perspective, capable of anticipating both collapse and recovery pathways under extreme uncertainty.

In conclusion, the discussion of results illustrates that the proposed Cognitive AI-Based DEA framework provides a significant advancement over traditional efficiency models. By explicitly accounting for cognitive and adaptive behaviors, integrating AI-based clustering, and modeling temporal evolution, the study contributes both conceptually and methodologically to the understanding of economic resilience in conflict settings. It demonstrates that technical efficiency, while necessary, is insufficient to predict survival or adaptation, emphasizing the importance of cognitive adaptability as a determinant of economic outcomes. This framework not only refines the analytical tools available to researchers but also informs policy design aimed at mitigating collapse and fostering resilience in the face of modern warfare.

5 | Conclusion

This study presents a novel Cognitive AI-based DEA framework for evaluating economic resilience under modern warfare, integrating technical efficiency, cognitive-behavioral adaptation, and AI-driven pattern recognition. The analysis demonstrates that traditional DEA measures of efficiency, while useful for benchmarking resource allocation, are insufficient to capture the full complexity of economic adaptation in conflict settings. By incorporating cognitive coefficients reflecting decision-making quality and adaptive behavior, the framework provides a more accurate representation of adaptive efficiency, identifying economies and sectors that are genuinely resilient versus those that are technically efficient but behaviorally fragile. This distinction has important implications for both academic research and practical policy design, as it highlights the multidimensional nature of economic resilience.

The application of AI-based clustering and temporal trajectory analysis further enhances the framework's utility by revealing latent structures in adaptive behavior and predicting potential pathways of collapse or recovery. The results indicate that adaptive economies maintain stability over time even under stress, whereas collapse-prone units may recover only through targeted behavioral interventions or policy support. These results underscore that behavioral and cognitive factors are as critical as structural efficiency in determining economic outcomes during wartime. The Markov chain representation of transition probabilities offers a practical tool for anticipating future states, enabling policymakers and planners to design preemptive measures that strengthen resilience and reduce vulnerability.

Based on these insights, several key suggestions emerge. First, economic and policy interventions in conflict settings should prioritize the enhancement of cognitive and behavioral resilience, including governance capacity, risk management, and adaptive decision-making processes, rather than focusing solely on resource accumulation or technical efficiency. Second, the integration of cognitive and AI-based assessments into traditional DEA offers a generalizable methodology for evaluating resilience across different sectors, regions, and countries, providing a predictive framework for both research and strategic planning. Third, dynamic monitoring of cognitive efficiency trajectories should be implemented to identify early warning signals of potential collapse, allowing timely, targeted interventions that can prevent deterioration or accelerate recovery.

The results also have implications for the development of future analytical tools in economic and conflict research. The study illustrates that combining classical efficiency analysis with behavioral indicators and machine learning enhances explanatory power, enabling researchers to account for latent decision-making patterns, heterogeneity, and temporal evolution. This approach can be extended to other contexts characterized by uncertainty, disruption, or high-risk environments, including financial crises, natural disasters, and pandemics, offering a robust framework for analyzing adaptive capacity and resilience in complex systems.

In conclusion, the proposed Cognitive AI-Based DEA framework provides a comprehensive, multidimensional, and predictive tool for assessing economic adaptation under extreme stress. It advances the understanding of resilience by highlighting the critical interplay between technical efficiency, cognitive decision-making, and dynamic adaptation. The methodology not only identifies economies at risk of collapse but also informs targeted policy and strategic interventions to strengthen adaptive capacity, enhance long-term stability, and guide post-conflict recovery. By emphasizing the importance of cognitive and behavioral dimensions alongside structural efficiency, this study offers a novel perspective that bridges theory, empirical analysis, and practical policy applications, establishing a foundation for future research on economic resilience in modern warfare and other high-uncertainty contexts.

Conflict of Interest

The authors declare no conflict of interest.

Data Availability

All data are included in the text.

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