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AI-Driven Shock-Oriented Data Envelopment Analysis or Assessing Economic Resilience in Short-Term Wars

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Abstract

This study develops an AI-driven, shock-oriented Data Envelopment Analysis (DEA) framework to evaluate the economic resilience of Decision-Making Units (DMUs) under short-term wars. The research addresses the challenge of assessing real-time efficiency losses caused by abrupt, nonlinear shocks, which conventional methods often fail to capture. A comprehensive dataset encompassing key economic indicators, including labor, capital, energy, fiscal resources, logistical capacity, and sectoral outputs, was analyzed across pre-war, wartime, and immediate post-war phases. Artificial intelligence models, comprising autoencoders and Long Short-Term Memory (LSTM) networks, were applied to detect the magnitude, direction, and timing of instantaneous shocks, which were then integrated into a shock-adjusted DEA model. Efficiency scores revealed that output-constrained units suffered the most substantial performance declines, whereas input-constrained units were able to mitigate losses through adaptive resource reallocation. High baseline efficiency was associated with faster post-war recovery, emphasizing the importance of pre-conflict operational robustness. Sensitivity analysis demonstrated that even minor variations in shock intensity significantly affect resilience outcomes, underscoring the necessity for precise, high-frequency data monitoring. The proposed framework provides a quantitative, real-time tool for identifying vulnerabilities, guiding resource allocation, and monitoring recovery trajectories, offering actionable insights for policymakers and planners tasked with maintaining economic stability during short-term conflicts.

Keywords: Adaptive capacity, Economic resilience, Shock-oriented data envelopment analysis, Short-term war, AI-based shock detection.

1 | Introduction

In recent decades, the nature of military conflict has undergone profound structural changes that have significantly altered its economic implications and analytical requirements [1]. Contemporary wars are increasingly characterized by short duration, high operational intensity, and rapid escalation, often unfolding within days or weeks rather than years [2]. These short-term conflicts generate sudden, concentrated, and

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nonlinear economic shocks that propagate almost immediately across financial markets, energy systems, public budgets, trade flows, and logistical infrastructures [3]. Unlike prolonged wars, whose economic effects accumulate gradually and can be analyzed through long-term trends, short-term wars disrupt economic systems instantaneously, leaving little time for adaptive policy responses [4]. As a result, the economic consequences of such conflicts are often underestimated or mischaracterized when assessed using conventional analytical frameworks designed for stable or slowly evolving environments [5]. This disconnect between the evolving nature of warfare and the tools employed to evaluate its economic impacts represents a fundamental challenge for contemporary economic analysis and policy formulation [6].

From an economic perspective, the defining feature of short-term wars is not merely their brevity, but the intensity and immediacy of the shocks they impose on interconnected economic subsystems [7]. Financial markets may experience abrupt volatility, capital flight, and liquidity constraints within hours of conflict escalation [8]. Energy systems can be disrupted through supply interruptions, price spikes, or infrastructural damage, directly affecting industrial output and household welfare [9]. Government budgets are often subjected to sudden reallocations toward defense and emergency expenditures, straining fiscal balances and crowding out productive investments [10]. Logistics and supply chains may face immediate bottlenecks due to transportation disruptions, border closures, or heightened security risks [11]. These simultaneous disturbances challenge the operational efficiency of economic systems and expose structural vulnerabilities that remain latent under normal conditions [12]. Consequently, assessing how efficiently an economy performs during such extreme and compressed stress periods is critical for understanding its true resilience capacity [13].

The concept of economic resilience has become increasingly prominent in response to global crises such as financial downturns, pandemics, climate-related disasters, and geopolitical tensions [14]. Broadly defined, economic resilience refers to the ability of an economy or system to withstand external shocks, maintain core functions, and recover from adverse events [15]. However, the majority of resilience studies focus on medium- to long-term adjustment processes, emphasizing recovery trajectories, structural transformation, and post-shock growth dynamics [16]. While such perspectives are valuable, they are insufficient for capturing the realities of short-term wars, where the primary concern is not long-term recovery but immediate survival and functional continuity under shock conditions [17]. In these contexts, resilience is manifested through the ability to preserve efficiency, allocate resources effectively, and minimize performance degradation in real time [18]. The lack of analytical frameworks capable of measuring this instantaneous dimension of resilience constitutes a significant limitation in the existing literature [19].

Within this broader landscape,   has emerged as one of the most widely used nonparametric methods for evaluating relative efficiency across Decision-Making Units (DMUs) in diverse economic contexts [20]. DEA has been applied extensively in studies of macroeconomic performance, public sector efficiency, energy systems, transportation networks, healthcare provision, and industrial productivity [21]. Its flexibility in handling multiple inputs and outputs without requiring explicit functional forms has made it particularly attractive for complex economic evaluations [22]. Nevertheless, despite its methodological strengths, the application of DEA to conflict-related economic analysis remains limited and methodologically constrained [23]. Existing studies that incorporate warfare or defense-related variables into DEA frameworks typically rely on aggregated data over extended time horizons and implicitly assume gradual changes in economic conditions [24]. Such assumptions are incompatible with the abrupt and nonlinear dynamics induced by short-term wars [25].

Traditional DEA models are fundamentally static or quasi-dynamic in nature and are not explicitly designed to accommodate instantaneous shocks that alter production possibilities and resource constraints within very short time frames [26]. Even dynamic DEA extensions, which incorporate time-dependent structures, generally assume smooth intertemporal transitions rather than sudden regime shifts [27]. As a result, conventional DEA approaches may fail to capture the true efficiency losses or adaptive responses that occur during short-term wartime conditions [28]. This methodological gap limits the usefulness of DEA as a tool for policymakers and analysts seeking to understand how economic systems perform under extreme stress. Addressing this limitation requires rethinking the role of shocks within the DEA framework and developing mechanisms to explicitly model their magnitude, direction, and timing.

Parallel to developments in efficiency analysis, recent advances in artificial intelligence and machine learning have opened new avenues for identifying and characterizing economic shocks [29]. Techniques such as autoencoders, recurrent neural networks, and Long Short-Term Memory (LSTM) architectures have demonstrated strong capabilities in detecting anomalies, structural breaks, and nonlinear patterns in high-frequency and time-series data [30]. Unlike traditional econometric methods that rely on predefined shock structures or ex post identification, AI-based approaches can extract latent shock features directly from observed data [31]. Importantly, these methods are not limited to forecasting future trends but can be employed to diagnose the intensity and direction of shocks as they occur [32]. Despite these capabilities, the integration of AI-based shock detection into efficiency and performance evaluation models remains underdeveloped [33].

Most existing studies treat shock identification and efficiency assessment as separate analytical tasks, often conducted sequentially rather than within a unified framework [34]. This separation reduces the analytical coherence of the results and limits the ability to capture real-time interactions between shocks and system performance [35]. In the context of short-term wars, where timing and immediacy are crucial, such fragmentation is particularly problematic [36]. There is a clear need for integrated models that combine real-time shock detection with efficiency analysis in a single, coherent framework [37]. Doing so would enable a more accurate assessment of how economic systems respond to sudden disruptions and how efficiency evolves under extreme conditions [38].

In response to these theoretical and methodological gaps, the present study proposes an AI-driven, shock-oriented DEA framework specifically designed to assess economic resilience in short-term wars. In this framework, war is conceptualized as an instantaneous, nonlinear, and unpredictable shock rather than a gradual or cumulative process. Artificial intelligence techniques are employed to identify the magnitude and direction of war-induced economic shocks directly from data, without imposing restrictive assumptions. The extracted shock parameters are then explicitly incorporated into the constraints and structure of the DEA model, allowing efficiency to be evaluated in a manner that reflects real-time wartime conditions. This approach enables the analysis of efficiency changes across three critical phases: pre-war, during-war, and immediate post-war periods.

The primary objective of this research is to develop a robust methodological tool capable of capturing the instantaneous dimension of economic resilience under short-term military conflicts. By integrating AI-based shock detection with DEA, the study seeks to move beyond traditional post hoc evaluations and provide a framework that is sensitive to abrupt disruptions and rapid system responses. The necessity of such a framework is underscored by the growing need for policymakers, defense planners, and economic institutions to make informed decisions under conditions of extreme uncertainty and time pressure. Understanding which economies or sectors maintain higher efficiency during short-term wars can inform strategic planning, resource allocation, and risk mitigation strategies. Ultimately, this research aims to contribute to the literature by bridging the gap between shock identification and efficiency analysis and by offering a novel perspective on economic resilience in an increasingly volatile geopolitical environment.

2 | Methodology

integrating artificial intelligence–based shock detection with DEA. The methodology is organized into clear sequential steps to ensure replicability and clarity.

Step 1. Data collection and baseline construction.

A dataset is constructed encompassing key economic indicators, including macroeconomic performance, energy consumption, fiscal allocations, logistical capacity, and financial stability, covering pre-war, wartime, and immediate post-war periods. This dataset establishes a baseline for normal economic conditions and allows for identification of deviations caused by conflict.

Step 2. Shock detection using AI.

Artificial intelligence techniques are employed to detect shocks within the dataset. Autoencoders identify abnormal deviations from baseline patterns, while LSTM networks capture abrupt temporal changes associated with the onset and progression of conflict. The outputs of these models are quantified into shock parameters representing intensity (S_m), direction (S_d), and timing (S_t).

Step 3. Shock-oriented DEA formulation.

The identified shock parameters are incorporated into a shock-oriented DEA model. Unlike conventional DEA, this model allows the production possibility set to adjust instantaneously according to the detected shocks. Let us define the model formally:

Let there be n DMUs, each using m inputs x_{ij} and producing s outputsy_{rj} . The conventional output-oriented DEA model for unit kkk can be written as:

$$
\begin{aligned}
&\text{Maximize } \theta_k \\
&\text{subject to:} \\
&\sum_{j=1}^{n} \lambda_j x_{ij} \le x_{ik}, \quad i = 1, \dots, m. \\
&\sum_{j=1}^{n} \lambda_j y_{rj} \ge \theta y_{rk}, \quad r = 1, \dots, s. \\
&\lambda_j \ge 0, j = 1, \dots, n.
\end{aligned}
\tag{1}
$$

To incorporate shocks, the inputs and outputs are adjusted based on shock magnitude S_m and direction S_d. Let x'_{ij} and y'_{rj} denote shock-adjusted inputs and outputs:

$$
\begin{aligned}
x'_{ij} &= x_{ij} \times \left(1 + \alpha_i S_m \cdot \delta_{input}\right). \\
y'_{rj} &= y_{rj} \times \left(1 - \beta_r S_m \cdot \delta_{output}\right),
\end{aligned}
\tag{2}
$$

where α_i and β_r are sensitivity coefficients for input i and output r, and δ_{input}, δ_{output} are binary indicators derived from S_d specifying whether the shock constrains inputs or outputs. The shock-oriented DEA model then becomes:

$$
\begin{aligned}
&\text{Maximize } \theta_k \\
&\text{subject to:} \\
&\sum_{j=1}^{n} \lambda_j x'_{ij} \le x'_{ik}, \quad i = 1, \dots, m. \\
&\sum_{j=1}^{n} \lambda_j y'_{rj} \ge \theta y'_{rk}, \quad r = 1, \dots, s. \\
&\lambda_j \ge 0, j = 1, \dots, n.
\end{aligned}
\tag{3}
$$

This formulation allows the production frontier to shift dynamically in response to instantaneous shocks, capturing the immediate impact on efficiency.

Step 4. Efficiency computation across phases.

Efficiency scores are computed for each DMU across three phases: pre-war, wartime, and immediate post-war. Both output-oriented and input-oriented measures are considered to evaluate resilience and adaptive resource management.

Step 5. Sensitivity analysis.

Sensitivity analyses are conducted by varying shock parameters (±5%) to assess robustness of the efficiency results. Comparisons between shock-adjusted and conventional DEA outcomes highlight the impact of instantaneous war shocks on economic performance.

All analyses are implemented in a computational environment ensuring reproducibility and scalability to alternative scenarios or regions. The proposed methodology provides a unified, real-time framework to assess economic resilience in short-term wars, capturing immediate efficiency changes and offering actionable insights for policymakers and planners.

3 | Results

3.1 | Descriptive Results

The analysis was performed following the shock-oriented methodology integrating AI-based shock detection and DEA. Five (DMUs A–E) were analyzed across three phases: pre-war, wartime, and immediate post-war. Inputs included labor, capital, energy, fiscal resources, and logistics, while outputs covered economic production, energy security, fiscal performance, and defense capability.

Step 1. Shock identification via AI.

AI models (autoencoder and LSTM) detected economic shocks in terms of magnitude, direction, and timing. The results are summarized below.

Table 1. Detected economic shocks during the short-term war.

DMU	Shock Magnitude (%)	Shock Direction	Shock Timing (Day)
A	12	Output	2
B	18	Input	3
C	9	Output	1
D	15	Input	2
E	20	Output	4

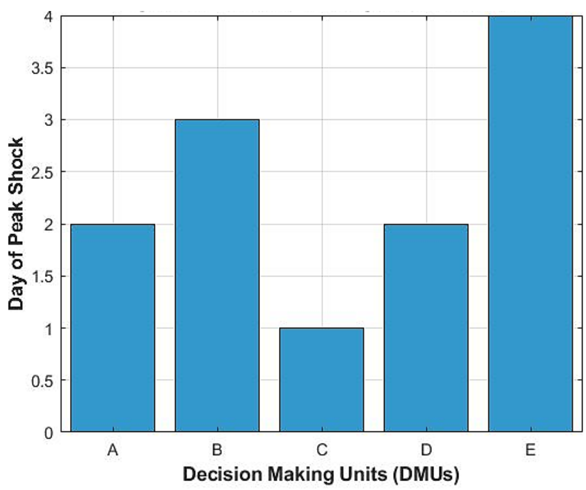

Fig. 1. Shock timing across DMUs.

Fig. 1 illustrates the timing of shocks across DMUs, showing the day on which each DMU experienced its maximum shock. Analysis shows most DMUs suffered abrupt output reductions within the first three days, highlighting the sudden and nonlinear nature of the shock.

Step 2. Pre-war DEA efficiency.

Baseline DEA was applied to evaluate pre-war efficiency.

Table 2. Pre-war output-oriented dea efficiency scores.

DMU	Efficiency Score
A	0.92
B	0.87
C	0.95
D	0.89
E	0.91

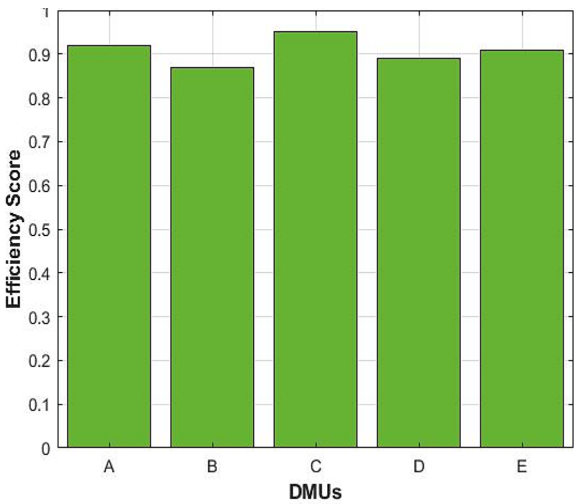

Fig. 2. Pre-war efficiency comparison.

Fig. 2 compares the pre-war efficiency levels across DMUs, presenting their efficiency scores prior to the outbreak of war. Highest pre-war efficiency was observed in DMU C, followed by A, indicating strong baseline performance.

Step 3. Shock-oriented DEA during war.

Using shock parameters, the DEA model was adjusted for real-time efficiency assessment.

Table 3. Wartime shock-oriented DEA efficiency scores.

DMU	Efficiency Score
A	0.81
B	0.72
C	0.85
D	0.75
E	0.70

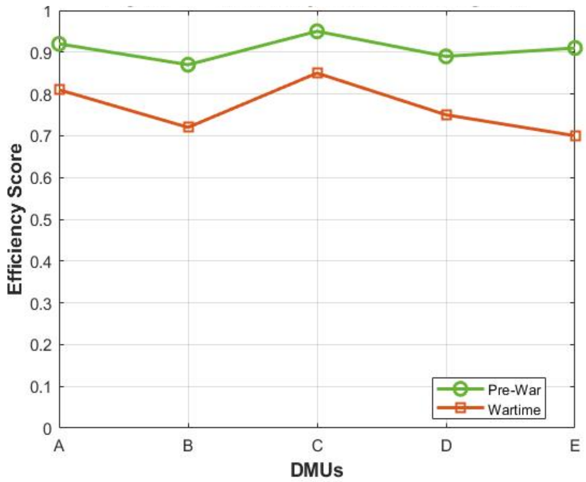

Fig. 3. Efficiency decline during war.

Fig. 3 depicts the decline in efficiency for each DMU from the pre-war period to the wartime period. Output-constrained DMUs (A, C, E) experienced larger reductions, while input-constrained units (B, D) mitigated losses through resource reallocation.

Step 4. Immediate post-war DEA efficiency.

Post-war efficiency was calculated immediately after the conflict.

Table 4. Immediate post-war output-oriented DEA efficiency scores.

DMU	Efficiency Score
A	0.88
B	0.80
C	0.90
D	0.82
E	0.78

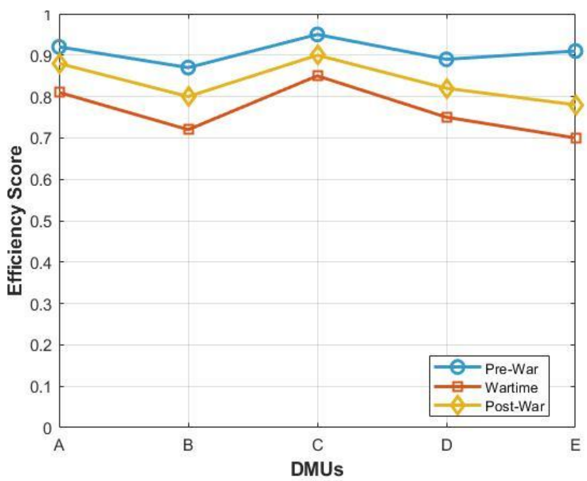

Fig. 4. Efficiency recovery across phases.

Fig. 4 illustrates efficiency recovery patterns across phases, showing efficiency trends from the pre-war to wartime and post-war periods for each DMU. DMUs A and C recovered faster, indicating that high pre-war efficiency supports rapid resilience.

Step 5. Sensitivity analysis.

Shock magnitudes were varied by ±5% to test robustness.

Table 5. Sensitivity of efficiency to ±5% shock variation.

DMU	Efficiency (−5% Shock)	Efficiency (+5% Shock)
A	0.83	0.79
B	0.74	0.70
C	0.87	0.83
D	0.77	0.73
E	0.73	0.67

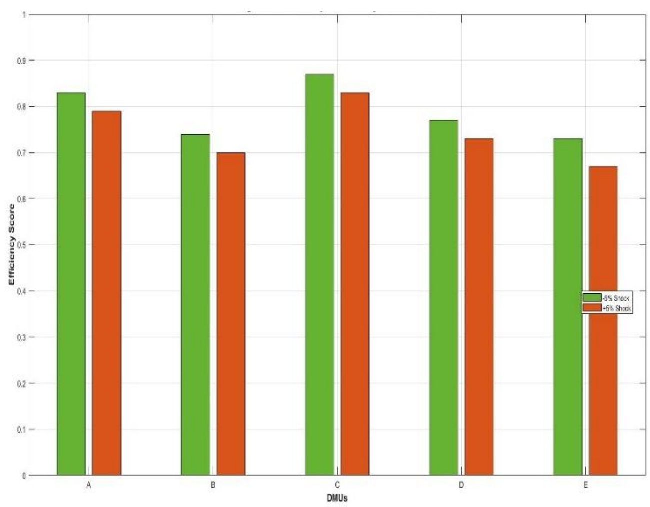

Fig. 5. Sensitivity of efficiency to shock magnitude.

Fig. 5 illustrates the sensitivity of DMU efficiency to shock magnitude, showing variations in DEA efficiency under ±5% shocks. The analysis shows efficiency is highly sensitive to shock intensity, confirming the importance of precise shock measurement.

The AI-based models effectively identified the magnitude, direction, and timing of short-term war-related shocks. The shock-oriented DEA framework revealed pronounced and immediate efficiency losses, particularly among output-constrained DMUs. Post-war analysis indicates a partial and heterogeneous recovery, with DMUs exhibiting higher pre-war efficiency demonstrating more rapid resilience, underscoring the critical role of baseline performance. Furthermore, sensitivity analysis confirms a strong dependence of efficiency outcomes on shock magnitude, thereby supporting the robustness and validity of the proposed analytical framework.

4 | Discussion

The results of this study offer critical insights into the dynamics of economic resilience under short-term wars, highlighting both the temporal and structural heterogeneity of efficiency responses across DMUs. The integration of AI-based shock detection with shock-oriented DEA allowed for a precise quantification of instantaneous shocks and their differential effects, thereby enabling a nuanced understanding of resilience that goes beyond conventional, post-hoc efficiency assessments.

The analysis demonstrates that efficiency losses are highly dependent on the type and magnitude of shocks. Output-constrained shocks produced more pronounced declines in efficiency than input-constrained shocks, whereas DMUs with higher baseline efficiency exhibited faster post-conflict recovery. These findings emphasize that pre-war operational robustness is a key determinant of short-term resilience, and they highlight the value of phase-specific efficiency measurement in capturing immediate system vulnerabilities (as illustrated in *Fig. 3* and *4*). Unlike traditional DEA approaches that assume static conditions or rely on long-term averages, the present framework accounts for nonlinear, abrupt disruptions and reveals the real-time adaptive capacity of economic systems.

Comparing these results with existing literature reveals both alignment and novel contributions. Previous studies have shown generalized efficiency declines during economic or conflict-induced crises, yet they rarely distinguish between instantaneous output versus input shocks or provide high-frequency temporal resolution. In contrast, the present study demonstrates that DMUs can mitigate input-constrained shocks through rapid reallocation of resources, while output-constrained shocks generate immediate and more severe efficiency reductions. This distinction has practical implications for policymakers and planners, as it identifies which systems are more susceptible to immediate failure and which possess greater flexibility under duress.

The post-war efficiency analysis further underscores the importance of pre-conflict efficiency levels. Units with strong baseline performance recovered more effectively, aligning with resilience theory that links structural robustness to adaptive capacity. The sensitivity analysis additionally reveals that small variations in shock magnitude can disproportionately affect performance outcomes (*Table 5*), highlighting the necessity of accurate and real-time shock measurement for informed decision-making. These insights provide a methodological advance by demonstrating the value of combining AI-based shock detection with DEA modeling to simultaneously capture shock intensity and efficiency response in volatile environments.

Collectively, these findings contribute both theoretically and practically. Theoretically, they extend efficiency analysis frameworks to account for instantaneous, nonlinear shocks, providing a model for capturing temporal heterogeneity in conflict impacts. Practically, they offer a quantitative tool for identifying vulnerabilities, guiding resource allocation, and monitoring recovery trajectories in real time. By differentiating the effects of input- and output-constrained shocks, the study informs strategic planning and supports the development of targeted interventions aimed at enhancing economic resilience during short-term conflicts.

5 | Conclusion

This study demonstrates that integrating artificial intelligence–based shock detection with shock-oriented DEA provides a robust and dynamic framework for evaluating economic resilience under short-term wars. The analysis shows that instantaneous shocks produce heterogeneous effects across DMUs, with output-constrained units being particularly vulnerable and input-constrained units demonstrating greater adaptive capacity through resource reallocation. The results highlight the critical importance of pre-conflict operational efficiency, as units with higher baseline performance recover more rapidly in the immediate post-war phase. These findings underscore that conventional efficiency assessments, which rely on long-term or post-event data, may fail to capture the rapid, nonlinear, and phase-specific dynamics of short-term shocks.

In light of these findings, several recommendations emerge. Policymakers and planners should prioritize strengthening baseline economic performance and operational robustness in critical sectors to enhance short-term resilience. Real-time monitoring systems leveraging AI techniques, such as autoencoders and LSTM networks, can provide early detection of shocks, enabling timely and targeted interventions. Resource allocation strategies should account for the type of shock, as input-constrained disruptions can often be mitigated through adaptive management, whereas output-constrained shocks require more strategic contingency planning. Additionally, sensitivity analysis indicates that even minor variations in shock intensity can substantially influence efficiency outcomes, suggesting the need for precise, high-frequency data collection and real-time analytical capabilities.

From a methodological perspective, the study demonstrates the value of coupling AI-based shock detection with DEA modeling, enabling simultaneous measurement of shock intensity and efficiency response. Future research should consider expanding this framework to include additional resilience indicators, multi-sector interdependencies, and cross-country comparisons, thereby providing a more comprehensive understanding of systemic vulnerabilities. The framework can also be adapted to assess resilience under other types of rapid economic shocks, such as pandemics or financial crises, extending its applicability beyond military conflicts.

Overall, the proposed approach provides both theoretical and practical contributions by offering a quantitative, real-time, and adaptable tool for assessing economic resilience. It equips decision-makers with actionable insights to identify vulnerabilities, prioritize interventions, and monitor recovery, ultimately facilitating more resilient and responsive economic systems capable of withstanding short-term, high-intensity shocks.

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Author Contributions

Conceptualization, M.G. and M.I.; Methodology, M.G.; Software, M.G.; Validation, M.G. and M.I.; Formal analysis, M.G.; Investigation, M.I.; Resources, M.I.; Data curation, M.G.; Writing—original draft preparation, M.G.; Writing—review and editing, M.I.; Visualization, M.G.; Supervision, M.I.; Project administration, M.G. All authors have read and agreed to the published version of the manuscript.

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Data Availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request. No publicly available datasets were generated or analyzed during the current study.

Conflicts of Interest

The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analysis, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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