A systems-based analysis of energy demand reduction policies success using fuzzy cognitive maps

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ABSTRACT

Energy demand reduction (EDR) policies are crucial for addressing both energy security and climate change. However, despite their strategic importance, they often face significant barriers, including institutional resistance, limited funding, and short-term political priorities that tend to overlook long-term efficiency gains. This study utilizes fuzzy cognitive maps (FCMs) to model the factors influencing EDR policy effectiveness across European countries. To capture the importance and interrelation of factors predefined from the literature, expert knowledge was leveraged through interviews with European energy agency representatives. Qualitative expert assessments were then transformed into numerical values, generating weighted causal matrices. Centrality measures subsequently identified key factors within an aggregated European model. Results revealed six pivotal factors: continuous financial support, favourable regulatory frameworks, consumer engagement, ease of implementation, long-term policy mandates, and support from industry and stakeholders. Scenario analysis explored the impact of three policy interventions: increased market actor support, weakened monitoring frameworks and increased energy literacy for end-consumers. The results of the interventions indicated that isolated interventions had limited impact on overall EDR system outcomes, underscoring its complexity. However, consumer literacy initiatives mitigated negative behavioural effects, such as rebound effects and misaligned targeting, while weakened monitoring frameworks diminished policy coherence and increased redundancies. These findings reinforce the need for long-term policy stability, regulatory clarity, and robust end-user engagement. A systems-based approach, accounting for interdependencies and system dynamics, is crucial for effective EDR policy design, as isolated interventions are insufficient.

Keywords

Energy Demand Reduction (EDR); Fuzzy Cognitive Maps (FCMs); Systems-Based Approach; Climate and energy policy; Scenario Analysis

Introduction

Europe's energy landscape is being reshaped by geopolitical shocks, notably the Russian invasion of Ukraine, which exposed the risks of reliance on volatile fossil fuel markets. Traditionally framed around security, affordability, and sustainability (Sovacool & Mukherjee, 2011), energy policy is now increasingly skewed toward short-term security, often at the cost of climate and social goals. Many countries are expanding fossil fuel imports, delaying the energy transition and deepening inequalities (Zhang & Wang, 2024). Yet this response reveals a paradox: true energy security depends on accelerating the shift to a more resilient and sustainable system. Fossil fuel dependence invites volatility, while renewables and demand-side strategies offer greater stability and autonomy (Pollitt et al., 2024). Energy Demand Management (EDM) is central to this shift. It includes three key approaches: (1) improving energy efficiency (EE), (2) reducing consumption through energy demand reduction (EDR) strategies like sufficiency and behavioural change, and (3) increasing demand flexibility to better align use with supply (Barrett et al., 2022). Beyond cutting emissions and enhancing security, EDM improves health, comfort, and equity (Borragán et al., 2023; Finn & Brockway, 2023), stabilizes the grid (Ribó-Pérez et al., 2021), and addresses unequal energy use (Büchs et al., 2023).

Over the past decade, European energy policies have increasingly adopted efficiency obligations, promoting more rational energy use and reducing waste (Bertoldi & Mosconi, 2020). Research on energy-saving behaviours has enabled targeted interventions, while the concept of energy sufficiency—meeting needs without excess—is gradually gaining traction (Best et al., 2022). Technological advances further bolster the case for Energy Demand Management (EDM). Despite some reductions, final energy consumption per capita in the EU decreased by just 1% between 2000 and 2022 (Odyssee-MURE, 2023). Much of this modest change is due to the relocation of industrial activities, rather than deep domestic shifts. While industry has declined, transport and services sectors have seen demand rise—driven by factors like increased mobility and a transition to a service-based economy. Though this shift can improve energy intensity (FEC/GDP), it still leads to higher absolute consumption (Marrero & Ramos-Real, 2013). The EU has embedded the "energy efficiency first" principle into its energy strategy, focusing largely on improving energy intensity. However, this approach may fall short, as efficiency gains are often offset by rising activity levels—especially in transport, where technological advances have been outweighed by larger vehicles, longer distances, and growing demand (Ruzzenenti & Basosi, 2008). Key drivers of this transition include the Energy Efficiency Directive (EED), revised multiple times since its 2006 introduction (Economidou et al., 2020), and reinforced by National Energy Climate Plans (NECPs) and Energy Efficiency Obligation Schemes (EEOS), adopted by all 27 Member States by 2023 (EUR-Lex, 2023). The Energy Performance of Buildings Directive (EPBD) has also been pivotal, introducing benchmarks like NZEBs and EPCs to elevate building standards. Yet, implementation challenges persist. Assumptions embedded in policy design often diverge from real-world outcomes (Gupta & Sushil, 2024). Reducing demand is a sociotechnical challenge requiring not just innovation, but alignment with institutional, cultural, and historical systems (Sorrell, 2015). A lack of systemic understanding can hinder progress, as isolated interventions risk reinforcing existing consumption patterns. As Stroh (2015) argues, system optimization depends on understanding the relationships among parts, not just improving individual components. Systemic approaches have already yielded insights in areas like wind energy deployment (Ghaboulian Zare et al., 2022), participatory water governance (Shahvi et al., 2021), and circular bioeconomy pathways (Morone et al., 2021). Building on this, the present study explores the broader ecosystem of factors shaping the success of EE and EDR policies. The central research question is:

> "*What are the key systemic factors and interactions that determine the success of energy demand reduction policies, and can relatively simple, scenario-based simulations support the design of more effective interventions?*"

To answer this question, we draw on expert knowledge to identify the drivers that can be activated to facilitate policy implementation. We also explore how different scenarios affect the broader system dynamics.

The study employs Fuzzy Cognitive Mapping (FCM) as a system mapping tool to analyse the network of interactions influencing EE/EDR policy success. This method helps to capture the system's structure and behaviour, facilitating the development of an expert-informed model for testing alternative policy pathways (Perusich, 1996). As part of this approach, we implemented three intervention scenarios to explore how different system configurations, including support for industry and stakeholders, reduced monitoring efforts, and increased energy literacy among consumers, influence policy outcomes. These simulations are intended to identify key leverage points, potential unintended consequences, and feedback effects within the system.

Methods

Fuzzy Cognitive Maps (FCM)

Fuzzy Cognitive Maps (FCMs) are a way to model complex systems using expert knowledge. First introduced by Kosko (1986), FCMs improve on traditional cognitive maps by allowing relationships between elements to be flexible rather than fixed. In an FCM, key ideas or factors are shown as nodes (e.g., N1, N2, N3), connected by arrows that represent how one factor affects another. These arrows have weights between –1 and +1. A positive number means one factor increases the other, a negative number means it decreases the other, and zero means there's no effect. Unlike models that only use yes/no or on/off values, FCMs use a range of values to reflect how strongly one factor influences another. This makes them useful for understanding the complexity of real-world situations (Parreño & Pablo-Martí, 2024; Mkhitaryan et al., 2022).

Mathematical Representation of an FCM

An FCM can be conceived as a simplified model in which nodes and weighted causal relationships form a connection matrix, with each element representing the strength of a specific relationship. The formal mathematical definition of an FCM is as follows:

- *E* is defined as a function from N × N to K, where K ∈ [−1,1]. Each element e_{ij} corresponds to a pair of concepts (N_i, N_j), representing the direct causal weight (i.e., the arc) from node N_i to N_j. For all $i \neq j$, e_{ij} takes a real value in the interval [-1,1]; for $i = j$, $e_{ij} = 0$, meaning there are no self-loops.
- The connection matrix W, also known as the adjacency matrix, captures all causal influences in the system and is expressed as:

$$W = \begin{bmatrix} e_{11} & e_{12} & \cdots & e_{1n} \\ e_{21} & e_{22} & \cdots & e_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ e_{n1} & e_{n2} & \cdots & e_{nn} \end{bmatrix}$$

Equation 1

- Connections between nodes can be expressed as:

$$C(t+1) = f(C(t) + W * C(t))$$

Equation 2

where:

- C(t +1) r refers to the state of the system at the next time step
- C(t) is the state vector representing the activation levels of all nodes at iteration t.

- W is the connection matrix.
- f is the transformation function, often a logistic function used to confine values within a bounded range [0,1].

Simulation and dynamic behaviour of an FCM

The core strength of an FCM lies in its ability to simulate system behaviour over multiple iterations. This is achieved by repeatedly updating the state of each node based on the causal influences exerted by other nodes. The simulation process starts with an initial state vector, which specifies starting values for all concepts (nodes). The values of nodes are then updated through multiple iterations, incorporating the cause-effect relationships defined in the FCM. During each iteration, the state of a node is updated based on the weighted sum of influences from connected nodes, adjusted by a transformation function — typically a logistic or hyperbolic tangent — to constrain values within a predefined range, such as [0,1] or [-1,1] (Mkhitaryan et al., 2022). The iterative process continues until the system reaches stability or equilibrium, meaning that node values no longer significantly change between iterations. In some cases, oscillatory or chaotic behaviour may emerge, reflecting feedback loops or instabilities in the modelled system.

Data acquisition

To construct the system maps, 13 experts from 11 energy agencies across Europe were interviewed, representing organizations such as Oeko-Institut and DENA (Germany), Energy Saving Trust (UK), RVO (Netherlands), ADENE (Portugal), AEA (Austria), SIEA (Slovakia), Energimyndigheten (Sweden), Informa Echo (Slovenia), DEA (Denmark), CENER (Spain), and SEAI (Ireland). Prior to the interviews, experts were provided with a list of factors and their definitions (Mkhitaryan et al., 2020), which had been previously identified based on two key literature sources addressing similar issues (Renders et al., 2018; Warren, 2015) (see Table S1). They were asked to review these factors beforehand to ensure familiarity with the content. The online interviews, each lasting approximately one hour, began with an introduction to the research question: "*What are the key factors contributing to the success of energy demand reduction policies in your country?*" Two definitions were provided to clarify the concepts of "*success*" and "*energy demand reduction policies*".

- Success in energy demand reduction policies was referred as:
  "*Achieving targeted reductions in energy consumption, enhancing energy efficiency, and meeting set objectives. It involves reducing energy usage, promoting sustainable practices, gaining public support, and delivering positive environmental, social, and economic outcomes*" (European Energy Research Alliance, 2023).
- Energy demand reduction policies were on its turn defined as:
  "*Policies that encompass various strategies aimed at decreasing energy consumption. These strategies include traditional concepts like energy efficiency as well as more nuanced approaches such as energy sufficiency. Additionally, they involve promoting "behavioural change," which influences decision-making patterns to facilitate the successful adoption of energy efficiency and sufficiency measures*".

Participants were then given a brief introduction to FCMs, including an explanation of their purpose and what was expected from them during the interview. To facilitate understanding, they were provided with clear instructions and a visual representation illustrating a simple FCM example.

> *"Fuzzy cognitive maps (FCM) are a tool that helps us organize and understand our thoughts about a particular topic. It's like creating a mental picture or model of how we perceive the issue. FCM focuses on how different factors or variables interact with each other".*

Participants were guided through three key aspects of FCM construction: (1) identifying the factors influencing the system, (2) determining the direction of relationships between variables (whether positive or negative), and (3) assessing the strength of these relationships using linguistic ratings (Very High, High, Medium, Low, Very Low) to enhance clarity in expressing the magnitude of connections (Mkhitaryan et al., 2022). During the interview, a neutral facilitation approach was used to ensure that participants reflected on the direction and strength of relationships without being influenced by the interviewer. They were also encouraged to introduce additional factors beyond the 19 pre-identified ones if they believed certain elements were missing. Once the mapping exercise was complete, participants received their constructed FCM and were invited to review, refine, or modify any connections or elements to ensure accuracy and completeness.

Analysis: Fuzzy cognitive map modelling in this work

Fuzzy logic processing and defuzzification in FCMs

Once the data was collected, fuzzy logic was applied in line with the FCM methodology to convert the linguistic ratings provided by experts (Very High, High, Medium, Low, Very Low) into numerical weights. This process utilized partial membership functions, which assign varying degrees of membership within a fuzzy set (Mkhitaryan et al., 2022). The fuzzy set is mathematically defined as:

$$\mathrm{A}= \{(x, \mu_{\mathrm{A}}(\mathrm{x})|\mathrm{x} \in U)\}$$

Equation 3

where,

- A represents the fuzzy set.
- x represents an element in the universe of discourse U.
- $\mu_A(x)$ represents the degree of membership of element x in set A.

The FCMpy Python module developed by Mkhitaryan et al. (2022), applying a triangular membership curve, was used to convert linguistic ratings into numerical weights (Mkhitaryan et al., 2022). The resulting membership functions were then aggregated both at the energy agency level (if more than two expert maps were available) and across all energy agencies. The family maximum aggregation operation was applied to determine the most likely cluster for a data point during the aggregation process of FCMs.

$$Max_{Family}\{\mathrm{A}^1, \mathrm{A}^2, \mathrm{A}_\mathrm{n}\} = \max\{\, a \in U \mid a \in A^i for\ some\ i \in \{1,2, \dots, \mathrm{n}\}\}$$

Equation 4

where,

- $\mathrm{Max}_{\mathrm{Family}}$: This represents the family maximum operation.
- A^1, A^2..., A^n: These represent the individual sets in the family (can be any number of sets).
- max: This represents the maximum function.
- a: This represents an element within the universe of discourse (set of all possible elements).
- U: This represents the universe of discourse.
- i ∈ {1,2,…,n}: Specifies that the element a must belong to at least one of the sets A^i.

The final step involved defuzzification using the centroid method to convert fuzzy memberships into crisp values for each data point (Mkhitaryan et al., 2022). This process calculates the centre of gravity of the cluster by applying a weighted sum, where the membership degree $\mu_c(x_i)$ serves as the weight for each data point x_i. Data

points with higher membership values, indicating a stronger association with the cluster, contribute more significantly to the weighted sum, ultimately determining the centroid's location.

$$centroid_c = \frac{\Sigma\left(\mu_c(x_i) * x_i\right)}{\Sigma\left(\mu_c(x_i)\right)}$$

Equation 5

where,

- $centroid_c$: It represents the final crisp value for cluster c.
- $\mu_c(x_i)$: The membership degree of data point xi in cluster c.
- x_i: The i-th data point in the dataset.
- $\sum\mu_c(x_i)$: The sum of all membership values within the cluster.

System centrality

In the context of Fuzzy Cognitive Maps (FCMs), centrality measures help identify the most influential concepts within a network by analysing the structure and strength of connections in the weight matrix. These measures highlight key nodes that drive information flow and significantly impact system behaviour. In this work, we calculate two complementary centrality measures: degree centrality and closeness centrality.

Degree centrality (overall connection count) is based on the assumption that important nodes tend to have more connections. It calculates the total number of connections (both incoming and outgoing edges) a concept has. A concept with high degree centrality is highly connected and potentially plays a significant role in information flow within the FCM. The formula is as follows:

$$centrality_{degree}(v) = \frac{d_v}{(|N| - 1)}$$

Equation 7

where,

- dv: is the degree of node v
- N: total number of nodes in the network

Closeness centrality measures how quickly information can be spread from a concept to all others. A concept with high closeness centrality is, on average, closer to all other concepts, suggesting it might be a key point for information dissemination. Closeness centrality is calculated by summing the shortest path lengths from the given concept (node) to all other concepts in the network. Shorter path lengths indicate more direct connections, allowing for potentially faster information flow. The formula is as follows:

$$centrality_{closeness}(v) = \frac{(|N| - 1)}{\Sigma d(v, j)} \text{ for all } j \neq v$$

Equation 8

where,

- $|N|$: Total number of nodes in the network

- j: represents all other nodes in the network except for node v ($j \neq v$)
- d(v, j): shortest path length between node v and node j

Scenario analysis

A combined approach was applied to generate the scenario analysis, where all interventions were based on modifications of baseline values for existing factors within the FCM (single-shot intervention; see Mkhitaryan et al., 2021). The creation and testing of scenarios aim to assess how varying conditions affect the system, providing insights into their influence on the primary goal in this study (the successful implementation of EDR policies) as well as on broader system dynamics, thanks to the captured dynamic interrelationships among the model's core concepts. Based on current policy and market trends, three scenarios were defined. These scenarios were predefined, and their descriptions are as follows:

- Scenario 1 examines how increased support from market actors, driven by R&D investments, impacts EDR efforts. It assumes strong participation from industry and stakeholders.
- Scenario 2 simulates the effects of deteriorating policy conditions on monitoring and evaluation, reflecting potential negative consequences for policy control and implementation.
- Scenario 3 explores the effects of providing targeted information to users to promote energy-saving behaviours.

Before conducting the simulations, the system's initial states were defined using an AI-based estimation tool to establish a baseline for scenario analysis. These estimates provided a structured starting point for modelling the system's behaviour under varying conditions. Based on these initial values, the system's equilibrium was computed using the *FcmSimulator* module from the *FCMpy* package (Mkhitaryan et al., 2022). To ensure convergence, the model was allowed a maximum of 50 iterations to reach a steady state prior to applying the different scenario interventions. To update the concept values over each discrete simulation steps, we employed the modified Kosko inference method:

$$A_i^{(t+1)} = f\left(A_i^{(t)} + \sum_{j=1}^{n} A_j^{(t)} * w_{ji}\right)$$

Equation 9

where,

- $A_j^{(t)}$: is the concept j at the simulation step t
- w_{ji} is the causal impact of concept j on concept i

A sigmoid transfer function was applied to the result to keep values within the [0,1] range.

$$f(x) = \frac{1}{1 + e^{\lambda x}}, x \epsilon \mathbb{R}$$

Equation 10

where,

- x: is the value calculated by applying the Kosko inference method

- λ: is steepness parameter for the sigmoid function

Results

Causal relationship strengths

Experts from the consulted European countries identified an average of 33 causal links between factors, with a 95% confidence interval ranging from 26.52 to 40.39. The distribution of linguistic terms used to describe these relationships was asymmetrical, with a higher frequency of positive associations. The calculated crisp values for each country, derived from the aggregated membership functions using the centroid method, were subsequently aggregated across all countries. This process quantified the strength of causal relationships at a global level. Figure 1 illustrates the causal relationship strengths between all the factors considered in the system (F1 to F23) by displaying the intensity and direction of their influence. The rows represent the cause factors, while the columns represent the effect factors. The colour gradient indicates the nature of these relationships: red shades signify a positive causal relationship, where an increase in one factor strengthens another, whereas blue shades indicate a negative causal relationship. This matrix enables the visualization of interdependencies, revealing factors that are highly interconnected, such as F4 ("Ease of Implementation"). Strong relationships between factors can be detected, such as F3 exerting a strong positive influence on F10 (0.9) or F12 negatively affecting F8 (-0.8), highlighting critical dependencies within the system. In addition, feedback loops (see Figure 2) can be identified within the system. For instance, a reinforcing loop between F2, F19, and F9, that illustrates how technological innovation (F2) enhances cost-effectiveness (F19) by making energy solutions more affordable and efficient (F2 → F19, +0.8). As technologies become more cost-effective, policymakers are more inclined to introduce favourable regulations (F9) that support these advancements (F19 → F9, +0.8). In turn, these favourable regulations stimulate further technological development by encouraging R&D investments, accelerating market adoption (F9 → F2, +0.6). The net effect of the reinforcing loop is positive, where each factor amplifies the next, creating a self-sustaining cycle of technological progress, cost-effectiveness, and regulatory support. Similarly, balancing loops can be observed in the matrix. For instance, greater flexibility in adopting changes (F10) decreases the lack of monitoring (F15) (F10 → F15, -0.8), as adaptable policies encourage more active and responsive oversight, ensuring compliance and effectiveness. Conversely, when monitoring is weak (F15 increases), policymakers tend to reduce flexibility (F10) (F15 → F10, -0.8) by imposing stricter controls to prevent inefficiencies or misuse. This balancing loop maintains a stable policy environment, allowing for adaptability while ensuring that monitoring remains effective and regulatory oversight is not compromised (see Figure 2).

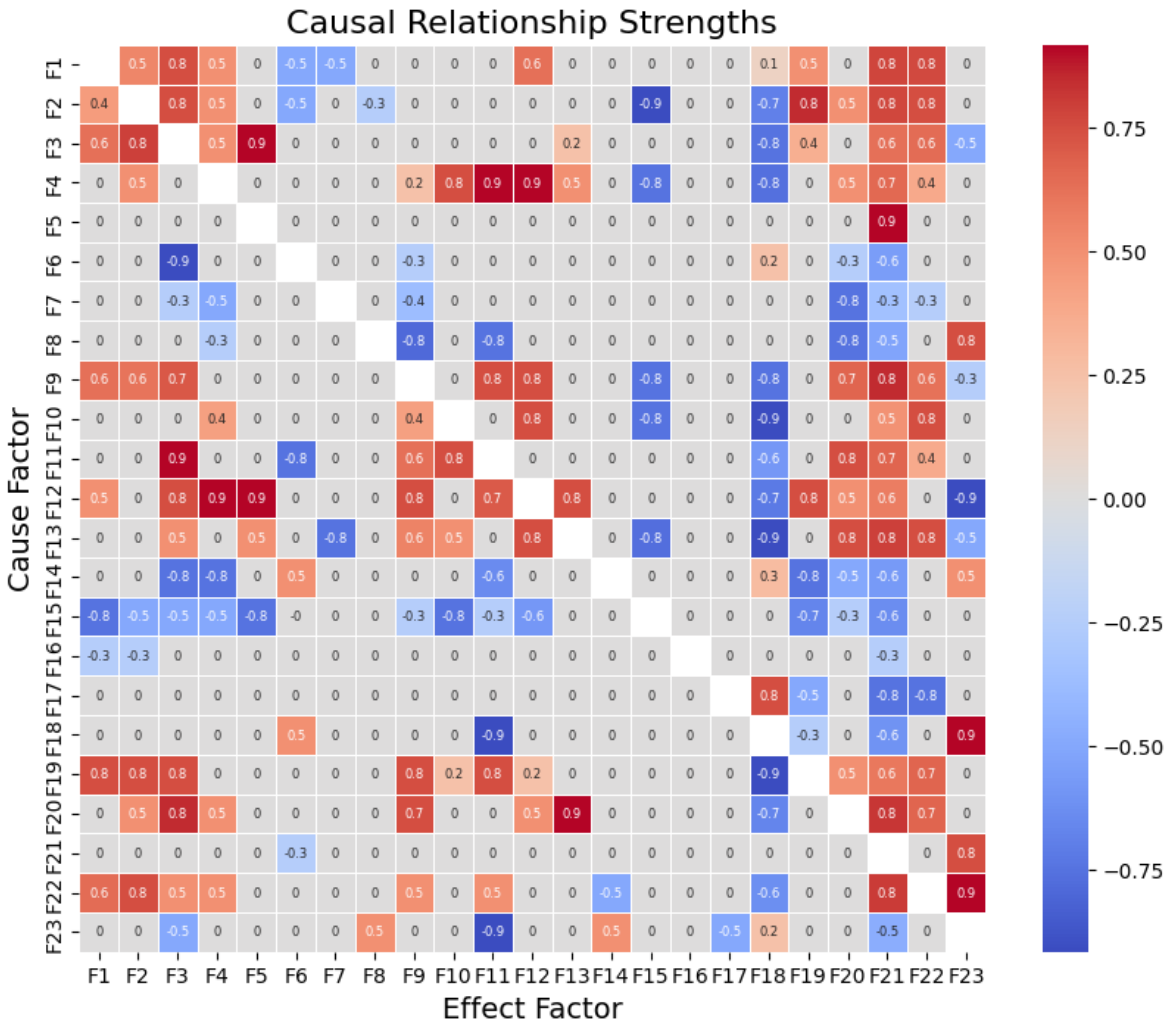

Figure 1: Matrix depicting the causal relationships among the different factors and the target (F21). Values are computed applying fuzzy logic to the linguistic terms used by experts to assess the relationships among the factors involved in the study and then aggregated to identify a unique causal strength.

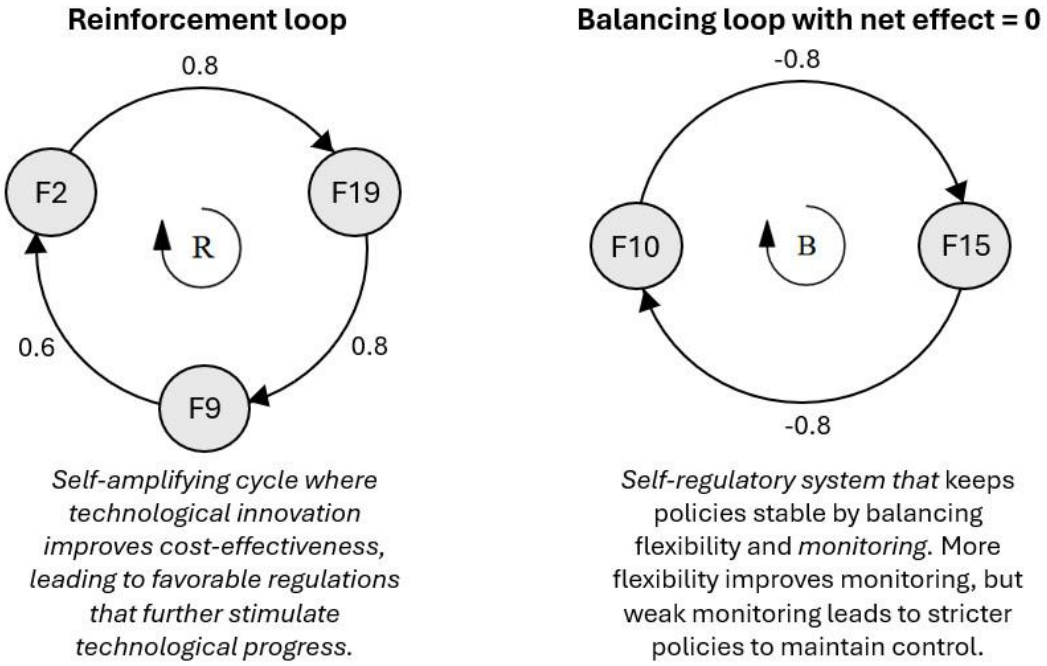

Figure 2: Diagram illustrating two feedback loops in the system.

Centrality analysis of factors shaping EDR policy success

Centrality measures were applied in this study to identify the most influential factors within the system, highlighting key nodes that either disseminate information widely or play a critical role in shaping system behaviour. Two centrality metrics were calculated: degree centrality, which identifies factors with numerous connections, and closeness centrality, which assesses how efficiently a factor spreads information across the system. The results (degree centrality; closeness centrality) indicate that the same set of factors ranked highest in both measures, underscoring their central role in promoting successful energy demand reduction (EDR) policies. These factors, which include favourable regulatory frameworks (0.82; 0.85), continuous financial support (0.82; 0.85), support from industry and stakeholders (0.73; 0.79), stable long-term policy with a clear mandate (0.73; 0.79), ease of implementation (0.73; 0.79), and poor consumer engagement (0.78; 0.81), exhibit high degree centrality, meaning they serve as key drivers in the system. Notably, poor consumer engagement shows a negative weight, suggesting a potentially detrimental effect on EDR policy outcomes. These factors were also the ones displaying higher closeness centrality, confirming their ability to efficiently transmit information across the system.

Scenario comparison

The next step in the analysis involved simulating system behaviour under a series of predefined scenarios, designed to explore how specific conditions may influence the success of EDR policies. Prior to running simulations, the system was initialized and brought to a steady state (equilibrium was found after 7 iterations), establishing a baseline for comparative analysis. Figure 3 presents the simulation results as percentage changes in factor values across different scenarios referred hereafter as interventions. Intervention 1, which introduced direct monetary support for industry and stakeholders, resulted in no significant changes across the system. However, the Intervention 2 that hindered policy monitoring, led to a 25% increase in overlapping or conflicting policies, and a slight decline (−2.9%) in ease of implementation. Intervention 3, promoting energy literacy,

reduced negative effects related to inappropriate group targeting (−20%) and behavioural rebound effects (−5.6%). Crucially, none of the interventions produced meaningful changes in the overall success of EDR policies, suggesting that the system is robust and resistant to isolated interventions.

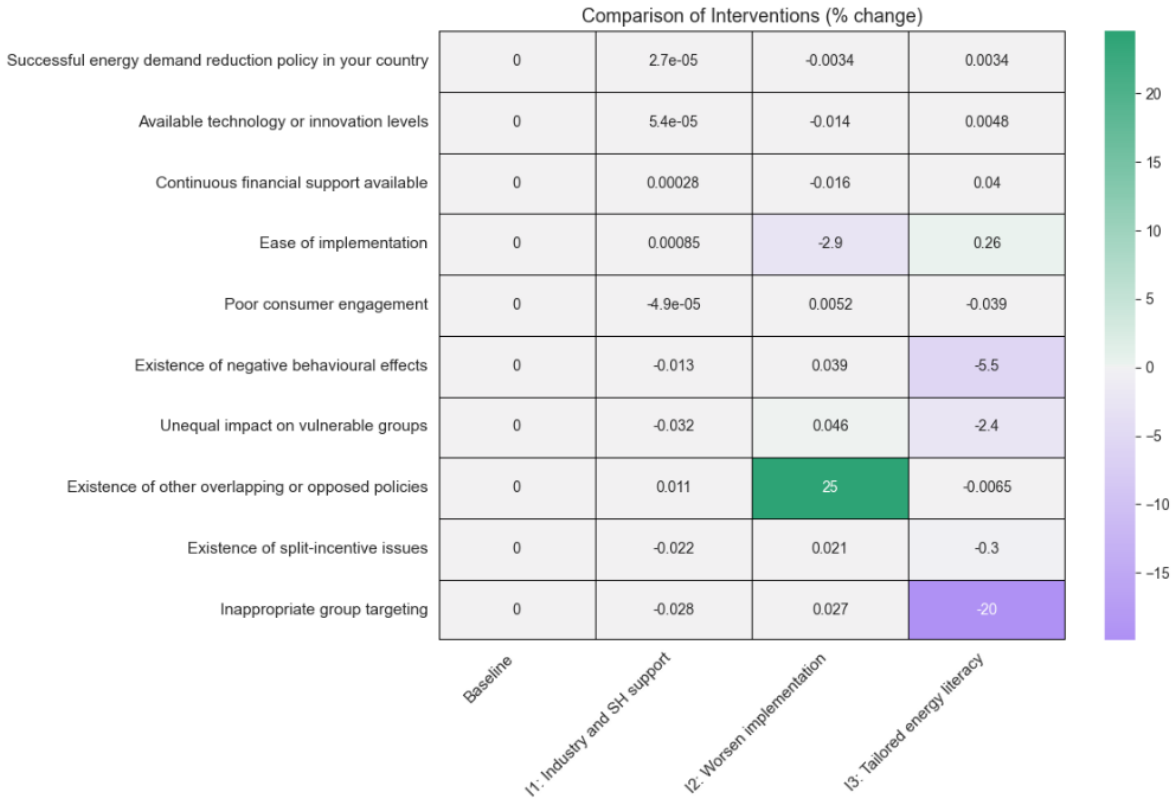

Figure 3: Heatmap matrix presenting the results of the simulated interventions (x-axis). The values reflect the direct effects (%) of each intervention on selected system factors (y-axis). To enhance readability, only the ten most central and influential factors are displayed.

Discussion

This study applied Fuzzy Cognitive Mapping (FCM) to capture expert insights on national-level dynamics influencing the success of energy demand reduction (EDR) policies. Centrality analysis identified six key factors: *Continuous financial support available*, *Favourable regulatory frameworks*, *Poor consumer engagement*, *Ease of implementation*, *Stable long-term policy with a clear mandate*, and *Support from industry and stakeholders*. These emerged as central nodes, suggesting they are not only highly connected but strategically positioned to influence other elements in the system. Both degree and closeness centrality confirmed their prominence, indicating that these nodes act as critical hubs—capable of accumulating and disseminating influence. In contrast, nodes with high degree but low closeness are locally important but poorly placed to affect the broader system, while high closeness and low degree nodes may be well-positioned but exert limited direct influence. From a policy perspective, the identified factors represent key leverage points, where interventions could yield broad ripple effects. These findings align with previous research. Sorrell et al. (2015) emphasized long-term stability and coherent regulation, while Moe et al. (2016) highlighted stakeholder support and consumer engagement. The case of Finland illustrates how stable mandates foster innovation in technologies like insulation and heat pumps. Conversely, the UK's fragmented policy landscape demonstrates how inconsistency leads to diminished effectiveness (Kern et al., 2017). Notably, several highly central nodes, such as *Ease of implementation* and *Continuous financial support*, exhibited low entropy, indicating strong expert consensus.

Prior studies echo this emphasis on implementability and robust financial mechanisms (Bertoldi et al., 2021; Sovacool, 2011). The simulation of policy interventions revealed varied effects. Increased support for industry and stakeholders (Intervention 1) showed limited system impact, likely due to node activation saturation in the FCM. However, the results highlighted a feedback loop between industrial engagement and technological innovation—consistent with findings that innovation is key for meaningful industrial participation (Dyer et al., 2008). In contrast, weakened policy monitoring and evaluation (Intervention 2) significantly reduced ease of implementation and increased policy overlap. This reinforces concerns about the EU's institutional complexity, which many experts see as a barrier to effective evaluation (Lenz et al., 2024; Schoenefeld, 2021). Promotion of energy literacy (Intervention 3) showed positive spillovers—mitigating poor targeting and behavioural rebound effects. These findings are in line with López-Bernabé et al. (2022), who found that environmental education helped reduce household heating costs. Behavioural responses remain pivotal in the energy transition, influencing not only demand patterns (Barrett et al., 2022) but also aspects like the integration of distributed energy resources (Borragán et al., 2024). Ultimately, this work underscores the need to challenge the long-standing assumption that increased consumption equates to economic well-being (Brown & Gathergood, 2020; Guillen-Royo, 2019).

Interestingly, none of the tested interventions had a major impact on the success of EDR policies, showing that the system is both stable and resistant to change. This aligns with research on complex energy systems, which often remain resilient due to their interconnected nature (Mutingi et al., 2017). It highlights a key challenge: EDR policies are shaped by many interacting factors, making them difficult to influence through isolated actions. Small changes—like slight increases in funding or minor regulatory adjustments—are often not enough to shift the system meaningfully. Without considering how these elements interact, such changes risk having little effect and may lead to inefficient use of public resources. Research suggests that combining multiple policy tools tends to produce stronger, cumulative effects (López-Bernabé et al., 2022; Morone et al., 2021). Therefore, a systems-based approach is essential. Policymakers need to understand the broader web of relationships within the system to design effective interventions that create lasting impact.

Study limitations

This study has several limitations. First, expert interviews revealed a sectoral bias, with respondents emphasizing their own domains. Although the diverse expert panel helped mitigate this, some focused mainly on EDR in industry, while others concentrated on buildings. Future research could explore sector-specific models, linked by common influencing factors. This would involve parallel testing, where experts assess models independently by sector. The findings underscore the value of more granular, less aggregated approaches—particularly for sectors like buildings, specific industries, and transport.

Conclusions

System mapping provides a structured framework for evaluating EDR policies, going beyond traditional analytical methods that typically examine direct relationships between individual drivers and policy goals. Instead, it captures the broader network of interactions within the policy landscape. This study underscores the complexity of transforming a system as intricate as EDR through isolated actions. Although factors like sustained financial support, favourable regulation, and consumer engagement emerged as central, adjustments to these alone did not significantly improve policy success. However, some interventions showed impact: cutting resources for monitoring and evaluation reduced effectiveness due to increased policy overlap, while targeted energy literacy programs effectively addressed issues like poor targeting and behavioural rebound effects, offering practical pathways for implementation.

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