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Perceived influence structures of resilience capabilities in agri-food supply chains and the role of big data analytics: Insights from a fuzzy hybrid decision model

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ABSTRACT

The agri-food supply chain (AFSC) needs resilience beyond organizational and dyadic levels due to its complex adaptive nature and increasing number of disruptions. Based on the investigation of expert perceptions, this study aims to explore the influence structure of social-ecological resilience capabilities to aid in understanding the complexity of resilience and informing decision making. Moreover, the prioritization of big data analytics (BDA) practices can support agri-food entities in adopting best practices for resilience improvement by using a fuzzy hybrid multiple-criteria decision analysis approach. To contribute to the two aims, first, responses from 26 distinguished supply chain resilience scientists were analyzed using a fuzzy DANP approach to uncover the influence relationships and priority weights of 19 organization, supply chain, and industry level social-ecological resilience capabilities. Second, 14 BDA practices categorized into three groups of sensing, seizing, and transforming—based on the dynamic capabilities perspective—were prioritized as judged by a total of 19 managers in three large food retailers using a fuzzy TOPSIS model, considering their assessed contribution to strengthening resilience capabilities. These capabilities have also been triangulated with secondary data to contextualize and corroborate case descriptions. The findings suggest the high prominence and net influence of adaptability and agility, alongside the centrality of collaboration, supply flexibility, and risk-aware culture within the elicited influence structure in AFSCs. Production and supply chain managers and policymakers in AFSCs can use the results to assess organizational, supply chain, and industry resilience, guiding strategic planning based on identified capability interdependencies and priority weights. In addition, retail managers can use the evaluation method to reach a consensus in their organization to better understand and implement the critical BDA practices that are prioritized for resilience enhancement in their specific context.

1. Introduction

The sustainability, survivability, and stability of nations worldwide depend on the security, availability, and accessibility of reasonably priced food (Bellemare, 2015; Brinkman and Hendrix, 2011). The agriculture industry, responsible for cultivating, processing, distributing, warehousing, and retailing food products is affected by various disruptions such as geopolitical conflicts, which cause a ripple effect beyond the firm-level throughout the supply chain (SC) (Dolgui et al., 2018).

Recently, the vulnerability of the food sector and its entities was brought under the spotlight after several disruptive events shook not only the food organizations but the whole industry, for instance, the impact of the COVID-19 pandemic (Hobbs, 2020), the Russian-Ukrainian Conflict (Jagtap et al., 2022), and climate change (Wieland et al., 2023). The vulnerability exposed by unpredictable disruptions showcases the high complexity and interconnection of the food system on various levels. The highly efficient and lean structure of the agri-food supply chain (AFSC) is usually effective at countering the low profit margins (Hobbs,

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2020) but leaves AFSC vulnerable in an era of frequent disruptions. For instance, the COVID-19 pandemic disrupted the access to raw materials (e.g., seeds), leading to decreased production output and missing the plantation season (FAO, 2023). This reduction resulted in retailers having empty shelves or increasing their prices, affecting the consumers' lifestyle or cost of living despite the intervention of governments, illustrating the ineffectiveness of solely relying on reactive measures to counter disruptions (Kazancoglu et al., 2024). Thus, to secure availability and accessibility of sufficient amounts of food, AFSC not only requires a more comprehensive and inclusive view of itself and its components' resilience but also to take advantage of modern technological innovations in the field (Ali and Govindan, 2023; Belhadi et al., 2024; Sharma et al., 2025; Sutar et al., 2024).

Traditionally, SC and AFSC resilience was dominated by the engineering resilience view (Castillo, 2023), which considers the SC a closed-loop system under the control of managers (Wieland and Durach, 2021). This is primarily due to the field's roots in industrial engineering and mathematical modeling. Latest research discussed the inability of the engineering view of resilience to fully capture the reality of the system under study. Wieland et al. (2023) discuss resilience in light of recent black swan events, in particular, what we can learn from social-ecological resilience to adapt and transform. From this perspective, we argue that AFSC is a social-ecological system that requires the same kind of resilience to ensure the movement of food products from farms to retailers to consumers (Stone and Rahimifard, 2018; Wieland and Durach, 2021).

Social-ecological resilience draws on the persistence, adaptation, and transformation of organizations and SCs depending on the effective use of resilience's formative capabilities, which is still in infancy and requires further research (Akpınar and Ozer Caylan, 2023). Current literature has compiled lists of resilience capabilities and explained them from organizational and SC levels in the AFSC (Stone and Rahimifard, 2018; Zhao et al., 2022). Still, several issues have not been resolved yet that keep SCs in general and AFSC in particular from achieving higher resilience levels: first, the interrelationships among resilience capabilities remain largely untested (Sharma et al., 2025; Stadtfeld and Gruchmann, 2024). Second, the empirical validation of assumed influence structures of resilience capabilities remains unaddressed (Sharma et al., 2025). Third, social-ecological resilience needs further exploration in the AFSC domain due to its specific nature explained above (Padovano and Ivanov, 2025), and fourth, recent literature called for elaborating the theory on SC resilience by integrating different scales (time, space, and function) to it. This development is however still in its infancy with only some conceptual (Novak et al., 2021) or qualitative contributions (Sauer et al., 2022). In effect, these scales are overlooked in the SC literature as firm resilience is used as a proxy for SC resilience (Choi et al., 2025; Novak et al., 2021). Moreover, scholars in this field argue that research should expand the scope of resilience capabilities into the critical agriculture industry (Ramezankhani et al., 2018). This can be achieved by (i) evaluating AFSC resilience capabilities beyond the context of the pandemic (Kumar et al., 2022); (ii) incorporating a wider range of AFSC resilience capabilities (Sharma et al., 2023); (iii) using hybrid approaches to discover the most important capabilities (Kazancoglu et al., 2024); (iv) exploring the influence structure among the resilience capabilities (Sharma et al., 2025); and (v) researching risk analysis and technology adoption using multi-criteria decision analysis (MCDA) models (Greco et al., 2025; Kumar et al., 2022), especially to explore the relative salience and interdependence of resilience capabilities in technology adoption (Akpınar and Ozer Caylan, 2023). Thus, the first research objective (RO) of this study is the following:

RO 1. Quantifying the relative importance of social-ecological resilience capabilities and modeling the perceived influence structures among them based on expert judgment to establish a weighted framework for social-ecological resilience decision-making.

Beyond the research on resilience in general in SCs and AFSC, it has been found that the intervention of advanced technologies can counter

the uncertainty caused by the disruption in the AFSC (Belhadi et al., 2024). It is thus relevant to apply the abovementioned perspective to the use of technologies in AFSC since Industry 4.0 technology adopters in the agri-food industry have reported less exposure to SC risks compared to non-adopters (Ali and Govindan, 2023). Furthermore, recent findings highlight that big data analytics (BDA), among ten other Industry 4.0 technologies, was identified as top three contributors to AFSC resilience and impacting almost all resilience capabilities (Sharma et al., 2025). The benefits of BDA in identifying vulnerabilities and calculating real-time solutions have been instrumental in countering disruptions (Li et al., 2023) since BDA's influence on resilience spans many of AFSC processes, ranging from its positive influence on the resilience of upstream actors (Asgari, 2025) and can enhance the resilience of last-mile food delivery (Alaeddini and Asgari, 2025). Therefore, due to its variability and immense potential, exploring BDA constructs and underlying mechanisms stands to support AFSC resilience and SC resilience theory (Hasan et al., 2024).

Some scholars have suggested exploring BDA capability in enhancing visibility and responsiveness, which are key capabilities of resilience, in the SC (Zamani et al., 2023), while others have called for expanding the proactive and reactive dimensions of resilience to gain richer insights into resilience creation through BDA (Jiang et al., 2024). In AFSC resilience, the influence of BDA on the readiness, response, and recovery phases has received minimal discussion, and further research on the social-ecological resilience has been emphasized due to a lack of research on adaptability and transformability (Asgari, 2025). As the final step in the AFSC, the food retail sector is prone to constant changes in customer preferences, which requires adaptive resilience to survive and thrive (Sutar et al., 2024). Given the inherent trade-offs and limited resources preventing AFSC managers from relying on resilience capabilities and BDA practices at the strategic and operational levels, prioritizing BDA practices to enable resilience is necessary for the global resilience of the agri-food system and its entities (Alaeddini and Asgari, 2025). While previous research has relied on more subjective measures to explore the influence of BDA on resilience, MCDA methods have been recommended to investigate these links more transparently and systematically (Singh et al., 2025). This will deepen our understanding of resilience capabilities and extend them by learning from the agricultural sector and developed countries (Opoku, 2025). Thus, the second RO is as follows:

RO 2. Developing a decision-aiding, case-specific ranking model of BDA practices to support organizational, SC, and industry level resilience through the lens of dynamic capabilities.

To address the research gaps and achieve the stated objectives, we extracted AFSC resilience capabilities focused on social-ecological resilience from the literature for RO1. For RO2, we reviewed the literature on BDA micro-foundations and used a dynamic capabilities perspective to frame them. For the analysis, we selected a hybrid MCDA methodology using fuzzy DEMATEL-ANP (f-DANP) and fuzzy TOPSIS (f-TOPSIS) because of its strength in capturing conflicting or complementary views of experts and managing the associated uncertainty and subjectivity of experts' opinion. We applied these on both the experts' judgments on influence structures (Dytczak and Ginda, 2013) between social-ecological resilience capabilities as well as the judgments of various department managers of three large retailers in Europe and the Middle East to derive a structured prioritization of BDA micro-foundations in relation to the weighted resilience capability system. Our findings show the high centrality of risk-aware culture and adaptability, as well as the significant net influence of agility, adaptability, and compliance flexibility within the perceived influence structure judged by the experts. Regarding BDA, each organization prioritized different BDA practices to enhance resilience based on their strategies, current capabilities, strengths, and weaknesses when facing previous disruptions and lessons learned.

Drawing on gaps in previous research regarding untested interrelationships, the lack of consensus on central resilience capabilities

and their associated weights, the need for decision-relevant and transparent measures for BDA's influence, and the call for expanding theoretical application of resilience in AFSCs, our contributions are fourfold. First, we move beyond the engineering view of resilience and empirically explore social-ecological resilience capabilities within the AFSC context to examine their interdependencies and centrality as structured expert knowledge. Based on a vertical contrasting approach to theory elaboration (Fisher and Aguinis, 2017), we distinguish social-ecological resilience capabilities in three spatial scales across the levels of industry, SC and organization to investigate the interplay of these scales (Novak et al., 2021; Sauer et al., 2022). This addresses the need for a more comprehensive understanding of resilience beyond unweighted lists and controlled environments (Choi et al., 2025). We therefore contribute to validating prior conceptual claims about the complexity of social-ecological resilience structures by providing one of the first empirical investigations and indicating a need to move beyond simplistic top-down or bottom-up approaches (Choi et al., 2025). Second, we provide expert-elicited, fuzzy-aggregated weights for resilience capabilities, offering a transparent prioritization of critical areas for development and means for resilience-oriented decisions in AFSCs. These results contribute to the contextual applicability (Fisher and Aguinis, 2017) of the social-ecological resilience capabilities in the AFSCs field and can guide AFSC managers. Our findings underscore the dominant influence of SC level capabilities in AFSCs over the more redundancy-oriented capabilities emphasized in engineering studies and other sectors (Piffari et al., 2026). Third, adopting the dynamic capabilities perspective, we identify and rank the BDA micro-foundations prioritized by managers for enhancing resilience in three distinct food retail settings. Only four of the 14 practices are perceived to be central to all retailers. This contributes to our understanding of the deeply rooted context- and industry-specificity of BDA micro foundations (Wu et al., 2024). Lastly, we demonstrate the utility of fuzzy hybrid MCDA methods for prioritizing resilience capabilities and BDA practices in complex and uncertain environments based on expert judgments, advancing their practical application. Across these contributions, the primary form of generalization is analytical (Yin, 2018), involving the transferability of constructs, framework, and decision logic, while the perceived weights and rankings remain context-bounded to the expert panels and cases studied.

The rest of the paper is organized as follows: Section 2 provides both a theoretical background and a comprehensive review of the relevant literature. Section 3 presents the methodology used in this study. The findings of our research are presented in Section 4. Section 5 offers a discussion of these findings, and finally, Section 6 concludes the paper, summarizing the key insights and suggesting future research avenues.

2. Literature review

2.1. Theoretical background

Resilience is a well-established concept in the SC literature (Kamalahmadi and Parast, 2016) mostly dominated by the engineering resilience view. This view emphasizes time-to-recover and one specific state of equilibrium to reach after disruptions (Simchi-Levi et al., 2018). The engineering resilience considers SCs as linear and fail-safe systems, which are entirely at the control of practitioners and managers (Wieland, 2021). This view has been effective in controlled environments to determine optimal inventory allocation strategies to quickly mitigate losses. Recently, however, it has been criticized for being an oversimplified model in which only one node can be disrupted, or disruptions are predictable (Gao et al., 2019). Instead, social-ecological resilience has been advocated as a better fit for SCs because it considers them to be open, safe-fail systems that adapt and transform in the face of disruption (Wieland and Durach, 2021). This view, which is a recent development in the field of SC resilience, has been extensively researched in other fields, such as ecological sciences (Holling, 2001)

and is gaining ground quickly in the literature on SC resilience (Sauer et al., 2022). From this perspective, Wieland and Durach (2021) have redefined SC resilience as “the capacity of a supply chain to persist, adapt, or transform in the face of change” (p.316).

Having specific characteristics, the AFSC is unique due to its complexity and interconnectivity not only at the individual level (e.g., farmer) but also at the governmental and planetary levels (e.g., climate change). Due to the limitations of the traditional equilibrium-based resilience approaches and the AFSC's complex interconnected nature, resilience must extend beyond the individual actors to encompass the entire industry to guarantee food security (Hodobod and Eakin, 2015). This aligns with conceptualizing the supply chain as a Complex Adaptive System (CAS), where resilience is not a static capability but a dynamic, emergent property that arises from the self-organized, adaptive behaviors of all interacting firms (Massari and Giannoccaro, 2021). In light of the mentioned complexities of SCs, Novak et al. (2021) argue that the resilience of individual organizations operating in a SC does not equate to the resilience of the SC as a whole. Instead, they emphasize the importance of considering different scales, such as the spatial scale, when studying resilience. Firm-centered views, i.e., on a limited spatial scale, can lead to issues where the actions beneficial for one actor might not enhance, or could even detract from, the resilience of other SC entities or even the whole SC, i.e., an extended spatial scale. Therefore, an effective framework for SC resilience must adopt a more comprehensive perspective beyond organizational scale (Choi et al., 2025). Not limited to a single node's failure or considering disruptions as predictable, social-ecological resilience is thus more relevant for AFSCs since they are highly connected to the economic, political, and social systems of the supply network, therefore acknowledging that not all risks can be prevented (Statsenko et al., 2024; Stone and Rahimifard, 2018).

The firm-centered view is detrimental to the AFSC as its main goal is to ensure the availability and accessibility of food to consumers with or without disruptions. For instance, Sá et al. (2020) report in a SC of low interdependence, the preference of managers is resiliency at the node level, in other words, their own interest takes priority over the common goals of the SC and collaborative efforts to foster adaptability and learning, critical capabilities of social-ecological resilience. In contrast, in AFSC, social capital at both intra-firm and inter-firm levels was reported to be beneficial in achieving resilience to extreme climate change events (Ali et al., 2023). From a social-ecological perspective, Statsenko et al. (2024) use a multi-level scale to investigate resilience capabilities at the organizational, SC, and industry levels within the Australian defense SC. In a similar vein, Sauer et al. (2022) apply social-ecological resilience on a spatial scale divided into firm, SC, and beyond SC levels across five industries, including food processing. We thus argue that this multi-level investigation aligns with the social-ecological perspective required for the complex nature of the AFSC, enabling a more holistic approach to discussing resilience capabilities.

This paper uses the dynamic capabilities (DC) lens to better frame BDA, as unpredictable disruptions in the AFSC environment require the intervention of technological capabilities to make them somewhat predictable (Belhadi et al., 2024). Dynamic capability is defined as “the firm's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments” (Teece et al., 1997). Moreover, literature on adaptive resilience emphasizes developing capabilities and capacities to effectively recover from and learn from unforeseen events (Van Der Vegt et al., 2015). In the AFSC domain, the DC perspective has proven to be a promising theoretical lens in studies addressing disruptions alongside technology adoption (Pal et al., 2024). The study by Iftikhar et al. (2023) conceptualizes resilience itself as an adaptive capability and identifies BDA as a key dynamic capability that allows firms to “make sense of rapidly changing situations” and “dynamically adapt to changing conditions.” To frame BDA practices for this study, we focus on the micro-foundations defined by Teece (2007) as “the distinct skills, processes, procedures, organizational structures, decision rules, and disciplines which undergird enterprise-level sensing,

seizing, and reconfiguring capacities.” These micro-foundations should typically include three types of managerial activities that make a capability dynamic: identifying and assessing business opportunities and threats (sensing), mobilizing resources to capture value from sensed elements (seizing), and continuous renewal (transforming). Thus, when applied to a complex adaptive system like the AFSC, these micro-foundational activities drive its resilience (Nacchiero et al., 2024).

These micro-foundations are argued to provide additional and complementary insight into each of the DC capacities (Massari et al., 2025), from organizational activities to industry level initiatives, which is suitable to study BDA since the micro-foundation perspective moves beyond high-level, abstract associations and breaks down the intricate details of ways that BDA enables resilience capabilities (Felin et al., 2015). In addition, Felin et al. (2015) argue that micro-foundations allow researchers to dismantle explanatory black boxes by dissecting large-scale concepts, such as BDA capability, into their smaller, more clearly defined constituent parts. BDA can sense opportunities and risks, seize advantages, and transform or reconfigure resources and capabilities in the face of a constantly changing environment (Conboy et al., 2020). As the business environment becomes more dynamic and unpredictable disruptions are omnipresent, managers need to focus on developing intangible capabilities by using BDA to create increased resiliency to better predict environmental changes and adapt (Wu et al., 2024).

Empirical studies converge on the view that concrete BDA micro-foundations are powerful enablers of SC resilience because they translate data into early warnings, coordinated responses, and strategic adaptations. Drawing on Iranian manufacturing and service contexts, Bahrami and Shokouhyar (2022) demonstrate that BDA sensing capabilities (e.g., market, supplier, and process sensing) improve information quality and innovative capability, which, in turn, provide real-time visibility of upstream and downstream flows and enable firms to predict and address potential disruptions before they occur. This constitutes the core of a risk-aware, anticipatory supply chain. A complementary survey by Bahrami et al. (2022) reveals a mediated effect: investments in analytics improve performance not only directly but also indirectly through stronger resilience and innovation, meaning firms that sense and learn faster can also recover and reconfigure more quickly and thus protect service levels amid volatility. In agri-food settings, Belhadi et al. (2024) further differentiate levels of BDA maturity: downstream, better-digitalized actors use advanced analytics, scenario modeling, and what-if analyses to seize and transform operations by formulating worst-case disruption assumptions and launching proactive mitigation strategies (e.g., alternative sourcing, rerouting, and stock rebalancing), while upstream, less digitalized actors use lighter tools (e.g., mobile/cloud dashboards) and mostly build basic sensing and follow a more reactive, wait-and-see posture. Taken together, these findings imply that analytics can support resilience at two layers: (i) a strategic/transformational layer, where BDA informs redesign, redundancy, and continuity planning, and (ii) an operational/real-time layer, where BDA drives monitoring, rapid reallocation, and collaborative problem-solving. However, the literature lacks a managerially actionable mapping that tells decision-makers, given their context, which BDA practices they should enable first and which resilience capabilities these practices will most likely reinforce. The framework developed in this study fills that gap by first consolidating the resilience capabilities and BDA micro-foundations in subsequent sections and then positioning them so that managers can sequence, tailor, and prioritize analytics initiatives to maximize resilience in their supply chains. In doing so, we treat these linkages as structured expert judgments about expected enabling relationships.

2.2. Social-ecological resilience capabilities

The ability to navigate disruptions through persistence, adaptability,

and transformation depends on effectively using the formative capabilities that constitute resilience (Stone and Rahimifard, 2018; Zhong et al., 2024). Many different terminologies have been used to describe resilience capabilities, including elements, enablers, antecedents, and strategies. However, emerging studies have adopted the DC perspective to frame these capabilities (Stadtfeld and Gruchmann, 2024). In AFSC, several systematic reviews have listed capabilities at either the SC level (Zhao et al., 2022) or the organizational and SC levels (Stone and Rahimifard, 2018). However, to our knowledge, no previous study has considered the presence of social-ecological resilience and its capabilities at all spatial levels. Table 1 presents a consolidated list of the 19 resilience capabilities grouped into three levels. The ‘capability’ and ‘definition’ columns of this list are derived from a review of SC and AFSC social-ecological resilience literature. Adopting theory elaboration approaches of splitting and contrasting the capabilities, as suggested by Fisher and Aguinis (2017), we build a categorization into organization, SC, and industry levels to address the multi-level nature of resilience (Choi et al., 2025; Novak et al., 2021). To provide accurate definitions and determinants of these capabilities, Table 1 offers an explanation of each capability, including references to studies that suggest them, as well as a list of ‘means-objectives’ (Clemen et al., 2013). This makes the capabilities more tangible and improves comparability and clarity of elicitation, and reduces ambiguity. These means-objectives have been extracted from the literature and refined by resilience experts, as described in Section 3.2.

Summarizing earlier literature, the discourse on resilience capabilities has evolved, moving from identifications of broad resilience capabilities to the analysis of capabilities and their interrelationship. Soni et al. (2014) identified ten general resilience capabilities, including agility, collaboration, and visibility for overall SC resilience, and presented interrelationships among these capabilities. Subsequent research has increasingly focused on specific sectors and circumstances, for example, pandemic preparedness in AFSC (Kazancoglu et al., 2024; Kumar et al., 2022), fresh food SCs incorporating green agile, and sustainable practices in addition to resilience (Sharma et al., 2023), and AFSC generally (Zhong et al., 2024). These studies collectively highlight a recurring set of core capabilities with many scholars emphasizing only the centrality of certain capabilities.

Beyond identifying and prioritizing capabilities, the literature started to explore their complex interrelationships and the methodological approaches to their study. For instance, Soni et al. (2014) noted mutual influences between collaboration and visibility, while Kumar et al. (2022) found leadership enhances visibility, and Sharma et al. (2023) reported financial strength contributes to information sharing through risk-aware culture. Zhong et al. (2024) presented a model showing the directional influence structure of 15 SC capabilities using interpretive structural modeling (ISM), and Kazancoglu et al. (2024) described a highly interconnected network of 8 resilience capabilities using graph theory matrix in which risk awareness fosters agility, which in turn enables collaboration and adaptability. Methodologically, initial studies utilized deterministic modeling and graph theory (Kazancoglu et al., 2024; Soni et al., 2014), but beyond this, there has been a persistent call for, and adoption of, diverse approaches including fuzzy theory (Kumar et al., 2022), and hybrid methods (Kazancoglu et al., 2024; Sharma et al., 2023). In addition, Zhong et al. (2024) called for further quantifying the importance of resilience to develop more precise measures for future research and Sharma et al. (2025) suggested more rigorous, empirically grounded examinations of proposed influence structures. In response to these calls, the present study offers transparent, expert-elicited modeling of influence structures and priority weights across a broader set of capabilities and multiple spatial levels.

2.3. Big data analytics capability’s micro-foundations

BDA involves using advanced analytics techniques, such as statistical analysis, data mining, and advanced forecasting, at the descriptive,

Table 1
Social-ecological resilience capabilities.

Level	Capability	Definition	Means-objectives
Organization (O)	Risk-aware culture (O1)	The infrastructure of an organization to manage risks (e.g., Liao et al., 2025; Stone and Rahimifard, 2018).	<ul style="list-style-type: none"> • Efficiency standards such as Six Sigma • Contingency plans • Business continuity plans/teams • Risk-related training • Enterprise risk management plans
	Knowledge management (O2)	Ability to capture, structure, share, and apply tacit and explicit knowledge from disruptions (e.g., Al Naimi et al., 2021).	<ul style="list-style-type: none"> • Knowledge sharing among employees • Dissemination of lessons learned • Organization's understanding of the interactions and structures inside the SC
	Operational flexibility (O3)	The ability to rapidly and efficiently reschedule/reconfigure production, delivery, and volume (e.g., Statsenko et al., 2024).	<ul style="list-style-type: none"> • Redirection of production or personnel capacity • Reconfiguration of resources • Internalization of key capabilities • Adaptation and management of schedules
	Operational visibility (O4)	The ability to obtain a timely, end-to-end, and accurate view of processes, resources, and data within the organization (e.g., Statsenko et al., 2024).	<ul style="list-style-type: none"> • Inventory levels monitoring • Order status monitoring • Shipment tracking • Production progress monitoring
	Buffering redundancy (O5)	The deliberate provision of spare capacity within the organization to absorb variability and disruptions (e.g., Statsenko et al., 2024).	<ul style="list-style-type: none"> • Inventory buffers • Production capacity buffers • Transport capacity buffers • Time buffers (added lead time) • Workforce buffers
	Anticipation (O6)	The ability to systematically detect and interpret weak signals and emerging risks to take preemptive action (e.g., Pettit et al., 2010; Silva et al., 2023).	<ul style="list-style-type: none"> • Early warning systems • Risk forecasting • Near-miss and deviation analysis • Scenario planning
	Financial strength (O7)	The extent to which an organization's solvency, liquidity, earnings quality, and capital flexibility allow it to withstand shocks, meet obligations, and invest in growth (e.g., Pettit et al., 2010; Silva et al., 2023).	<ul style="list-style-type: none"> • Insurance • Diversification of portfolio • Cash reserves and liquidity at hand • Price margin
	Security (O8)	The risk-based system of governance, policies, and controls that protect the organization and its physical, digital, and informational assets (e.g., Stone	<ul style="list-style-type: none"> • Supply chain assets protection • Information and systems safeguard • Incident response plans

Table 1 (continued)

Level	Capability	Definition	Means-objectives
Supply chain (SC)	Innovation (O9)	and Rahimifard, 2018). The ability to turn ideas into innovative solutions by actively seeking and encouraging advancements (e.g., Kähkönen et al., 2023).	<ul style="list-style-type: none"> • Development of new processes and technologies • Manufacturing new products • Processes redesign after disruptions
		Ability to withstand shocks with minimal performance loss (e.g., Stone and Rahimifard, 2018).	<ul style="list-style-type: none"> • Perform without failure during disruption • Maintain the original state of the organization after disruption • Maintain core operations after any perturbation
	Supply flexibility (SC1)	The ability to adapt sourcing and procurement activities to ensure reasonable quality and cost and to maintain the flow of goods or respond to changes (e.g., Statsenko et al., 2024; Stone and Rahimifard, 2018).	<ul style="list-style-type: none"> • Reshore the supply • Switch suppliers at ease • Diversification of suppliers • Localization of suppliers
		The accurate and timely view of the upstream for early detection of risks and transparency in the supply chain (e.g., Statsenko et al., 2024; Stone and Rahimifard, 2018).	<ul style="list-style-type: none"> • Real-time tracking systems • Supplier data platforms • Supplier performance and risk indicators • Data formats and communication protocols
	Strategic redundancy (SC3)	The risk-informed duplication and dispersion of critical capabilities at the supply chain level (e.g., Statsenko et al., 2024; Stone and Rahimifard, 2018).	<ul style="list-style-type: none"> • Dual or multi-sourcing strategies • Multiple qualified suppliers • Regional or local sourcing alternatives • Redundant inventories and warehouse locations • Alternative transportation modes and routes
		The end-to-end ability to reconfigure and shift with speed to respond to disruption or change (e.g., Statsenko et al., 2024; Stone and Rahimifard, 2018).	<ul style="list-style-type: none"> • Quick response to disruption, demands, or market changes • Supply chain process agility and fast decision making • Quickness of supplier recovery • Expedited delivery
Collaboration (SC5)	The effective and efficient work carried out with other SC entities for a common goal (e.g., Statsenko et al., 2024; Stone and Rahimifard, 2018).	<ul style="list-style-type: none"> • Joint decision making • Risk sharing • Information sharing • Expediting orders with suppliers 	
	Systemwide ability to adapt, evolve, or transform	<ul style="list-style-type: none"> • Adjust operations or processes in response to changes 	

(continued on next page)

Table 1 (continued)

Level	Capability	Definition	Means-objectives
Industry (I)	Leadership (I1)	incrementally or completely in response to a changing environment (e.g., Silva et al., 2023 ; Stone and Rahimifard, 2018).	<ul style="list-style-type: none"> in the market or environment Build learning and evolution capabilities
		The ease of driving resilience strategies in the market (e.g., Pettit et al., 2010 ; Silva et al., 2023).	<ul style="list-style-type: none"> Sufficient market share in the industry Sufficient market power in comparison to other firms Product differentiation strategies Relationship with the customers via loyalty programs
		Ability to adapt to industry, societal, and governmental changes despite higher costs (e.g., Statsenko et al., 2024).	<ul style="list-style-type: none"> Ease of implementing required industry standards or certifications Ease of conforming to laws and regulations Encouragement of local and domestic suppliers
Compliance flexibility (I2)	Partnership (I3)	The long-term, co-governed commitment beyond bilateral collaboration among multiple sector actors for strengthening resilience and competitiveness (e.g., Statsenko et al., 2024).	<ul style="list-style-type: none"> Involvement of local suppliers in design Formation of strategic partnerships Reception of government support Issue SME grants

predictive, and prescriptive levels to uncover new insights from large data sets ([Tiwari et al., 2018](#)). BDA capability is defined as “the ability of the firm to capture and analyze data towards the generation of insights, by effectively deploying its data, technology, and talent through firm-wide processes, roles and structures” ([Mikalef et al., 2019](#)). Several studies address the impact of BDA as a higher-order capability on AFSC resilience. Reviews on BDA’s influence on SC resilience show positive results in all phases of resilience ([Zamani et al., 2023](#)), yet in AFSC resilience literature, the influence of BDA on the adaptation and transformation phases has only been scarcely discussed ([Asgari, 2025](#)). With the Russian-Ukrainian conflict affecting African AFSCs, [Belhadi et al. \(2024\)](#) discuss the strong relationship between the dynamic capabilities of digital technologies, including BDA, and resilience at both intra- and inter-organizational levels. Advanced predictive analytics and expert systems have also been shown to mitigate disruption caused by the pandemic by improving decision-making in the Indian AFSC ([Nayal et al., 2022](#)). A range of BDA practices that have positively influenced resilience in AFSC have been discussed ([Asgari, 2025](#)). In addition, several, but isolated, micro-foundations of BDA, such as customer sensing, dynamic resource allocation, and business model creation, are discussed as enablers of dynamic capabilities ([Conboy et al., 2020](#)). Following an extensive review of the BDA practices relevant to AFSC and SC resilience, [Table 2](#) categorizes the 14 BDA micro-foundations into three groups: sensing, seizing, and transforming.

The strategic importance of BDA has led to scholars ranking its capabilities and selection criteria across different contexts. For instance,

Table 2

Micro-foundations of big data analytics.

Capacities	Micro-foundations	Explanation	Examples
Sensing	Market Sensing (P1)	Segment customers based on risks, geography, behavior, demography, etc., predict trends, identify needs of potential customers, monitor and analyze the needs and sentiments of customers (e.g., Asgari, 2025 ; Conboy et al., 2020).	Clickstream analysis; basket analysis; customer feedback mining; social media listening; web traffic and search trends
	Process Sensing (P2)	Identify inefficiencies in operations, equipment, personnel, etc., best practices within internal and external processes, and monitor and assure quality control (e.g., Asgari, 2025 ; Conboy et al., 2020).	OEE dashboards; sensor-based monitoring; cycle time analysis; defect pattern analysis; process mining
	Supplier Sensing (P3)	Track and evaluate suppliers, assess supply-side risks such as climate, political, and economic. etc., and maintain regulatory conformity (e.g., Papanagnou et al., 2022).	Supplier scorecards; financial health monitoring; ESG compliance dashboards; audit tracking
	Personnel Sensing (P4)	Track employee sentiments and morale, evaluate personnel performance, predict future workforce needs, identify turnover influences, and measure skills deficits (e.g., Papanagnou et al., 2022).	Pulse surveys; KPI dashboards for productivity; 360-degree feedback analysis; hiring pipeline analytics; AI-based resume and profile analysis
	Financial Sensing (P5)	Evaluate the financial state and performance metrics and track liquidity risks, losses, and other fiscal and economic instabilities (e.g., Yu et al., 2021).	Profitability analysis; cost-to-serve analytics; working capital monitoring; cash flow dashboards
Seizing	Data-driven action (P6)	Use key performance indicators, data mining, machine learning, etc., to initiate and take data-backed actions (e.g., Conboy et al., 2020).	Predictive maintenance; demand forecasting for inventory rebalancing
	Resource Allocation (P7)	Adjust resource allocation in real-time to ensure high responsiveness to changing market or operational states and optimal	Shelf-life analytics; Task scheduling algorithms; cold chain monitoring and reallocation

(continued on next page)

Table 2 (continued)

Capacities	Micro-foundations	Explanation	Examples
Transforming	Customer Engagement (P8)	efficiency (e.g., Conboy et al., 2020). Analyze risk profiles and client interactions to develop tailored engagement strategies to maximize ROI based on segments (e.g., Conboy et al., 2020).	RFM analysis; behavioral clustering; geo-segmentation; personalized promotions
	Risk Profiling & Continuity Plans (P9)	Create detailed profiles of recognized risks and establish strategic continuity plans to enhance readiness for SC and financial risks (e.g., Asgari, 2025; Conboy et al., 2020).	Supplier risk scoring; geopolitical and climate risk mapping; scenario analysis; business impact analysis; dynamic risk dashboards; automated alerts
	Advanced Forecasting (P10)	Apply advanced forecast models to match supply and demand to optimize sales and operations planning (e.g., Papanagnou et al., 2022).	Machine learning models for demand forecasting; short shelf-life product forecasting; lead time variability modeling
	Process reconfiguration (P11)	Reconfigure core processes through dynamic resource allocation for emergent issues or changes (e.g., Conboy et al., 2020; Papanagnou et al., 2022).	Workflow optimization; digital twins; rule-based engines; scenario-based playbooks
	Strategy Development (P12)	Develop innovative business strategies and services (e.g., Conboy et al., 2020).	What-if simulations; multi-objective optimization for portfolios; benchmarking analytics; network optimization models
	Personalized Campaigns (P13)	Transform the marketing strategy to deliver customized campaigns by utilizing customer insights and predictive sales data (e.g., Conboy et al., 2020).	Customer preference modeling; uplift modeling; A/B testing and multi-armed bandits; omnichannel personalization
	Operational Excellence (P14)	Put in place continuous improvement, re-engineering, automation, optimization, task prioritization frameworks to achieve operational excellence (e.g., Lorenc et al., 2021).	Continuous improvement & re-engineering using Lean/Six Sigma analytics; robotic process automation; AI-based task scheduling; energy and resource optimization; dynamic pricing engines

research in developing nations like Pakistan has highlighted the foundational importance of BDA capabilities of infrastructure, management, and human resources for firm’s performance (Yasmin et al., 2020). Ranking BDA tools illustrated the importance of selection criteria such as statistical power, product quality improvement, and performance enhancement for logistics managers (Büyükoçkan and Güler, 2021).

Regarding resilience specifically, findings from distinct sectors highlight the growing importance of BDA enablers and tools for improving resilience. BDA enablers such as capital investment and infrastructure were identified to highly improve resilience capabilities of financial capital, flexibility, and corporate culture to sustainability risks in manufacturing (Hsu et al., 2022). Also, the positive impact of predictive analytics and visualization on enhancing agility, adaptability, and visibility for healthcare SC was reported (Sumrit, 2025). As the literature emphasizes the need to extend BDA applications to critical sectors like the AFSC, there remains a specific need to explore the relative importance of distinct BDA practices to effectively enhance social-ecological resilience in AFSC, as we formulate it in RO2. In particular, the literature is limited in providing context-sensitive, decision-aiding prioritizations of BDA micro-foundations against a multi-level resilience capability system—a gap directly addressed by the present study’s hybrid MCDA design.

3. Methodology

Our research philosophy is pragmatic and decision-aiding (Munda, 1993), grounded in an epistemology that treats resilience assessment as a process of shaping and evincing knowledge from experts, rather than discovering a single ‘true’ optimum (Brugha, 2004). Accordingly, we view MCDA as an iterative structuring activity that alternates technical formalization with elicitation from decision makers, emphasizing stages where information is accessed, differentiated, and abstracted from stakeholders to be useable for choice under complexity. In line with post-normal science (Funtowicz and Ravetz, 2018), we acknowledge that facts are uncertain, values are disputed, stakes are high, and decisions are urgent in AFSCs. Thus, model quality depends on transparency, assessment of agreement and compatibility, robustness checks, and engagement with an extended peer community, rather than on closed-form proofs of optimality (Munda, 2004). Methodologically, we adopt fuzzy representations to account for subjectivity, imprecision, and partial comparability in judgments (e.g., weights, scores, and influence assessments). This approach is consistent with MCDA’s shift from solution-seeking to decision aid, as well as the need to disclose assumptions, manage incommensurabilities, and test stability rather than enforce artificial precision (Munda, 1993). Adopting critical-realist, abductive logic (Brugha, 2004), we treat our fuzzy, expert-elicited results as theoretically informed approximations of underlying generative mechanisms (Munda, 1993). Our findings are offered as context-bounded explanations, whose credibility rests on transparency and robustness rather than simply identifying specific causal effects. In this study, robustness primarily refers to (i) the stability of the results under plausible variations in expert inputs and aggregation and (ii) the degree of agreement and compatibility among experts rather than external statistical validation of causal effects.

3.1. Multiple criteria decision analysis approach

To address the ROs of this study, we adopted an MCDA approach, which is well-suited for solving multi-alternative, multi-criteria decision-making problems. Specifically, the two ROs can be expressed in MCDA terminology as follows: (i) recognizing the perceived interdependence of resilience capabilities (i.e., criteria) and calculating their weights in decisions related to resilience enhancement, and (ii) prioritizing BDA micro-foundations (i.e., alternatives) based on their perceived importance in enabling resilience capabilities and thereby enhancing the resilience of AFSCs. MCDA is particularly relevant given the growing complexity of the real-world decision-making, as it allows for the integration of diverse perspectives to support structured judgment and deliberation (Greco et al., 2025). By incorporating performances of alternatives and preferences of stakeholders, MCDA can strengthen the analytical rigor, transparency, and auditability (Amor et al., 2023). It also provides flexibility by merging subjective expert insights with available contextual and documentary evidence where

applicable (Dolan, 2010), and this is the main reason why MCDA has consequently gained popularity over the past five decades (Greco et al., 2025).

We also integrated fuzzy logic into MCDA to represent and manage the uncertainty and subjectivity associated with experts' responses, as expressions of opinions often contain some level of vagueness (Sharma et al., 2024). MCDA methods have been used extensively to explore perceived influence structures and perceived priorities of criteria in the fields relevant to this study. This encompasses, for example, the root causes of food waste among AFSC retailers (Mohammed et al., 2025), barriers and enablers of technology adoption (Kouhizadeh et al., 2021), and prioritizing projects from a strategic point of view (Quezada et al., 2022). Given their broad applicability in technological and strategic contexts and their strength in navigating complex, multi-perspective environments, MCDA methods are well-positioned to address the ROs outlined above. Table 3 provides an overview of similar studies on the resilience of the agri-food domain and draws a comparison with the current work as well.

3.2. Data collection

Data collection took place in two phases. First and aiming at RO 1, a detailed questionnaire, including full explanations of various resilience capabilities and their means-objectives in the context of social-ecological resilience, was designed and distributed to scientists specializing in SC and AFSC resilience. 59 experts were initially selected based on the relevance of their profiles as well as their proven track record in applying the social-ecological resilience perspective in the fields of SC or AFSC. This was evidenced by having at least one relevant publication on the topic from a managerial perspective in journals ranked in the most recent journal rankings of the French National Foundation for Business Management Education (FNEGE; version 2022) and the Chartered Association of Business Schools (ABS; version 2021)

Table 3
An overview of studies that used MCDA to examine resilience.

Scholars	Method	Alternative	Comparison to the current study
Kumar et al. (2022)	ISM f-DEMATEL	No	<ul style="list-style-type: none"> 64 survey responses vs. 26 expert judgments 14 vs. 19 criteria Pandemic vs. transversal scope of disruptions Additional subjectivity of ISM vs. additional structuring and traceability through f-DANP O + SC vs. O + SC + I levels^a
Kazancoglu et al. (2024)	Graph Theory Matrix	No	<ul style="list-style-type: none"> SC vs O + SC + I levels 8 vs. 26 expert judgments 8 vs. 19 criteria
Zhong et al. (2024)	DEMATEL ISM-MICMAC	No	<ul style="list-style-type: none"> 15 vs. 26 expert judgments 15 vs. 19 criteria SC + I vs. O + SC + I levels Additional subjectivity of ISM vs. additional structuring and traceability through f-DANP
Sharma et al. (2023)	FISM DEMATEL	No	<ul style="list-style-type: none"> Indian Fresh food chain vs. International AFSC retail 18 vs. 26 expert judgments 7 vs. 19 criteria Additional subjectivity of ISM vs. additional structuring and traceability through f-DANP
Asgari et al. (2026)	f-DEMATEL ANP f-VIKOR	Yes	<ul style="list-style-type: none"> f-DEMATEL + ANP vs. f-DANP f-VIKOR (trapezoidal) vs. f-TOPSIS (triangular) 23 vs. 26 expert judgments Defuzzification in all stages vs. the final stage Single- vs. multiple-case study

^a O: organization; SC: supply chain; I: industry.

available at the time of data collection. The experts were first tasked with validating the capabilities they considered relevant, which involved a binary (yes/no) assessment for each, based on the specific definitions and means-objectives provided for each capability (see Table 1). The experts also had the option to add missing details to the capabilities or suggest new ones based on their expertise. Four experts used this option, suggesting minor additions to single capabilities. These suggestions were reviewed by the author team against the literature on which Table 1 is based, concluding that they were covered by the literature and the 19 capabilities in the survey. Together with the validation question, this was judged by the authors as a validation of the set of 19 capabilities.

Following this validation, the experts indicated how they perceived the influence of each validated capability on the others. To ensure robust data quality and participant understanding, we followed up with each expert an average of three times, providing clarifications and verifying the completion of the questionnaire. Ultimately, this first phase yielded responses from 26 distinguished resilience experts out of the initial 59, who had, on average, 14.8 years of seniority in academia; more than 5500 citations and an *h*-index of more than 26 in Google Scholar (see Table A.1 in Appendix A).

The second data collection phase responds to RO 2 and involved a multiple case study design aiming for analytical generalization (Yin, 2018). Concretely, it aimed at elaborating and contextualizing theory based on Fisher and Aguinis (2017) by prioritizing BDA micro-foundations to enhance the most crucial identified resilience capabilities from the first phase within AFSCs. The selection of three food retailers followed a theoretical replication logic (Yin, 2018) leveraging their diverse application and strategic use of BDA solutions. Each case was meticulously selected based on the major classification of retailer formats—discounter, hypermarket, supermarket, merchandiser, and convenience store—to cover a single format or combinations of them distinct from the other cases (Bonfrer et al., 2022). This aligns to the theory elaboration approaches of contrasting for RO 1 and structuring for RO 2 as suggested by Fisher and Aguinis (2017).

Concretely, two of the retailers are headquartered in two different European countries; within each company, seven managers from departments such as business intelligence, demand planning, sales and marketing, sales and operations planning, and logistics were interviewed. The third retailer was based in the Middle East, where interviews were conducted with five managers: the data analysis manager, marketing manager, strategic planning manager, data science manager, and SC and logistics manager.

Data was collected during a call with the managers in which the BDA micro-foundations and the previously validated resilience capabilities were explained in detail to the managers, along with clear guidance on how to respond to the prioritization questionnaire during or after the call. No follow-up was necessary in this step as all managers provided the completed questionnaire either at the end of the interview or by the indicated deadline of 10 days. The goal of this ranking was to validate if the results from the previous phase can be used by managers for informing their decision-making aimed at increasing the resilience of the specific retailer they manage. For instance, when organizations seek to optimize their firm-specific investments in BDA practices to increase their resilience, our findings present them with validated expert knowledge linked to specific characteristics (e.g., locations, strategies) and conditions (e.g., current BDA solutions and practices), which they can compare their own firms to. Due to the different characteristics and conditions of firms, the prioritized BDA practices would vary from one firm to another.

Beyond the primary data, secondary data was collected from multiple sources for each retailer. These sources are presented in Table 4 and have been used for the presentation of the retailers below and for contextual triangulation (i.e., enriching case descriptions and checking the plausibility of the data) (Yin, 2018).

Table 4

Overview of secondary data sources (anonymized, all sources last accessed on November 12, 2025).

Retailer addressed	Publisher	Content (year of publication)
Retailer A	Retailer A	Sustainability report 2020 (n.d.)
	Retailer A	Company profile website (n.d.)
	Retailer A	Multiple website pages on its data analysis unit (n.d.)
	Media 1	Media article about retailer A (2024)
	Media 2	Multiple media articles about retailer A (2020–2024)
	Media 3	Media article on customer data analytics of retailer A (2024)
	Media 4	Media article on store data analytics of retailer A (2022)
Retailer B	Media 5	Media article on the use of AI in retailer A's supply chain analytics (2024)
	Media 6	Media article on the use of AI in retailer A's supply chain analytics (2024)
	Media 7	Media article on retailer A's innovation culture (2024)
	Retailer B	Annual report 2022 (2023)
	Retailer B	Annual report 2023 (2024)
	Retailer B	Annual report 2024 (2025)
	Retailer B	Vigilance plan 2023 (2024)
Retailer C	Media 8	Media article on cost savings at retailer B based on its post-COVID-19 recovery plan (2021)
	Media 9	Media article on how retailer B invested in improved supply chain data analytics capabilities (2024)
	Media 10	Media article about retailer B's efforts in supply chain management during the COVID-19 pandemic (2020)
	Retailer C	Company profile website (n.d.)
	Media 11	Media article about retailer C's anti-COVID-19 measures and arrangements (2020)
	Media 12	Multiple media articles on employee engagement and sentiment in retailer C (2020–2025)
	Media 13	Report on data-based monitoring capacities of retailer C in the context of COVID-19 (2020)
Retailer C	Media 14	Media report on the growth and competition in the national retail sector of retailer C (2017)
	Media 15	Media article on the economic presence and market dominance of retailer C (2019)
	Media 16	Media article on the digital transformation and financial management of retailer C (2025)

3.2.1. Retailer A, Europe

Retailer A strategically operates as a cost leader and is categorized as a discounter, with its core mission revolving around delivering optimal value to consumers. This retailer has around 200 thousand employees working in upwards of 7500 stores worldwide, with a revenue of more than 80 billion Euros in 2023. This strategic focus is actualized through optimized and lean operational processes deployed across an extensive network of physical stores in Europe. The retailer exhibits a considerable degree of technological sophistication. It leverages established enterprise resource planning systems specifically to enhance logistical efficiencies, optimize in-store operations, and improve inventory management, all of which are critical levers for cost control. Furthermore, retailer A maintains its own dedicated IT company, responsible for developing technological solutions based on the needs of the enterprise. This internal capability underscores its commitment to technological advancement and has facilitated increased investment in proprietary systems, particularly in response to the evolving retail landscape post-pandemic. Such technological investments have been instrumental in maintaining its price competitiveness as a discount retailer. In terms of market access, retailer A employs a multi-channel approach; while the vast majority of sales originate from its physical sales, it also maintains an online sales presence. The operational efficiency that underpins its cost leadership is further solidified by long-standing relationships with global partners, which ensure a highly streamlined and cost-effective SC.

3.2.2. Retailer B, Europe

With over 150,000 employees working in upwards of 2500 stores and a revenue exceeding 30 billion Euros in 2023, retailer B adopts a strategy primarily centered on enhancing the customer experience and journey. Retailer B is under the hypermarket categorization, which recently acquired another major retailer with many convenience stores. A key differentiator for this retailer is its commitment to sourcing products from local and national brands. This strategic choice is designed to support local firms and promote sustainability, contributing to a higher price point that its target customers understand and value. This local sourcing approach offers resilience with access to local produce during global SC disruptions, yet it also presents a vulnerability if national issues impede product availability locally. Central to its operations is the sophisticated collection and analysis of customer data, acquired predominantly through mobile application, website, and fidelity programs. This data-centric approach is critical for a consistent and personalized experience for all customers. While maintaining a core focus on customer experience, retailer B also pursues operational optimization, extending to in-store efficiencies aimed at cost reduction, though critically, without compromising the quality of the customer interaction. Post-pandemic, retailer B intensified its focus on leveraging data by investing in establishing and expanding its dedicated data analytics department. To facilitate these advanced analytics, the company utilizes third-party IT and cloud solutions. These technologies are instrumental in optimizing logistics through functions such as supplier evaluation and inventory management. However, they are substantially used for customer-oriented goals, enabling detailed churn analysis, customer risk profiling, and the execution of personalized marketing campaigns, all strategically aimed at increasing customer loyalty and retention, given the high cost associated with customer loss.

3.2.3. Retailer C, Middle East

Retailer C operates within its national borders in the Middle East, adopting a supermarket and franchise-based model to manage its extensive network of approximately 2000 stores and over 15,000 employees. The retailer receives over 4000 tons of goods daily in 35 warehouses spanning 220,000 square meters. A cornerstone of its strategy is a highly developed specialization in home delivery services, an economically viable operation significantly supported by low fuel costs. The retailer's environment is characterized by frequent disruptions, including considerable price instability exacerbated by the high cost of imported goods due to international sanctions, alongside frequent water and electricity cuts, all of which require adaptive operational measures. Discount offerings are a key promotional tactic, primarily communicated and made available within its physical store locations. Due to limitations in using third-party cloud and analytics services and restricted access to social media data, the retailer relies extensively on internal data from their website and competitor data available online. These systems enable customer segmentation because retailer C has an extended network of stores all over the country. Based on distinct geographical regions and their inherent cultural specificities, the customer segmentation is employed to manage the discounted offers, aiming to optimize promotional impact without conditioning customers to purchase solely on discount. This nuanced understanding enables effective engagement with the customer base. Unlike retailers A and B, sustainability is not a reported area of strategic focus for Retailer C.

3.3. Data analysis

In this study, we used a fuzzy hybrid approach combining fuzzy logic (Zadeh, 1965) and the DEMATEL, ANP, and TOPSIS methods. Unlike crisp numbers, fuzzy numbers refer to contiguous sets of potential values with degrees of membership in $[0, 1]$, allowing for partial rather than binary membership (Munda, 1993). Fuzzy logic is recommended for group decision-making (Li, 1999), and linguistic rating scales with fuzzy terms are suggested to be more effective than crisp Likert scales (Liou

and Chen, 2006). To ensure transparency in the fuzzification process, we converted linguistic terms into triangular fuzzy numbers (TFNs) according to the guidelines established in the literature on fuzzy decision analysis (Chen and Hwang, 1992; Zimmermann, 2011). Rather than performing defuzzification in the initial steps, as described by Chekry et al. (2024), we conducted all calculations using fuzzy sets. Only in the final step of each phase did we defuzzify the sets to generate crisp numbers for visual presentation or reporting the ranks. Performing defuzzification at later steps was advantageous because it preserved the inherent vagueness and uncertainty throughout the decision-making process, thus ensuring that the fuzzy nature of the data was maintained until the final stages. This approach allowed for more accurate and realistic modeling of real-world scenarios where precise values are often difficult to ascertain early on. By defuzzifying only at the end, we could provide clearer, more interpretable results without losing the benefits of fuzzy logic during intermediate calculations.

Based on the data collected from the resilience experts, a fuzzy DEMATEL model was used to calculate the influence structure (Dytczak and Ginda, 2013) of the capabilities perceived by the experts. Furthermore, a fuzzy ANP model was used to determine the perceived weight of each capability. Integrating DEMATEL with ANP decreased the time and complexity of the decision-making process, enhanced user understanding, simplified the challenging pairwise comparisons of criteria dependencies, minimized data transformation steps, and avoided potential data loss from filtering influences (Kadoić et al., 2019). Finally, a fuzzy TOPSIS model was used to rank the BDA micro-foundations that are perceived by managers to enhance resilience capabilities based on the data collected from the case companies.

The choice of scale size and fuzzy representation was guided by cognitive and methodological considerations. For f-DEMATEL, a five-point scale ranging from 'very low' to 'very high' was chosen to minimize the cognitive burden on the experts evaluating their perception of 19×19 interdependencies (Si et al., 2018). This ensured that the experts could make reliable judgments without becoming fatigued. Conversely, f-TOPSIS involved ranking 14 alternatives across 19 criteria, for which a seven-point scale ranging from 'extremely low' to 'extremely high' offered the necessary granularity for meaningful differentiation (Mahdavi et al., 2008). Since TFNs are widely used for subjective estimates, such as expert opinions (Ic, 2024), they were chosen over trapezoidal ones. TFNs provide a most likely value and two bounds, which reduces the effort required for elicitation and computational complexity. The methodology employed in the analysis of data is documented in Appendix B.

Beyond the analysis of the primary data, the secondary data presented in Table 4 were used for contextual triangulation and narrative corroboration of case characteristics, thereby strengthening interpretive credibility and transparency (Yin, 2018).

4. Findings

Linking back to the two ROs, sections 4.1 and 4.2 present the findings for RO1, while sections 4.3 and 4.4 present the results and robustness checks for answering RO2.

4.1. Influence structures among social-ecological resilience capabilities

To map how the experts perceive the influence structure among the social-ecological resilience capabilities, two indices of prominence ($R_i + C_i$) and relation ($R_i - C_i$) (see Appendix B) were calculated for each resilience capability, as explained in Section 3.3.1. Factors with a positive relation value are considered net influencers ('drivers'), and those with a negative value are considered net receivers ('dependents') within the system in the DEMATEL sense (Dytczak and Ginda, 2013; Chauhan et al., 2020). Other studies in the field have referred to the drivers as 'causes' and to the dependents as 'effects' (e.g., Mohammed et al., 2025). Since these classifications represent structured expert judgments about

directional influence rather than empirical proof of causal effects, we refer to them as drivers and dependents. Our findings show the following capabilities within the driver set and the dependent set:

drivers = {O5, O8, O9, O10, SC1, SC2, SC3, SC4, SC6, I2}

dependents = {O1, O2, O3, O4, O6, O7, SC5, I1, I3}

Based on this, the influence network relationship map (INRM), presented in Fig. 1, is constructed using the calculated prominence and relation degrees and includes four quadrants. Quadrant I 'core factors' has a high perceived prominence and relation value. This shows that the expert ratings indicate significant system centrality and net influence of the capabilities throughout the entire system and high salience within the capability configuration. The capabilities in Quadrant II 'driving factors' combine perceptions of a low prominence value, but a high relation value. Capabilities in this quadrant are perceived to have high outward influence on other capabilities, yet they are not seen to contribute to resilience directly. Quadrant III 'independent factors' is represented by capabilities perceived with low prominence and relation values. These capabilities are seen to have a small role in the perceived influence structure. The capabilities in Quadrant IV 'impact factors' are perceived to have a high prominence value and a low relation value. These capabilities are seen to have high contributions to resilience, yet no significant influence on other capabilities while being highly influenced by the other capabilities.

In line with Table 1, we split the presentation of the findings into three levels. On the organization level, risk-aware culture (O1) and knowledge management (O2) are seen to be the most prominent capabilities, highly influenced by the majority of other capabilities. Among these influential capabilities, security (O8), buffer redundancy (O5), robustness (O10), and innovation (O9) are perceived to have the highest net influence over the system compared to other capabilities respectively, yet they are not seen as prominent as operational flexibility (O3) and anticipation (O6). Among the strongest inferred influence links between capabilities, anticipation (O6), operational flexibility (O3), and knowledge management (O2) had the most substantial perceived influence on risk-aware culture (O1). Financial strength (O7) and operational visibility (O4) were found to be neither influential nor prominent in organizational level resilience. On the SC level, all capabilities, except strategic redundancy (SC3), are seen to be both prominent and influential in the perceived influence structure, with adaptability (SC6) as the most prominent and agility (SC4) as the most influential. Among the SC level capabilities, the strongest influence coefficients include the perceived influence of adaptability (SC6) on collaboration (SC5) and supply flexibility (SC1) alongside the perceived influence of agility (SC4) on adaptability (SC6) were the most significant. On the industry level, compliance flexibility (I2) was seen as the most influential capability over the other two prominent capabilities of leadership (I1) and partnership (I3) in said order, with the higher perceived influence of the latter over the former.

Considering all levels, the SC level has the highest perceived prominence and net influence over the other two clusters, with the industry level's perceived prominence and net influence surpassing that of the organization level. The social-ecological capabilities' influence on one another was not seen as limited to inside each cluster, with the top 1% of influences showing notable cross-level linkages. Based on the most significant ($\geq \mu + z_{0.025}\sigma$) perceived influences identified among capabilities in the present study, four capability groups emerge as shown in Fig. 2. The first group contains the 'single-drivers' capabilities of anticipation (O6), supply flexibility (SC1), and supply visibility (SC2), all of which are seen to have a strong influence on risk-aware culture (O1) in the dependents group. The second group contains the 'multiple drivers' capabilities of agility (SC4) and adaptability (SC6), which are perceived to influence all other capabilities in groups three and four, except for agility (SC4) on collaboration (SC5). The third group contains the 'intermediates' (mixed driver-dependent) capabilities, which are

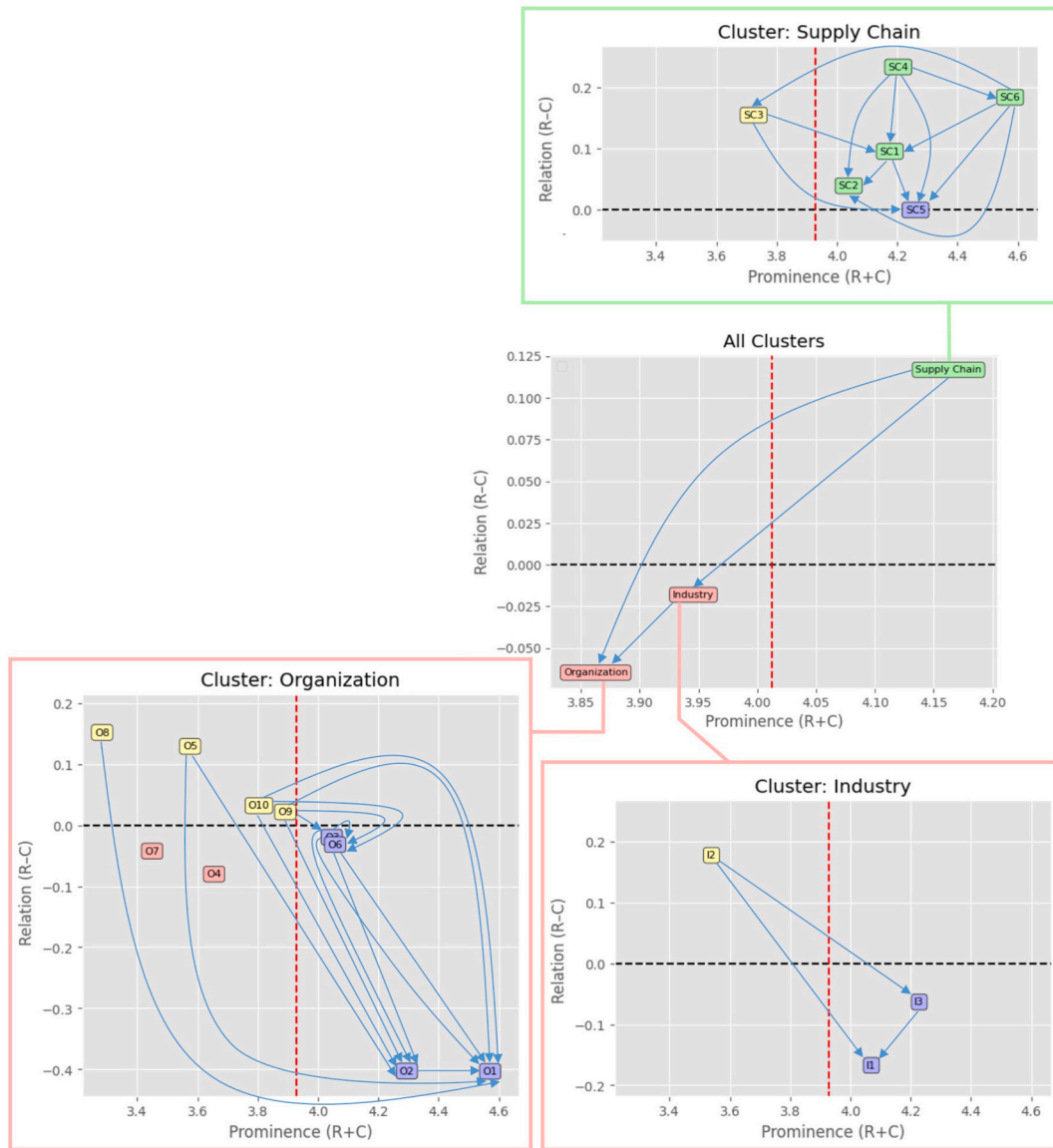


Fig. 1. The influence network relationship map (INRM) for the resilience capabilities (influences ≥ 0.2).

seen to be influenced by the second group capabilities and subsequently to influence the fourth group capabilities, with both collaboration (SC5) and partnership (I3) perceived to influence risk-aware culture (O1) and knowledge management (O2), with the latter also seen to influence the former in the dependent group.

4.2. Social-ecological resilience capabilities weights

To calculate the perceived weights of the criteria, the fuzzy ANP method was used. Table 5 presents the fuzzy weights associated with each capability. These perceived weights show the importance of resilience capabilities to drive overall SC resilience within the expert-elicited model in comparison to each other. Based on the results, adaptability (SC6), agility (SC4), supply flexibility (SC1), collaboration (SC5), and risk-aware culture (O1) have received the highest weightings by the experts, respectively, showcasing their importance to the overall resilience of the system. On the contrary, financial strength (O7), security (O8), operational visibility (O4), compliance flexibility (I2), and buffering redundancy (O5) have received lower weights compared to the rest. Four out of five top-ranking capabilities in terms of perceived weights are SC level resilience capabilities, and four out of five low-

ranking capabilities are organizational level resilience capabilities. The exception on the organizational level is risk-aware culture (O1), which was among the highest weighted capabilities. The remaining capabilities of partnership (I3), supply visibility (SC2), and operational flexibility (O3) leaned towards the highest weighted capabilities, while the rest such as anticipation (O6), innovation (O9), knowledge management (O2), strategic redundancy (SC3), robustness (O10), and buffering redundancy (O5) were leaning towards the lower range, albeit with higher weights compared to the other organizational resilience capabilities. The ranks of BDA practices in the next section are based on their evaluated contribution (as judged by managers) to the criteria most critical to the social-ecological resilience of the food retailer.

4.3. BDA micro-foundation prioritization

Table 6 presents the results of the fuzzy TOPSIS model on retailers A, B, and C based on judgments by their respective managers. The highest-ranking BDA practices for retailer A are market sensing (P1), supplier sensing (P3), strategy development (P12), personalized campaigns (P13), and financial sensing (P5). In retailer B, data-driven action (P6), process reconfiguration (P11), resource allocation (P7), financial

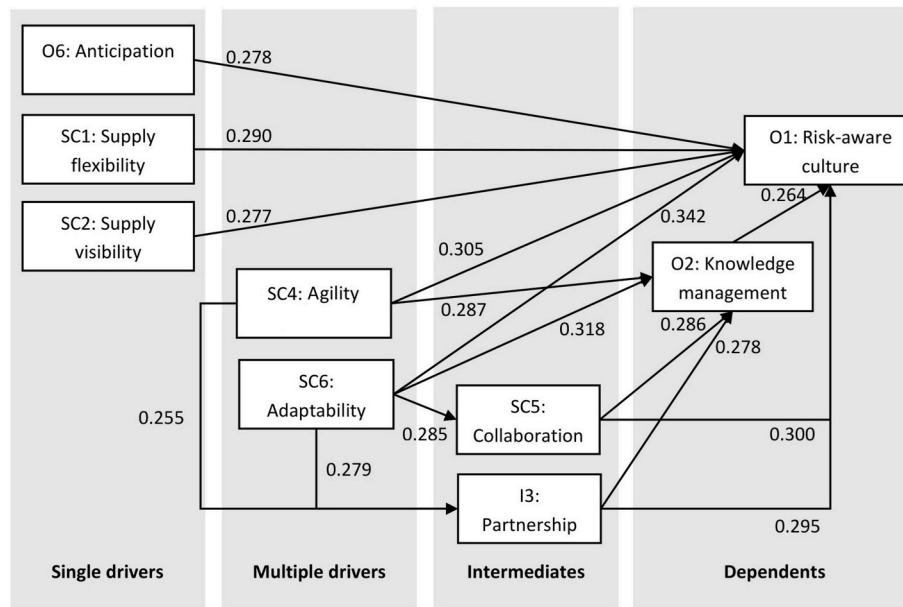


Fig. 2. Drivers-dependents diagram for the most important resilience capabilities (influence coefficients added).

Table 5
Fuzzy perceived weights of social-ecological resilience capabilities.

Capability	Perceived weight	Capability	Perceived weight	Capability	Perceived weight
O1	(0.055, 0.058, 0.058)	O8	(0.039, 0.039, 0.047)	SC4	(0.057, 0.064, 0.069)
O2	(0.049, 0.051, 0.052)	O9	(0.052, 0.052, 0.052)	SC5	(0.056, 0.058, 0.060)
O3	(0.053, 0.054, 0.056)	O10	(0.049, 0.050, 0.051)	SC6	(0.061, 0.071, 0.076)
O4	(0.042, 0.043, 0.048)	SC1	(0.056, 0.059, 0.062)	I1	(0.046, 0.051, 0.052)
O5	(0.044, 0.046, 0.050)	SC2	(0.054, 0.056, 0.056)	I2	(0.046, 0.046, 0.050)
O6	(0.053, 0.053, 0.054)	SC3	(0.050, 0.050, 0.052)	I3	(0.055, 0.055, 0.057)
O7	(0.040, 0.040, 0.046)				

sensing (P5), and operational excellence (P14) were ranked first by the managers. Retailer C ranked strategy development (P12), advanced forecasting (P10), personnel sensing (P4), financial sensing (P5), and supplier sensing (P3) as the most important BDA micro-foundations. Several micro-foundations were ranked similarly among two or more retailers. Financial sensing (P5) was the only micro-foundation ranked in the top five in all retailers. Retailers A and C also ranked strategy development (P12) and supplier sensing (P3) in their top five micro-foundations. Other micro-foundations of personalized campaigns (P13), customer engagement (P8), and risk profiling and continuity plans (P9) were ranked relatively the same among all retailers, with personalized campaigns (P13) leaning toward the top micro-foundations, customer engagement (P8) situated in the middle of the importance range, and risk profiling and continuity plans (P9) towards the least important of capabilities.

The lowest ranked micro-foundations for retailer A were process reconfiguration (P11), operational excellence (P14), risk profiling and

continuity plans (P9), advanced forecasting (P10), and resource allocation (P7). In retailer B, process sensing (P2), market sensing (P1), supplier sensing (P3), strategy development (P12), and advanced forecasting (P10) were ranked the lowest, whereas retailer C ranked operational excellence (P14), data-driven action (P6), market sensing (P1), risk profiling and continuity plans (P9), and resource allocation (P7) the lowest. Similarities between retailers A and B were their low prioritization of advanced forecasting (P10), whereas retailers A and C show more similarity in prioritizing capabilities of operational excellence (P14), risk profiling and continuity plans (P9), and resource allocation (P7). Retailers B and C also ranked market sensing (P1) among the five lowest micro-foundations.

Published records and secondary observations from retailer A support the validity of these findings. Leveraging AI-driven demand forecasting was reported to support the optimization of inventory and minimized stockouts, especially during panic buying in the pandemic. Real-time data was seen to enable rapid adjustments to product assortments and pricing to align with shifting consumer needs. Retailer A's swift launch of online grocery services showcased its ability to adapt channels quickly. Its dedicated analytics unit integrated customer insights into decision-making, which was reported to enable quick pivots toward value brands and essential goods during inflation. These market sensing (P1) capabilities can be seen to have empowered retailer A to better anticipate changes, respond quickly, and maintain service levels amid volatile conditions. In terms of supplier sensing (P3), retailer A reported to have gained real-time visibility across its logistics and supplier network by implementing an AI-powered global 'control tower,' enabling rapid responses to delays and risks. This centralized data model was seen to have improved coordination and allowed for dynamic rerouting and inventory adjustments during crises such as the 2021 Suez Canal blockage and pandemic-related port backlogs. Data-driven synchronization with suppliers was reported to have lowered costs, which is crucial for a discounter strategy, and embedded a risk-aware approach—potential supply interruptions due to a supplier factory shutdown or geopolitical delays and cost spikes were flagged earlier. Long-term supplier partnerships were further seen to have supported flexibility through collaborative initiatives on sustainability and localization. These data-driven practices were reported to have enabled retailer A to adapt quickly, maintain product flow, and strengthen supplier collaboration amid global supply chain volatility. Lastly, the strategy development (P12) process was seen to have promoted a risk-

Table 6
Ranks of BDA practices in all case retailers.

Capacities	Micro-foundations	Closeness			Ranking			Deviation among cases ^a
		A	B	C	A	B	C	
Sensing	Market Sensing (P1)	0.66	0.44	0.48	1	13	12	●
	Process Sensing (P2)	0.55	0.22	0.56	8	14	7	●
	Supplier Sensing (P3)	0.66	0.49	0.58	2	12	5	●
	Personnel Sensing (P4)	0.54	0.63	0.60	9	9	3	●
	Financial Sensing (P5)	0.61	0.68	0.58	5	4	4	○
Seizing	Data-driven action (P6)	0.60	0.79	0.36	6	1	13	●
	Resource Allocation (P7)	0.54	0.68	0.50	10	3	10	●
	Customer Engagement (P8)	0.57	0.67	0.53	7	6	9	○
	Risk Profiling & Continuity Plans (P9)	0.48	0.63	0.49	12	8	11	○
	Advanced Forecasting (P10)	0.50	0.55	0.61	11	10	2	●
Transforming	Process reconfiguration (P11)	0.44	0.78	0.56	14	2	6	●
	Strategy Development (P12)	0.64	0.54	0.77	3	11	1	●
	Personalized Campaigns (P13)	0.63	0.63	0.55	4	7	8	○
	Operational Excellence (P14)	0.45	0.68	0.34	13	5	14	●

^a Deviation degree: ● very high, ● high, ● medium, ○ low, ○ very low.

aware, adaptive culture at retailer A by incorporating data analytics into decision-making processes. After 2020, the company invested in proprietary IT and established a global data analytics office to guide strategic planning. Leaders use predictive models to adjust pricing, prioritize services, and redesign supply networks. A ‘mistake-friendly’ culture and decentralized decision-making empower rapid local responses. Analytics teams and staff training aim to ensure data-informed decisions at all levels. Disruption can therefore be seen as a catalyst for strategic evolution, with market and supplier sensing feeding scenario planning. Long-term moves, such as omni-channel expansion and AI-driven supply chain management, align with a strategy focused on resilience.

At retailer B, data-driven actions (P6) and tools such as AI and machine learning are reported to be used to increase agility and adaptability. In France, it uses AI-based demand forecasting with real-time data, such as weather, to anticipate demand spikes, like those during heat waves, and proactively adjust stock, reducing waste and ensuring availability. In Poland, retailer B deployed an AI-powered planning platform across all channels to optimize forecasting, promotions, and deliveries. This system is seen to improve visibility and collaboration by providing store teams with real-time control and enhancing coordination with suppliers. During the pandemic, retailer B digitized communication to overcome information gaps, which is reported to have promoted a risk-aware culture and enabled faster, more proactive responses to disruptions. In addition, retailer B has demonstrated strong resilience by quickly reconfiguring processes (P11) in the face of disruptions. In early 2020, panic buying in Romania caused demand for staple foods to spike overnight. The company expedited its e-commerce expansion plans, managing a surge in online food sales of over 72% in France and 100% in Poland and adapting fulfillment processes within weeks. The company’s adaptability and agility are evidenced by a 32% rise in online revenue in France that offset hypermarket losses. During the 2022 war in Ukraine, retailer B kept 99% of the food supply flowing by opening new pickup points in cities such as Irpin and Bucha despite damaged stores. These outcomes highlight how rapid process reconfiguration can strengthen supply flexibility and collaboration under pressure. Retailer B’s resilience is also seen to stem from its use of AI tools for real-time resource allocation (P7). In France, ‘delivery flow smoothing’ algorithms are used to balance shipments across stores and fleets, preventing overloads and ensuring the efficient use of trucks, labor, and space. Such real-time allocation can directly contribute to agility and adaptability in the face of disruptions, as the network can more easily absorb demand surges or supply delays when flows are smoothed. AI-driven replenishment is reported to maintain optimal inventory levels, reduce waste, and maintain buffers. During the pandemic, the company hired temporary staff and rerouted logistics to manage volume spikes in response to workforce shortages due to illness.

In Ukraine, over 2300 tons of goods were reallocated from warehouses in other countries to keep shelves stocked. This cross-country resource pooling highlights the company’s strong collaboration and agility in repositioning inventory and support where needed most.

At retailer C, strategy development (P12) is seen to have driven innovation and resilience against disruption. The company launched its e-commerce platform just before the onset of the pandemic, which enabled non-contact shopping and helped maintain revenue during lockdowns. By 2020, the company was opening 2–3 stores daily and had over 2000 outlets, which allowed for rapid distribution shifts during panic buying. Retailer C localized its supply chain, sourcing 60% of its products from domestic brands that ensured stock availability during geopolitical disruptions. The company partnered with farmers to improve the logistics of fresh produce and collaborated with other retailers to expand its offerings. A crisis task force and cautious expansion plans reflect its risk-aware culture. Moreover, the company’s advanced forecasting (P10) capabilities are seen to have improved resilience by enabling real-time alignment of supply and demand. During the pandemic, sales of food and hygiene products surged by over 60% in March 2020 alone, accounting for 15% of annual revenue. Retailer C’s analytics systems detected these shifts in demand early on, allowing for rapid inventory reallocation. For instance, one system enabled live inventory tracking and agile restocking, supported by 200 new trucks and 300 new stores. Forecasting also guided flexible sourcing, reducing reliance on imports. The company shared forecasts with suppliers to align production, and internal dashboards unified planning. Scenario modeling and early alerts promoted a risk-aware culture, ensuring proactive responses to disruptions. Unlike the other two cases, personnel sensing (P4) was seen as one of the most significant BDA practices at retailer C, enhancing resilience by monitoring staff well-being, skills, and needs. During the pandemic, the company reassigned staff (e.g., promoters to online fulfillment) and used digital human resource tools for rapid training. Despite absenteeism, operations continued because of cross-training, which ensured that over 20,000 employees were able to work. Real-time workforce tracking supported scaling last-mile delivery. Management built trust by maintaining open communication through surveys and a feedback hotline. This led to strong collaboration across stores and warehouses, where employees shared stock updates, covered shifts, and solved problems together. During the pandemic, staff in multiple regions volunteered with local authorities to assemble and distribute relief packages, demonstrating a united and resilient workforce.

4.4. Agreement and robustness checks

Classical consistency indices (e.g., FCJMC and IFPR) presuppose reciprocal preference relations. However, DEMATEL collects non-

reciprocal, directional influences. Therefore, we do not impose reciprocity post hoc. Instead, we assess inter-rater agreement by computing Kendall's W on the induced rankings from the fuzzy judgments. We obtained $W = 0.348$, indicating moderate agreement (Howell, 1992) for the 19×19 elicitation task, which is adequate for aggregation but warrants robustness checks. Furthermore, we quantify group consensus using a fuzzy, distance-based consensus/compatibility index tailored to nonreciprocal judgments (Chen, 2000; Xu et al., 2013). The overall consensus is 0.759 (moderate), with per-expert compatibility ranging from 0.593 to 0.809 (median around the upper-0.7s). This indicates broadly acceptable alignment, with some heterogeneity across raters.

To triangulate reliability and consensus, we apply a consensus-and-consistency-level (CCL) procedure at the expert-aggregation stage by optimizing expert weights on the simplex with regularization toward uniformity (Chen, 2000; Duchi et al., 2008; Herrera-Viedma et al., 2004, 2007) and setting a weight floor of $w_{\min} = 0.01$ to ensure that no expert is eliminated. The group consensus increased from 0.759 to 0.788 (an absolute increase of 0.029, or approximately 3.8%). Meanwhile, the optimized weights remained transparent and bounded (e.g., $\{0.01, 0.01, 0.01, 0.01, 0.055, \dots\}$), summing to 1.

Re-running f-DANP with the post-CCL aggregate produced modest changes in criterion salience. The mean absolute change in defuzzified weights was 0.0112 with a Spearman's ρ of 0.718 between the pre- and post-weight vectors, and a top-five overlap of three out of five (pre: $\{SC6, SC4, SC1, SC5, O1\} \rightarrow$ post: $\{SC6, I3, SC5, O1, O2\}$). Notably, SC6 remains dominant, and the reshuffle is confined to the margin of the top set. Overall, CCL improves agreement without materially distorting substantive conclusions. Hyperparameters α and w_{\min} , introduced in Appendix C, govern the trade-off between consensus gain and rank preservation.

4.5. Heterogeneity checks

A visual inspection of the relative closeness already suggested that four micro-foundations (P5, P8, P13, and P9) exhibited broadly similar priorities across the three retailers (see Table 6). To avoid inferring cross-context homogeneity from the visual pattern, we compared the rank profiles using Spearman's ρ and complemented this with Kruskal-Wallis tests on the relative closeness scores. For the full set of 14 items, Spearman's ρ is low and even negative for A-B ($\rho = -0.437, p = 0.118$) and B-C ($\rho = -0.336, p = 0.240$) and close to zero for A-C ($\rho = 0.147, p = 0.615$), which indicates that the three retailers do not share a common overall prioritization of BDA practices. When we isolate the four 'close' practices (P5, P8, P13, and P9), rank agreement increases markedly ($\rho = 0.800$ for both A-C and B-C), which is consistent with the visual pattern. The p -values remain large only because the core has $n = 4$, so test power is low. Conversely, when this core is removed, the A-B correlation for the remaining ten practices becomes more negative ($\rho = -0.576, p = 0.082$), confirming that the observed heterogeneity is primarily driven by non-core items.

The Kruskal-Wallis tests refine this interpretation. The per-item tests (P1 ... P14) do not indicate significance ($p = 0.368$), as expected, given that there is only one observation per retailer per item. However, when we aggregate only the core items (P5, P8, P13, and P9) and compare retailers A, B, and C jointly, the difference becomes significant ($H = 7.731, p = 0.021$). This shows that although retailers order the core items similarly, they do not attribute the same level of importance to them. For example, retailer B assigns higher closeness scores to the core items. In contrast, the aggregated test for the other ten (non-core) practices is not significant ($H = 0.730, p = 0.694$), meaning that across this broader set, the three profiles fall within comparable ranges. Overall, the evidence supports three claims: (i) there is a small, partially shared core of BDA practices; (ii) the intensity with which this core is emphasized remains context-specific; and (iii) outside this core, rankings diverge, so cross-context homogeneity cannot be claimed.

4.6. Sensitivity analysis

The sensitivity analysis was conducted to evaluate the robustness of the f-TOPSIS rankings of BDA practices under variations in the weights of the most influential resilience capabilities. Specifically, $\pm 5\%$ perturbations were applied to the fuzzy weights of criteria identified as having high influence or prominence (i.e., SC6, SC4, SC1, O1, and O2), while all other criteria weights were held constant. This analysis was performed separately for each retailer A, B, and C using their aggregated expert judgment data, enabling a focused understanding of how local context affects ranking stability.

As illustrated in Fig. 3, the relative closeness values of the BDA practices demonstrate notable stability across all perturbed scenarios for each retailer. For retailer A, slight variations are observed, particularly with regard to practices P1 through P4, but the overall ranking order remains largely consistent. Retailers B and C demonstrate even more consistent patterns, with the relative closeness values of most practices exhibiting minimal fluctuation under weight shifts. This suggests that the rankings produced by the f-TOPSIS method exhibit minimal sensitivity to minor alterations in critical weight assumptions, thereby substantiating the internal stability of the decision-making model.

A salient aspect of the analysis is its reflection of the unique contextual factors influencing retailers' stability profiles. For instance, retailer B displays a more limited range of relative closeness values across all practices, potentially attributable to more homogeneous expert opinions or a predominant prioritization logic. Retailer C displays a more pronounced dispersion in relative closeness, particularly among mid-ranked practices, yet maintains consistent ranking behavior under criterion perturbation. The overall pattern supports the interpretation that the ranking outcomes remain stable under small, plausible perturbations of key modeling assumptions, which is the relevant notion of robustness in a decision-aiding, expert-elicitation setting.

5. Discussion

5.1. Implications for theory and research

This study set out to answer two ROs, which we will use to discuss its implications and contributions. Consistent with our pragmatic, decision-aiding mindset, the study's primary contribution is the structured elicitation and modeling of expert knowledge regarding the relative importance and perceived influence structure of resilience capabilities and BDA practices rather than the estimation of objective causal effects. Beyond the full representation of results in the findings and especially Figs. 1 and 2, we develop a set of four propositions that capture and highlight the key results of the study in conjunction with their discussion in the following paragraphs. Our line of reasoning is mainly guided by the theory elaboration approach by Fisher and Aguinis (2017). RO1 focused on eliciting and structuring experts' assessments of the relative importance of social-ecological resilience capabilities and the direction and strength of perceived influence structures between them to establish a weighted framework for decision-making and theory elaboration. Then, RO2 focused on developing a decision-aiding ranking model of BDA practices to support multi-level resilience in food retailing through the lens of dynamic capabilities.

Regarding RO1, prior research has discovered interrelationships among core resilience capabilities (e.g., collaboration, visibility, agility, and flexibility) yet calls for broader capability sets, untested interdependencies, and explicit attention to spatial scales (Liao et al., 2025; Sauer et al., 2022). Accordingly, we incorporate, validate, and model 19 social-ecological resilience capabilities across three spatial levels to capture their complexities (Novak et al., 2021) using a fuzzy hybrid MCDA design that jointly maps perceived influence structures and derives capability weights based on expert judgments. By providing one of the first multi-level investigations, we find substantial cross-level differences in AFSCs, with the SC level showing the highest perceived

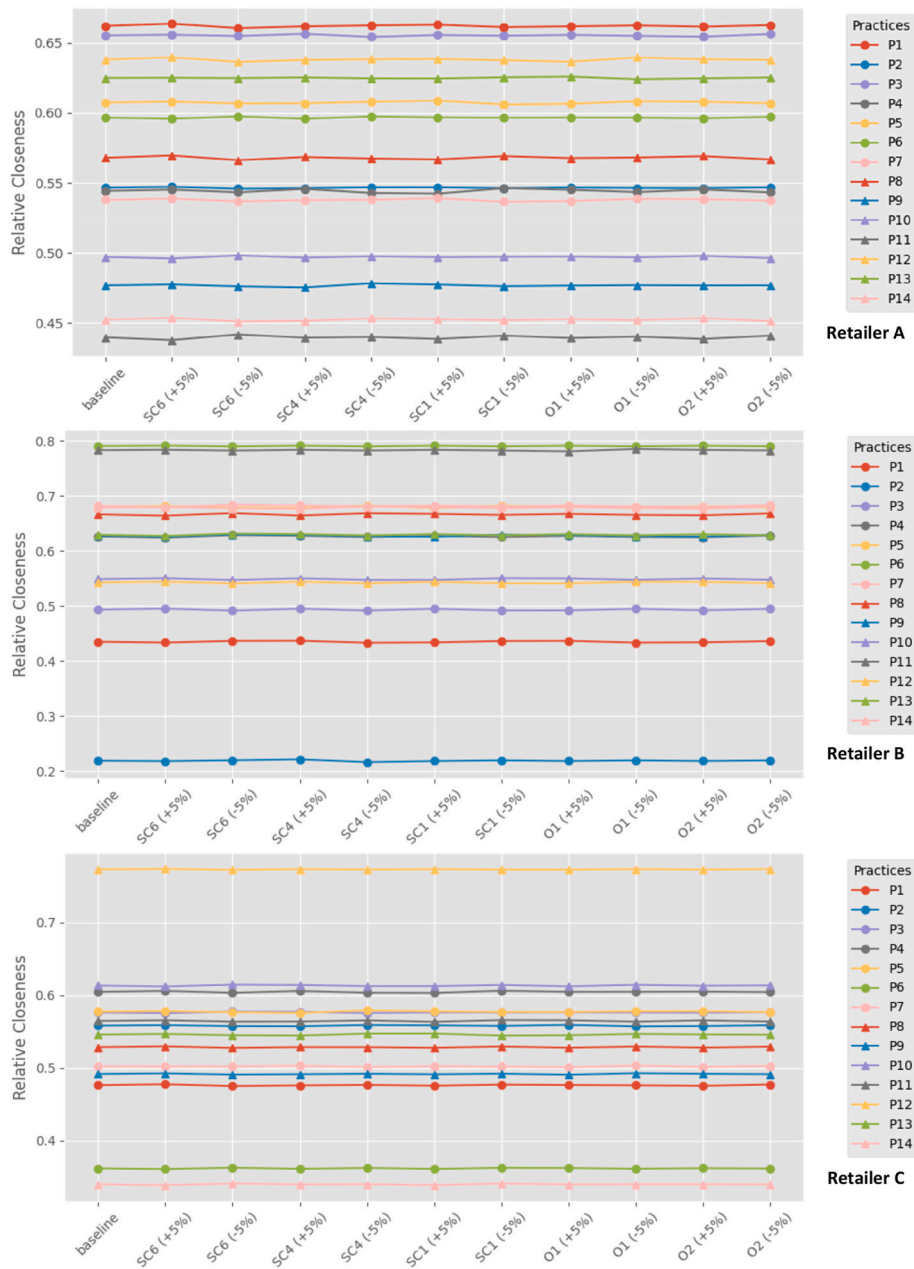


Fig. 3. Sensitivity analysis of BDA practices under $\pm 5\%$ criterion weight changes.

net influence over organizational and industry levels (see Fig. 1). This indicates where experts locate influence within the capability system, while it does not evidence cross-level causal effects, and is less likely to reflect framing because the level distinction was not disclosed during elicitation. The observed concentration of perceived influence at higher levels aligns with multi-level resilience arguments (Choi et al., 2025; Sauer et al., 2022) and the view that SC resilience exceeds the sum of partner organizations' resilience (Novak et al., 2021), particularly under a social-ecological lens (Wieland and Durach, 2021). Thus, consistent with a vertical contrasting approach to theory elaboration (Fisher and Aguinis, 2017), SC and industry level capabilities are seen as system-shaping conditions in AFSCs, while the derived weights, which extend prior ISM and graph theoretic treatments and narrower contexts (Sharma et al., 2023), respond to the call to quantify resilience capabilities (Zhong et al., 2024) and highlight the priority configuration in which strong SC level capabilities complemented by an organizational level risk-aware culture are seen as the most critical means for resilience.

This echoes well with earlier findings on the more cooperative and inter-organizational nature of the social-ecological view of SC resilience that contrast with the more operative and organizational level focus of the engineering view of resilience (Sauer et al., 2022; Simchi-Levi et al., 2018). Based on this, we develop the following proposition (P).

P1. In AFSCs, SC level capabilities are perceived as the primary drivers for enhancing social-ecological resilience that shapes the salience of industry and organizational level capabilities, while the industry level is also seen to influence the organizational level.

Deepening the insights on perceived influence of SC level capabilities over other capabilities in AFSCs, we found that beyond the single SC capabilities, a risk-aware culture as an organizational capability is perceived as one of the most critical capabilities. This criticality aligns with earlier research (Kazancoglu et al., 2024; Liao et al., 2025; Soni et al., 2014) and is complemented in this study by findings that such a

risk-aware culture is perceived to be impactful on the resilience of AFSCs and to be influenced by the other capabilities from all levels with three capabilities being intermediate in this influence structure (see Fig. 2). This is consistent with a mechanism in which attentional and interpretive capacities shape how resources are mobilized during disruption (Liao et al., 2025). Moving beyond earlier studies, our results provide one of the first multi-level investigations of social-ecological resilience (as called for by Novak et al., 2021; Sauer et al., 2022) and contribute to the discussion in AFSCs by underlining that this risk-awareness needs to extend into the organization itself, as well as the SC and industry it is embedded in. Across these three levels, the SC is seen to have the strongest influence on the risk-aware culture, while industry level capabilities are perceived to have less influence and organizational capabilities are seen to have the lowest influence. This focus on the SC level may be due to the strong interconnectedness of actors in the AFSC (Hodobod and Eakin, 2015; Mohammed et al., 2025). Overall, our results contribute to the rejection of simplistic top-down or bottom-up approaches in creating resilience in AFSCs. Instead, we contribute to the view that general SC resilience concepts are applicable to a wide set of SCs, but the influence structure between the single capabilities remain highly context- and industry-specific (see also Piffari et al., 2026). These results can inform further research on refinements of the perceived influence structures as well as decisions and investments into specific capabilities to enhance AFSC resilience based on the enhanced understanding of how capabilities are seen to influence each other. Based on this, we propose P2.

P2. In AFSCs, a risk-aware culture at the organizational level is perceived as an impactful capability for enhancing social-ecological resilience that is seen to be amplified by the capabilities from all spatial levels and especially high-influence SC capabilities.

Our RO2 findings on BDA micro-foundations in AFSC retailing address the call for sophisticated methods to investigate the effective use of big data (Surbakti et al., 2020) and the need for deeper attention to dynamic capability micro-foundations in AFSC resilience (Belhadi et al., 2024). Consistent with our replication logic (Yin, 2018), rankings differ across retailers A–C and indicate meaningful heterogeneity in strategies, BDA maturity, and operating environments. We therefore advance a contingency view of the BDA–resilience relationship, in which retailer types and disruption regimes can be seen as determinants of which micro-foundations are prioritized (Scholten et al., 2025). For retailer A (a discounter) with notable buying power, market sensing (P1) and personalized campaigns (P13) suggest a demand-steering orientation that is perceived to reinforce adaptability (SC6), agility (SC4), and collaboration (SC5). For retailer B (a pan-European hypermarket/convenience platform), reliance on advanced third-party stacks is seen to be linked with prioritizing process reconfiguration (P11), data-driven action (P6), and resource allocation (P7) aimed at strengthening SC agility (SC4) and visibility (SC2). For retailer C (a fast-expanding supermarket facing shocks), strategy development (P12), advanced forecasting (P10), supplier sensing (P3), and financial sensing (P5) are seen to reflect a survival or hedging logic that supports adaptability (SC6), supply flexibility (SC1) and a risk-aware culture (O1). Meanwhile, operational excellence (P14) and market sensing (P1) recede under volatile demand. Based on the differences in the provided judgments, we propose P3.

P3. In AFSC retailing, the BDA–resilience linkage is seen to be contingent on the type (discounter, hypermarket, supermarket, merchandiser, and convenience store), BDA maturity, and disruption regime conditions of a specific retailer, typically leading to different BDA priorities for different retailers.

Moving beyond the differences, heterogeneity tests (Spearman's ρ and Kruskal–Wallis) indicate a small, cross-case 'core' of BDA priorities

in AFSC retailing alongside a context-specific ordering. All three retailers converge on a limited set of BDA micro-foundations, i.e., financial sensing, customer engagement, personalized campaigns, and risk profiling and continuity plans, suggesting a retail baseline of resilience-relevant analytics that is commonly prioritized across the three cases, regardless of country, format, or disruption profile. In low-margin, high-volume agri-food retail business (Hansen, 2024), disruption conditions make analytics for liquidity and margin visibility (Herbert et al., 2018; Ivanov, 2024) and customer retention and retargeting (Brüggemann et al., 2025; Ivanov, 2024) particularly salient. In contrast, continuity-plan analytics are comparatively deprioritized in day-to-day operations (Holgado and Niess, 2023). This is consistent with the most weighted resilience capabilities. In our cases, rapid financial visibility is seen to support agility and adaptability by enabling the investigated retailers to reprice, re-promote, or reallocate resources quickly (Khan et al., 2024; Swink et al., 2024). It also seen to inform collaboration via data-backed negotiations because the studied retailers must negotiate with their suppliers using current cost and demand data (Bodendorf et al., 2022). Customer analytics is found to naturally complement agility and adaptability in AFSC retail settings (Baldi et al., 2024; Gao and Liu, 2023). If demand shifts online, toward smaller baskets, or toward local substitutes, retailers are seen to need granular customer data to influence behavior toward available options. Based on this, we formulate P4 on baseline BDA practices for enhancing the resilience of AFSC retailers:

P4. In AFSC retailing, financial sensing and customer-facing analytics form a perceived baseline of resilience-relevant analytics—a baseline analytics logic—across different retail contexts, while continuity-plan analytics are comparatively deprioritized in day-to-day operations.

Overall, the results highlight that there is no one-size-fits-all BDA pathway to resilience in AFSCs. Comparing the AFSC-specific results of this study to other industries, we also need to underline that the fast-paced nature of AFSCs and their retailing parts (Padovano and Ivanov, 2025) puts specific strains on the firms involved in such SCs that also impact their resilience. The low margins in AFSCs (Hansen, 2024) and the perishability of the products (Mohammed et al., 2025) may be seen as reasons for the lower weight of inventory and redundancy-related resilience capabilities in AFSC than, for example, in technology-centered industries (e.g., Statsenko et al., 2024) or the healthcare SC (Piffari et al., 2026). In turn, agility and flexibility capabilities are seen as more influential than in other industries. The connection to BDA micro foundations in our study deepens this context-specificity and helps to explain how the fast-paced nature of the industry and the steady demand for food, again compared to volatile demand for technology, is shaping the perceived importance of sensing capacities over seizing and transforming. This is underlined by the managers judgments of three sensing capacities among the top-five capacities. These encompass market, supplier and financial sensing, while, for example, process and personnel sensing were ranked lower, which again underlines the specificity of the industry as well as the prevailing importance of SC level aspects over organizational ones. Our empirical findings contribute to the validation of the currently mostly theoretical claims that social-ecological resilience is more outward-facing, i.e., mobilizing rather SC level than organizational level capabilities, than engineering resilience approaches (Wieland and Durach, 2021; Sauer et al., 2022). Moreover, we underline the strong need for context-specificity in investigating the interrelationships between both specific resilience capabilities and BDA practices (Piffari et al., 2026; Sharma et al., 2025; Stadtfeld and Gruchmann, 2024) and care in claiming wide generalizability of academic findings.

Accordingly, the BDA rankings in Table 6 should be interpreted as context-specific outputs of a decision-aiding model rather than as universally applicable prescriptions. Their value lies in applying the

constructs and modeling logic to derive case-specific priorities (Munda, 1993). To sharpen the theoretical contribution, we developed four propositions (P1 to P4) understood as abductive insights inferred from the structured expert knowledge we have collected and analyzed rather than as tested universal laws. Our study underlines how BDA micro-foundations are perceived to aid in the development of higher-order social-ecological resilience capabilities in AFSCs, thus contributing to the literature by further establishing the use of dynamic capabilities in the AFSC, resilience, and BDA literature. Applying MCDA, the findings show the extent to which each BDA micro-foundation is perceived to enhance resilience capabilities and gain a competitive advantage in rapidly changing and volatile environments. This study extends the application of BDA on social-ecological resilience by incorporating capabilities spread across organizational, SC, and industry levels beyond the proactive and reactive phases (Jiang et al., 2024). Rather than confirming causal effects, we offer a transparent and replicable representation of the influence linkages elicited from experts and managers. Therefore, generalization is primarily analytical: the framework, constructs, and decision logic are transferable, but the specific weights and rankings are bound to the expert panels and cases studied.

5.2. Implications for practice

The results of RO1 include various implications for practitioners and policymakers. AFSC managers and policymakers may use the framework to formulate specific and tangible strategic plans based on the state of resilience capabilities in their organizations and SCs. Our study offers a comprehensive overview of SC resilience capabilities in Table 1, which can be used for a self-evaluation of how extensively the concept of resilience is addressed in an organization. Moreover, sections 4.1 and 4.2 provide insights into the relevance and interrelation of the individual resilience capabilities. This can be used by decision makers to prioritize future actions and investments into SC resilience on different levels. As such, the addition of the spatial scale in this study is also useful to practitioners in understanding the importance of combining organizational with SC and industry level capabilities to achieve enhanced resilience. This can help managers and policymakers to move from an engineering view of resilience towards more social-ecological resilience that has proven superior during the last pandemic (Sauer et al., 2022). However, these implications should be interpreted as guidance for decision-making derived from structured expert knowledge in AFSCs, not as evidence-based prescriptions that guarantee performance effects in all settings. In this sense, the value of the results lies in supporting sense-making, prioritization, and dialogue among stakeholders.

The identified driving power of the SC level capabilities in AFSCs underlines that focal firms, governments, and public institutions operating on an industry level in the food sector may consider strengthening partnership and compliance flexibility to strengthen the overall AFSC resilience. Stronger partnerships, specifically through issuing small and medium-sized grants and involving local suppliers in design, may bring much-needed inclusivity to smaller actors, like farmers or small enterprises, whose connectivity to the market and social relationships influence social-ecological change (González-Mon et al., 2024). On an organizational level, fostering knowledge management and a risk-aware culture are seen to be critical, especially considering the high perceived effect of the former on the latter. Building operational flexibility and anticipation capabilities are perceived to be beneficial due to their high prominence and relatively high influence on other capabilities. On a SC level, adaptability is not only seen as a prominent capability but an influential as well; therefore, by developing this capability, SC managers can reasonably expect (based on the expert-perceived influence structure) that it will support their level of resilience and be associated with other SC resilience capabilities such as supply flexibility, collaboration, and strategic redundancy. Based on the interdependencies and weights of resilience capabilities, decision-makers can assess and reflect on their

current strategies and subsequently devise strategic plans to tackle the most central, most influential, or the missing resilience capabilities at organizational, SC, or industry levels. The social-ecological resilience view adopted in this study captures the complexities of AFSCs, not limited to the organizational or dyadic levels. This broader perspective can help agri-food stakeholders to recognize that, concerning resilience, the whole is greater than the sum of its parts. At the same time, while the results do not prove the superiority of one resilience paradigm, they do indicate that experts place great importance on cross-actor, system-level capabilities that are central to a social-ecological approach.

Despite the desire and appetite for BDA, the intended value from BDA is not always achieved (Surbakti et al., 2020). RO2 findings, therefore, provide an evaluation method and decision support system to aid managers in quality decision-making in the complex and highly volatile environment of the AFSC to choose the most suitable BDA micro-foundation for their context-specific resilience goals. By testing the proposed model, individual organizations can assess the BDA micro-foundations they collectively agree are the most critical to the resilience capabilities most important to their system. This is especially useful when implementing all BDA micro-foundations and resilience capabilities is unrealistic due to real-world constraints. Although the BDA prioritization yielded various results based on each organization, the cases were selected to cover different classifications of retailers (Bonfrer et al., 2022), therefore, other large food retail managers with similar classifications, strategies, geographical locations, and extent of BDA usage can use the model to run their own expert-elicitation exercise and derive a context-specific prioritization of which BDA capabilities are most aligned with their targeted resilience capabilities. Thus, the model is best positioned as a configurable decision aid that supports the adoption of more anticipatory and transformative approaches rather than as a template whose specific rankings can be transferred directly across firms.

6. Conclusions

In this paper, a fuzzy DANP, fuzzy TOPSIS method is proposed to evaluate the AFSC resilience capabilities in terms of perceived interrelationships and centrality and to rank the BDA micro-foundations that are seen to support these capabilities in the food retail sector as the final step in the AFSC. The resilience capabilities on organizational, SC, and industry levels were validated and weighted based on the responses of 26 carefully selected SC resilience researchers and professors. The BDA micro-foundations' ranking was based on a total of 19 managers working in two large European and one large Middle Eastern food retailers heavily invested in BDA. The findings indicate the perceived importance of adaptability (SC6), agility (SC4), supply flexibility (SC1), collaboration (SC5), and risk-aware culture (O1) for the constitution of social-ecological resilience in AFSCs. Adaptability (SC6), agility (SC4), compliance flexibility (I2), strategic redundancy (SC3), buffer redundancy (O5), robustness (O10), and supply flexibility (SC1) were seen as the most influential capabilities on other social-ecological resilience capabilities in AFSCs.

Regarding the BDA micro-foundations, the results showed a clear link to how the strategies of the investigated retailers in their customer relationships and operations alongside their BDA maturity enabled them to shift their focus on other types of value-creating BDA practices. The latter were often more complex or lacking and enabled the retailers to adapt and transform in face of disruptions, showing the shift towards a social-ecological resilience perspective in the food industry. Similarly, the three diverse cases of retailers show the importance of finding context-specific priorities of sensing, seizing, and transforming BDA capabilities to enhance social-ecological resilience in AFSCs. In our study, this specificity considered the variability of retailer classification, strategy, BDA use, geopolitical, and economic circumstances.

This work is not without limitations, which give rise to several research directions. First, the data used in this study is limited to a single

point in time, while the weights of the investigated SC resilience capabilities likely change over time. Therefore, we propose longitudinal approaches to better track the evolution of resilience capabilities and technologies at the single spatial levels. Moreover, such approaches can further generalize the case- and context-specific findings of our study that warrant only analytical generalizability. Second, this study considered the often-overlooked spatial scale of organization, SC, and industry levels in the agri-food sector. Still, the temporal and functional scales suggested in conceptual and qualitative models (Novak et al., 2021; Sauer et al., 2022) may further enrich future studies. Third, future research can analyze BDA prioritization in cross-country contexts or companies operating in developing countries, which can again improve generalizability beyond the focus of this study. Fourth, methodological improvements may include integrating the entropy method with f-DANP to mitigate subjectivity in weighting (Mei et al., 2016). A fuzzy-entropy inference system, which relies on measurable sub-criteria, could be a beneficial resilience assessment tool for practice and research to deal with disruptions. In addition, future work should broaden the BDA prioritization sample, by company size or geographical location, and increase the number of resilience experts consulted to enhance generalizability and reliability. Fifth, while our findings primarily rank BDA practices based on their perceived role in enhancing resilience capabilities, they do not evaluate the impact of BDA use on the perceived relationships between these capabilities. Future empirical studies are recommended to measure the impact of key resilience capabilities on each other and examine the role of BDA capability as a moderator of the perceived impacts presented in Fig. 2. More specifically, studies could investigate whether cost-leadership retailers can achieve adaptability and agility from customer-oriented analytics, whereas hypermarket/convenience platforms benefit more from a process-centric focus. Another path would be to validate if supermarkets in high-distress contexts, such as retailer C, achieve greater resilience by prioritizing continuity analytics over other BDA configurations, thus testing the moderating role of both business model and operational

context.

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CRedit authorship contribution statement

Alireza Asgari: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Data curation, Conceptualization. **Morteza Alaeddini:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Philipp C. Sauer:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Conceptualization. **Paul Reaidy:** Writing – review & editing, Supervision, Resources, Project administration.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used Google Gemini and DeepL Write in order to improve the readability of the manuscript. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Declaration of competing interest

The authors declare that they have no known competing interests.

Appendix A. Details on resilience experts

Table A.1
Characteristics of social-ecological resilience experts.

Metric	Min	Max	Average
Years in academia	5	38	14.8
Total citations	93	107,670	5,781.5
h-index	5	149	26.2

Appendix B. Data analysis methodology (f-DANP, f-TOPSIS)

Throughout our calculations, we used triangular fuzzy sets, represented as a triplet (l, m, u) , which are commonly used to handle uncertainties and vagueness in real-world decision-making (Si et al., 2018). Here, l , m , and u represent the smallest, most promising, and largest possible values, respectively, describing the fuzzy event. A fuzzy subset \tilde{z} of \mathbb{R} is defined by a membership function $\mu_{\tilde{z}} : \mathbb{R} \rightarrow [0, 1]$, where $\mu_{\tilde{z}}(x), \forall x \in \mathbb{R}$, indicates the degree to which x belongs to \tilde{z} . A TFN \tilde{z} is a normal, convex fuzzy subset of \mathbb{R} , with a piecewise linear membership function $\mu_{\tilde{z}}$, defined by:

$$\mu_{\tilde{z}}(x) = \begin{cases} \frac{x-l}{m-l}, & l \leq x \leq m \\ \frac{u-x}{u-m}, & m \leq x \leq u \\ 0, & \text{otherwise} \end{cases}$$

B.1. Fuzzy DEMATEL for influence structure analysis of resilience capabilities

The fuzzy decision making trial and evaluation laboratory (f-DEMATEL) method combines the DEMATEL approach (Gabus and Fontela, 1972) with fuzzy sets and fuzzy logic. This integration allows subjective factors to be considered in the decision-making process by addressing the challenge of human judgments being vague and difficult to quantify precisely (Wu and Lee, 2007). DEMATEL creates a structured model to analyze influence relationships between complex criteria and uses graph theory and mathematical matrix tools to provide a graphical framework based on relationships between criteria, utilizing professionals' expertise. With this approach, one can calculate the centrality and net influence ('relation') of each criterion, draw relationship diagrams, and classify criteria into higher-net-influence ('driver') and higher-net-dependence ('dependent') groups in the DEMATEL sense (Thakkar, 2021). In this study, these outputs are interpreted as structured patterns of influence based on the perceptions of experts, rather than as empirical proof of causal effects. Combining the DEMATEL approach with fuzzy set theory overcomes limitations when dealing with subjective expert judgments (Wu and Lee, 2007).

We defined the linguistic terms as TFNs by means of the following scale: N or blank (no influence) = (0, 0, 0.25); VL (very low influence) = (0, 0.25, 0.5); L (low influence) = (0.25, 0.5, 0.75); H (high influence) = (0.5, 0.75, 1); and VH (very high influence) = (0.75, 1, 1), which are shown in Figure B.1.

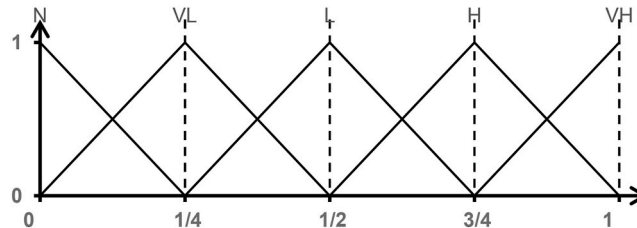


Fig. B.1. Triangular fuzzy numbers for linguistic terms used in the f-DEMATEL model.

Step 1: Construction of the direct influence matrix

The experts were asked to complete a questionnaire in which they indicated the influence of capability i on capability j using the five aforementioned linguistic variables. For each expert k , we converted the linguistic terms into fuzzy numbers and obtained a non-negative matrix $\tilde{Z}^k = [\tilde{z}_{ij}^k]_{n \times n}$, with (0, 0, 0) on the diagonal. After the individual assessments were gathered, the aggregate fuzzy performance ratings were calculated for all ϵ judges using extended addition and scalar multiplication to create a total fuzzy direct influence matrix $\tilde{Z} = [\tilde{z}_{ij}]_{n \times n}$, in which:

$$\tilde{z}_{ij} = (l_{ij}, m_{ij}, u_{ij}) = \left(\frac{1}{\epsilon} \sum_{k=1}^{\epsilon} l_{ij}^k, \frac{1}{\epsilon} \sum_{k=1}^{\epsilon} m_{ij}^k, \frac{1}{\epsilon} \sum_{k=1}^{\epsilon} u_{ij}^k \right)$$

Step 2: Normalization of the direct influence matrix

To obtain the normalized fuzzy matrix \tilde{S} , the matrix \tilde{Z} was standardized as follows:

$$\tilde{S} = \frac{\tilde{Z}}{\max \left(\max_{1 \leq i \leq n} \sum_{j=1}^n u_{ij}, \max_{1 \leq j \leq n} \sum_{i=1}^n u_{ij} \right)}$$

Step 3: Construction of the total influence matrix

The total fuzzy influence matrix $\tilde{T} = [\tilde{t}_{ij}]_{n \times n}$ was derived as follows, where I is the identity matrix.

$$\tilde{T} = \tilde{S}(I - \tilde{S})^{-1}$$

Step 4: Extraction of influence maps (relation–prominence diagrams)

The row and column sums of \tilde{T} yielded the following:

$$\tilde{R} = [\tilde{r}_i]_{n \times 1} = \left[\sum_{j=1}^n \tilde{t}_{ij} \right]_{n \times 1}, \tilde{C} = [\tilde{c}_j]_{1 \times n} = \left[\sum_{i=1}^n \tilde{t}_{ij} \right]_{1 \times n}$$

After these calculations, we performed defuzzification on \tilde{R} and \tilde{C} to obtain their crisp values R and C . We then used these values to calculate 'prominence' ($R + C$) and 'relation' ($R - C$). Prominence reflects the significance or importance of a criterion within a given system. Criteria with higher prominence values are considered more influential in driving changes within the system. Relation, on the other hand, measures the net direction of influence versus dependence within the expert-perceived network. For this step, we used the best non-fuzzy performance (BNP) method as

follows, which is a widely used defuzzification method for transforming fuzzy values into crisp values. It is particularly effective for TFNs.

$$BNP = \frac{(u - l) + (m - l)}{3} + l$$

B.2. Fuzzy ANP for weight derivation of resilience capabilities

The fuzzy analytic network process (f-ANP) method combines the ANP approach with fuzzy logic (Saaty, 1996). ANP incorporates interdependencies and feedback among criteria and alternatives within a decision network to address complexities (Saaty and Vargas, 2013). ANP incorporates networks of influence with dependence and feedback. Each decision network consists of clusters, their elements, and the links between these elements. In a typical ANP model, all links between elements and those connected to them within a given cluster are used for pairwise comparisons. Due to the high number of interdependencies among resilience capabilities, performing these comparisons was challenging (Büyükožkan and Gülerüyüz, 2016). In our hybrid model, these comparisons were obtained from f-DEMATEL. Further calculations were carried out using ANP and incorporated into the supermatrix. We used the same TFNs for f-ANP as for f-DEMATEL to create our f-DANP model.

Step 1: Construction of the unweighted supermatrix

First, the total influence matrix \tilde{T} was considered as the total influence matrix \tilde{T}_C between the m resilience clusters. Next, each submatrix \tilde{T}_C^{ij} with m_c elements, was normalized by calculating the coefficient of $\tilde{d}_{C_k}^{ij}$ for each row k , which is obtained from the sum of the elements in that row of the submatrix and is calculated as follows. Then, \tilde{T}_C was normalized to obtain \tilde{T}_C^* . Finally, \tilde{T}_C^* was transposed to obtain the unweighted supermatrix $\tilde{U} = (\tilde{T}_C^*)'$.

$$\tilde{T}_C = \begin{bmatrix} \tilde{T}_C^{11} & \dots & \tilde{T}_C^{1j} & \dots & \tilde{T}_C^{1m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{T}_C^{i1} & \dots & \tilde{T}_C^{ij} & \dots & \tilde{T}_C^{im} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{T}_C^{m1} & \dots & \tilde{T}_C^{mj} & \dots & \tilde{T}_C^{mm} \end{bmatrix}$$

$$\tilde{T}_C^{ij} = \begin{bmatrix} \tilde{t}_{11}^{ij} / \tilde{d}_{C_1}^{ij} & \dots & \tilde{t}_{1j}^{ij} / \tilde{d}_{C_1}^{ij} & \dots & \tilde{t}_{1m_c}^{ij} / \tilde{d}_{C_1}^{ij} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{t}_{k1}^{ij} / \tilde{d}_{C_k}^{ij} & \dots & \tilde{t}_{kj}^{ij} / \tilde{d}_{C_k}^{ij} & \dots & \tilde{t}_{km_c}^{ij} / \tilde{d}_{C_k}^{ij} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{t}_{m_c 1}^{ij} / \tilde{d}_{C_{m_c}}^{ij} & \dots & \tilde{t}_{m_c j}^{ij} / \tilde{d}_{C_{m_c}}^{ij} & \dots & \tilde{t}_{m_c m_c}^{ij} / \tilde{d}_{C_{m_c}}^{ij} \end{bmatrix}$$

$$\tilde{d}_{C_k}^{ij} = \sum_{l=1}^{m_c} \tilde{t}_{kl}^{ij} \text{ for } k = 1, 2, \dots, m_c$$

Step 2: Construction of the weighted supermatrix

First, the dimensional unweighted matrix \tilde{T}_D was constructed. In this matrix, each submatrix \tilde{T}_D^{ij} was calculated as $\tilde{T}_D^{ij} = \text{Average}(\tilde{T}_C^{ij})$. Then, \tilde{T}_D was normalized to obtain the matrix \tilde{T}_D^* , in which each submatrix \tilde{T}_D^{*ij} was calculated as $\tilde{T}_D^{*ij} = \tilde{T}_D^{ij} / \sum_{l=1}^m \tilde{T}_D^{il}$. Next, the matrix \tilde{T}_D^* was transposed to obtain the dimensional weight coefficient matrix $\tilde{\omega}$. Finally, matrix $\tilde{\omega}$ was assigned to the unweighted supermatrix \tilde{U} to obtain the weighted supermatrix \tilde{W} , which is a fuzzy stochastic matrix with a column vector of (1, 1, 1).

$$\tilde{W} = \begin{bmatrix} \tilde{U}_{11} \times \tilde{\omega}_D^{11} & \dots & \tilde{U}_{1j} \times \tilde{\omega}_D^{1j} & \dots & \tilde{U}_{1m} \times \tilde{\omega}_D^{1m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{U}_{i1} \times \tilde{\omega}_D^{i1} & \dots & \tilde{U}_{ij} \times \tilde{\omega}_D^{ij} & \dots & \tilde{U}_{im} \times \tilde{\omega}_D^{im} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{U}_{m1} \times \tilde{\omega}_D^{m1} & \dots & \tilde{U}_{mj} \times \tilde{\omega}_D^{mj} & \dots & \tilde{U}_{mm} \times \tilde{\omega}_D^{mm} \end{bmatrix}$$

Step 3: Construction of the limit supermatrix

Next, an exponential operation was performed on the weighted supermatrix \tilde{W} . If convergence occurred, we used the converged matrix as the weights of the resilience capabilities. To this end, the p th power of the stochastic matrix \tilde{W} was found until convergence, $\lim_{p \rightarrow \infty} \tilde{W}^p$, yielding the

converged matrix \tilde{L} , where each column is the weight value \tilde{w}_j of the resilience capability.

B.3. Fuzzy TOPSIS for prioritization of BDA micro-foundations

The fuzzy technique for order of preference by similarity to ideal solution (f-TOPSIS) combines the TOPSIS approach (Hwang et al., 1993) with fuzzy sets. TOPSIS creates a model that ranks and selects alternatives based on their distance from an ideal solution. It uses mathematical matrix tools to provide a framework based on the relationships between the alternatives and the criteria and utilizes professionals' expertise. Using this method, one can calculate the closeness of each alternative to the ideal solution and rank the alternatives accordingly using their closeness coefficient. Combining TOPSIS with fuzzy set theory overcomes limitations when dealing with subjective expert judgments (El Alaoui, 2021). For this phase of analysis, we defined the linguistic terms as TFNs by means of the following scale: EL (extremely low) = (0, 0, 1/6); VL (very low) = (0, 1/6, 1/3); L (low) = (1/6, 1/3, 1/2); M (medium) = (1/3, 1/2, 2/3); H (high) = (1/2, 2/3, 5/6); VH (very high) = (2/3, 5/6, 1); and EH (extremely high) = (5/6, 1, 1), which are shown in Figure B.2.

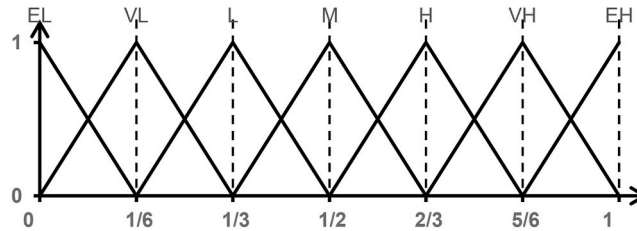


Fig. B.2. Triangular fuzzy numbers for linguistic terms used in the f-TOPSIS model.

Step 1: Construction of the weighting matrix

The experts were asked to complete a questionnaire in which they indicated the influence of BDA practice i on resilience capability j using the seven aforementioned linguistic variables. For each expert ℓ , we converted the linguistic terms into fuzzy numbers and obtained a non-negative matrix $\tilde{X}^\ell = [\tilde{x}_{ij}^\ell]_{m \times n}$. After gathering the individual assessments, the aggregate fuzzy performance ratings were calculated for all judges. Extended addition and scalar multiplication were used to create a fuzzy matrix $\tilde{X} = [\tilde{x}_{ij}]_{m \times n}$. The matrix \tilde{X} was then multiplied with the weight matrix \tilde{L} calculated by the f-DANP. Finally, we obtained the weighting matrix \tilde{V} .

$$\tilde{V} = \tilde{X} \tilde{L} = [\tilde{v}_{ij}]_{m \times n}$$

Step 2: Determination of the positive and the negative ideal solutions

The fuzzy positive ideal solution (PIS) and the fuzzy negative ideal solution (NIS)—the two hypothetical alternatives that have the best and worst possible values for all criteria—were calculated as follows.

$$\tilde{A}^+ = \left\{ \max_i \tilde{v}_{ij} \right\} \quad \text{and} \quad \tilde{A}^- = \left\{ \min_i \tilde{v}_{ij} \right\}$$

Step 3: Calculation of the Euclidean distances

Subsequently, the Euclidean fuzzy distances between each alternative and the positive and negative ideal solutions were calculated using the following equations:

$$\tilde{d}_i^+ = \sqrt{\sum_{j=1}^n (\tilde{v}_{ij} - \tilde{A}_j^+)^2} \quad \text{and} \quad \tilde{d}_i^- = \sqrt{\sum_{j=1}^n (\tilde{v}_{ij} - \tilde{A}_j^-)^2}$$

Step 4: Calculation of the closeness coefficients

The goal of TOPSIS is to rank alternatives based on how close they are to ideal solutions. The best alternative is the one closest to the PIS and farthest from the NIS. According to this principle, the alternatives were ranked based on their defuzzified closeness coefficients CC_i , calculated as follows:

$$CC_i = BNP \left(\frac{\tilde{d}_i^-}{\tilde{d}_i^+ + \tilde{d}_i^-} \right), 0 \leq CC_i \leq 1$$

Appendix C. Methods used for agreement and robustness check

C.1. Fuzzy consensus/compatibility index

Assume ϵ experts, n criteria, and each expert k provides a fuzzy matrix $\tilde{Z}^k = [\tilde{z}_{ij}^k]_{n \times n}$, where each \tilde{z}_{ij}^k is triangular (l, m, u) with support in $[0, 1]$ as described in Appendix B.1.

Step 1: Group prototype (fuzzy mean) per cell

For each cell (i, j) , the component-wise mean was computed across experts:

$$\tilde{z}_{ij}^* = \text{mean}(\tilde{z}_{ij}^1, \dots, \tilde{z}_{ij}^\epsilon) = (\bar{l}, \bar{m}, \bar{u})$$

Step 2: Fuzzy distance per cell and expert

We measure how far each expert's TFN at cell (i, j) is from the group prototype (i.e., the component-wise mean TFN) using the vertex/Euclidean distance adapted from Chen (2000) The normalized Euclidean distance is calculated as follows:

$$d(\tilde{z}_{ij}^k - \tilde{z}_{ij}^*) = \sqrt{\frac{(l - \bar{l})^2 + (m - \bar{m})^2 + (u - \bar{u})^2}{3}}$$

Step 3: Per-cell consensus

In literature on reaching consensus (e.g., Herrera-Viedma et al., 2007, 2004), group agreement is typically quantified based on the (dis)similarities or distances between experts' evaluations and an aggregate or central assessment. Higher distances indicate lower consensus and vice versa. Following that logic, and adapted from Xu et al. (2013), the expert-to-prototype distance at (i, j) is averaged, normalized by the maximal feasible distance on the scale, d_{\max} , and transformed to an agreement value:

$$\bar{d}_{ij} = \frac{1}{\epsilon} \sum_{k=1}^{\epsilon} d(\tilde{z}_{ij}^k - \tilde{z}_{ij}^*), \text{Consensus}_{ij} = 1 - \frac{\bar{d}_{ij}}{d_{\max}}$$

This lies in $[0, 1]$, and the higher the consensus, the greater the agreement. Here, consensus is considered an indicator of how closely expert judgments converge, supporting interpretive credibility and stability assessment rather than causal validation.

Step 4: Aggregates

We aggregate by row, column, and overall to compute the per-expert compatibility later, which is the normalized mean distance to the prototype. Row and column consensus are the arithmetic means across the cells of each row or column, respectively. Overall consensus is the mean of all Consensus_{ij} .

Step 5: Per-expert compatibility

The following is an average representation of how close an expert is to the group prototype:

$$\text{Compat}^k = 1 - \frac{1}{n^2 d_{\max}} \sum_{ij} d(\tilde{z}_{ij}^k - \tilde{z}_{ij}^*)$$

The median and minimum values across the experts are examined.

C.2. Consensus-and-consistency-level (CCL)

The purpose of CCL in this study is to test the stability of aggregation under various expert-weighting schemes and document how sensitive the results are to group heterogeneity. Let ϵ experts each provide an $n \times n$ fuzzy influence matrix, $\tilde{Z}^k = [\tilde{z}_{ij}^k]$. Let $w \in \mathbb{R}^\epsilon$ be non-negative expert weights on the probability simplex $\Delta^{\epsilon-1} = \{w \geq 0, \mathbf{1}^T w = 1\}$ (Duchi et al., 2008).

Step 1: Weighted group prototype (per cell)

For each (i, j) , the prototype (i.e., the aggregate fuzzy value) is defined as the weighted mean of the expert fuzzy numbers, computed component-wise:

$$\tilde{z}_{ij}^*(w) = \sum_{k=1}^{\epsilon} w_k \tilde{z}_{ij}^k$$

Step 2: Distance and consensus

The standard vertex/Euclidean distance on fuzzy parameters (Chen, 2000) is used to quantify disagreement:

$$d(\tilde{z}_{ij}^k - \tilde{z}_{ij}^*(w)) = \sqrt{\frac{(l - \bar{l})^2 + (m - \bar{m})^2 + (u - \bar{u})^2}{3}}$$

With the scales set to $[0, 1]$, d_{\max} is set to 1. The overall consensus (Herrera-Viedma et al., 2004, 2007) for the weights, w , is defined as follows:

$$\text{Cons}(w) = 1 - \frac{1}{n^2} \sum_{i=1}^n \sum_{j=1}^n \left(\frac{1}{\varepsilon} \sum_{k=1}^{\varepsilon} \frac{d(\tilde{z}_{ij}^k - \tilde{z}_{ij}^*(w))}{d_{\max}} \right) \in [0, 1]$$

Higher values indicate stronger group agreement.

Step 3: Surrogate objective for CCL (weight optimization)

Maximizing $\text{Cons}(w)$ directly is non-smooth; therefore, adapted from Duchi et al. (2008), a transparent convex surrogate is used to minimize the distance-weighted, linear term with a regularizer to avoid degenerate weights:

$$\min_{w \in \Delta^{\varepsilon-1}} J(w) = \sum_{k=1}^{\varepsilon} c_k w_k + \alpha \|w - \nu\|_2^2, \nu = \frac{1}{\varepsilon} \mathbf{1}$$

where c_k is the mean distance of expert k to the uniform-weighted prototype $\tilde{z}_{ij}^*(\nu)$, i.e.:

$$c_k = \frac{1}{n^2} \sum_{ij} d(\tilde{z}_{ij}^k - \tilde{z}_{ij}^*(\nu))$$

This shifts the weight toward the experts who are closer to the group, while regularizing toward equal weights ($\alpha \in [10^{-3}, 10^{-1}]$). After solving for w^* , the following steps are taken: re-aggregation with w^* , re-computation of $\text{Cons}(w^*)$, and reporting of pre- and post-CCL.

Data availability

Data will be made available on request.

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