ACHIEVING EFFICIENT RESILIENCE THROUGH HUMAN ADJUSTMENTS OF ALGORITHM PRESCRIPTIONS – A RETAIL MANAGEMENT APPLICATION

Completed Research Paper

Katharina Berendes, University of Goettingen, Goettingen, Germany, katharina.berendes@uni-goettingen.de

Maik Hammerschmidt, University of Goettingen, Goettingen, Germany, maik.hammerschmidt@wiwi.uni-goettingen.de

Aliasghar Arabmaldar, University of Hertfordshire Business School, Hatfield, United Kingdom, a.arabmaldar@herts.ac.uk

Dominic Loske, Technical University of Darmstadt, Darmstadt, Germany, loske@pscm.tu-darmstadt.de

Matthias Klumpp, Politecnico di Milano, Milan, Italy, matthias.klumpp@polimi.it

Abstract

As the frequency of significant market disruptions rises, retailers are forced to respond through resilience activities which often comes at the cost of sacrificing operational efficiency. To alleviate this resilience-efficiency trade-off, retailers increasingly rely on digital technologies, particularly artificial intelligence (AI). Specifically, they are employing AI-based algorithm prescriptions to guide humans in operational decision-making, aiming to improve resilience while maintaining high efficiency. In our field study involving 341 stores of a large European retailer, we examine the effects of human-AI collaboration on this resilience-efficiency trade-off. Our results indicate that human adjustments of algorithm prescriptions regarding supply strategy factors (i.e., delivery frequency and delivery pattern) can intensify the trade-off. However, if organizational experience and product differentiation are high, adjusting algorithm prescriptions helps to reduce the conflict between resilience and efficiency. For practice, we offer important implications on how firms can leverage the potential of AI-based tools in retail stores to become both resilient and efficient.

Keywords: Algorithm Prescriptions, Human Adjustment, Efficient Resilience, Retail Management.

1 Introduction

Nearly 40% of all German retailers increasingly struggle with disruptions stemming from several sources (Ifo Institute, 2023). For example, global crises have changed customers' channel preferences making demand more volatile, and have amplified product harm problems and capacity breakdowns, leading to escalated demand and supply-side disruptions. Altogether, those disruptions impose increased uncertainty levels for retail businesses, forcing them to change structures and processes to make them more resilient against any type of disruption. Resilience describes the adaptive ability of a system to respond to and recover from disruptions (Tukamuhabwa et al., 2015). However, increasing resilience typically comes at the cost of sacrificing the efficiency of a system. Arguably, in order to respond flexibly to disruptions, additional resources for redundant systems or surplus logistics capacity are needed, causing efficiency losses due to increased input levels (e.g., costs) (Ivanov, 2022). In an effort to be resilient, a firm might also impose restrictions on its outputs. For example, it may choose not to take on every customer order or may limit the range of products offered, leading to decreased outputs (e.g., sales). Thus, particularly in the retail context, recent studies highlight the challenge to manage this trade-off between resilience and efficiency and hence to minimize the efficiency losses associated with resilience activities (Auf der Landwehr et al., 2023; Shen and Sun, 2023).

To address this challenge, there is a common trend to support operational decision-making processes by relying on digital technologies such as artificial intelligence (AI). Specifically, retailers are utilizing algorithm prescriptions for operational decisions in the hope of increasing resilience while preserving high efficiency. In this context, AI often takes on an augmenting role, e.g., by generating recommendations to assist human decision-makers. For example, retail stores use AI tools that prescribe the optimal store supply strategy (i.e., delivery frequency for pre-ordered products). This outcome enables the efficient management of resilience activities by determining a delivery strategy that ensures continuous availability of product assortments to meet customer demand at the lowest cost and hence minimum waste of personnel and logistics resources. However, no study so far has explored whether such human-AI teams, defined as collaborative partnerships where humans and AI systems work together, are indeed capable of mitigating the conflict between resilience and efficiency or even worsening it.

Over the past two decades, resilience research has delved into AI solutions to foster, maintain, and enhance resilience while achieving efficient operations. For instance, Belhadi et al. (2024) underscore AI's impact on enhancing resilience without further efficiency losses through improved information processing capabilities. Subsequent studies (e.g., Gupta et al., 2023) have probed how using AI in supply chains bolsters the efficiency of resilience activities by eliminating superfluous resources. Furthermore, these studies highlight that AI-driven analyses elevate decision-making speed and accuracy in crisis situations, thus aiding both resilience and efficiency. Despite these promising findings, existing literature is limited by its lack of accounting for the human aspect of AI technology deployment, highlighting a significant research gap in the resilience literature. Lindebaum et al. (2020) point out the risk of using AI-based technologies without understanding their interplay with humans. This oversight is notable, given the vastly different outcomes of human-AI collaboration compared to the use of AI alone as demonstrated by a recently emerging stream of studies on human-AI interaction outside the resilience context (Jussupow et al., 2024).

On the one hand, studies highlight that AI, due to its advanced data processing and pattern recognition capabilities, can enrich human capabilities, leading to powerful human-AI teams (Balasubramanian et al. 2022; Jain et al., 2021; Krakowski et al., 2022) that can outperform humans and AI alone. In the retail industry, the study by Revilla et al. (2023) on human-AI collaboration in demand forecasting indicates that human intervention in AI solutions may lead to efficiency losses, especially if rapid decisions are required. This perspective suggests that adhering to algorithm prescriptions without adjusting them could empower retail stores to respond to unexpected disruptive events with less efficiency sacrifices. In contrast, other studies show the negative effects of human adherence to AI recommendations. If humans always conform to algorithm prescriptions, they may forego the possibility of replacing insufficient or incomplete algorithm information through superior human knowledge (Kesavan and Kushwaha, 2020; Sun et al., 2021). The study by Loske and Klumpp (2021) on human-AI collaboration in route planning in retail logistics demonstrates that human adjustments positively influence efficiency, as it considers factors that may not be fully captured by AI, such as customer preferences intricacies. From this perspective, conforming to AI solutions could also cause additional inefficiencies when implementing resilience activities instead of reducing inefficiencies. Hence, for promptly responding to unexpected disruptions, deviating from the prescription could be beneficial in order to adjust the suboptimal algorithm solutions that would otherwise lead to insufficient processes generating additional costs. Given these inconclusive perspectives, understanding whether humans should adhere to or adjust AI solutions in the face of disruptions to alleviate the resilience-efficiency trade-off is crucial. This knowledge helps to identify beneficial forms of collaboration between employees and AI technologies that allow for achieving high resilience and high efficiency simultaneously. To address this gap, we formulate our first research question:

RQ1: *How does human-AI collaboration (i.e., human adherence to or adjustment of algorithm prescriptions) influence the resilience-efficiency trade-off for retail stores?*

Recently, research across fields has explored the deployment of AI-driven technologies for different business functions (Kuhn et al., 2021; Sun et al., 2021). Their results show that the benefits of these technologies vary depending on boundary conditions. This is particularly relevant for retail stores, which face challenges due to internal dynamics and market complexities (Grewal et al., 2020; Ivanov and Dolgui, 2018). Internal dynamics are connected to resource-driven characteristics like organizational experience, while market complexities are primarily linked to consumer-driven characteristics such as product differentiation. Studies have begun to investigate these boundary conditions in human-AI collaboration (e.g., Jia et al., 2023) and in resilience research (e.g., Wamba et al., 2020). However, their findings lead to mixed results. Therefore, these boundary conditions are crucial and must be considered when optimizing human-AI teams towards the resilience-efficiency trade-off. Hence, as a second research question, we ask:

RQ2: *How do boundary conditions (i.e., organizational experience, product differentiation) influence the relationship between human-AI collaboration and the resilience-efficiency trade-off?*

For quantifying the resilience-efficiency trade-off, robust Data Envelopment Analysis (RDEA) has been established as a state-of-the-art technique in the literature (Arabmaldar et al., 2024; Toloo et al., 2022). RDEA combines the common DEA's output-to-input efficiency measurement with robust optimization techniques to model the resilience of a system in terms of its robustness after output-and-input disruptions. Thus, RDEA measures the resilience-efficiency trade-off as the efficiency loss associated with achieving a certain level of resilience. Drawing on the augmentation capabilities framework (Helfat et al., 2023), we examine how human-AI collaboration can shift the resilience-efficiency trade-off by utilizing a dataset from a large European grocery retailer that uses AI-generated prescriptions for store supply strategies.

Our study provides important theoretical and practical implications. We unveil the role of human-AI collaboration in influencing the efficiency losses due to resilience activities, highlighting that, in general, deviations from algorithm prescriptions reinforce the trade-off. While this insight is alarming, we show that such deviations are not always bad. We identify boundary conditions (i.e., high organizational experience, high product differentiation) in which adjusting AI solutions can be desirable in terms of reducing efficiency losses of resilience activities. In doing so, we advance the augmentation capability framework by introducing important contingencies that inform firms on how to leverage AI tools to achieve both resilient and efficient systems.

The paper is structured as follows: Initially, we introduce our theoretical background and the state of research regarding the resilience-efficiency trade-off and human adjustments of algorithm prescription. Subsequently, we develop hypotheses and present our research model, which is then tested using a unique real-world dataset from grocery retail stores. For this purpose, we outline the data description, describe RDEA as our approach for calculating our dependent variable resilience-efficiency trade-off, and outline our Tobit regression model for hypothesis testing. The results are presented next and then discussed. We complete the paper with theoretical and practical implications, limitations, and future research directions.

2 Theoretical Background and Related Work

Our theoretical framework draws on the resource-based view (RBV) which has been pivotal in explaining a firm's economic efficiency and resulting competitive advantage (Barney, 1991). This theory has recently been introduced to resilience research (e.g., Brandon-Jones et al., 2014), as it allows to delve into how firms can leverage their unique resources and which capabilities behind the resources are valuable to navigate challenges and maintain performance (Helfat et al., 2023). RBV contends that the existence or absence of valuable, rare, inimitable, and non-substitutable strategic resources supports or impedes competitive advantages (Wernerfelt, 1984). The traditional view holds that competitive advantages are particularly created by human resources due to their low fungibility and scalability (Helfat and Peteraf, 2015). The latest advancements of the theory show that new bundles of resources are being created if humans possess augmentation capabilities, allowing them to combine their own human resources with AI information (Krakowski et al., 2022). This means that firms should turn away from the traditional understanding of human capital and acknowledge that the augmentation capabilities of humans in collaboration with AI are the decisive factor for creating unique and sustainable advantages (Helfat et al., 2023). Human limitations regarding cognitive capabilities can be compensated by augmentation capabilities that enable employees to leverage AI resources. We employ the new concept of augmentation capabilities for elaborating whether, and under which conditions human-AI teams can mitigate the resilience-efficiency trade-off, as human-AI collaboration settings reflect exactly an augmentation of human capabilities.

2.1 Resilience-efficiency trade-off

Resilience has become increasingly important due to the rapid proliferation of unexpected disruptive events. Resilience denotes the ability to respond to such disruptions in a way that a system remains robust and stable despite such adverse events (Tukamuhabwa et al., 2015). Extant literature frequently highlights a conflict between resilience and efficiency with efficiency reflecting the ratio of outputs produced to inputs deployed (Auf der Landwehr et al., 2023; Shen and Sun, 2023). The studies emphasize that quickly responding to disruptions is associated with additional costs for activities that assure flexibility and redundancy in assets such as capacity reservations and safety stocks, all causing decreases in efficiency (Ivanov et al., 2014). Moreover, the fact that resilience requires redundancies to maintain the flow of goods, and information conflicts with business practices such as lean approaches (Ivanov, 2022) that focus on the elimination of all types of waste within a company. In addition, being forced to respond to disruptive events poses additional constraints in managing resources, leading to fewer degrees of freedom in deploying inputs and outputs and hence efficiency losses (e.g., if not every customer order can be fulfilled). Thus, higher resilience often comes at the cost of lower efficiency through higher amounts of inputs needed (e.g., employees) or fewer outputs (e.g., sales) generated.

Building on the previous argumentation, the resilience-efficiency trade-off reflects the loss of efficiency associated with achieving high resilience. As we outline in more detail in the methodology section, for quantifying this efficiency loss we rely on RDEA as a well-established technique (Arabmaldar et al., 2024; Toloo et al., 2022). While DEA is a state-of-the-art method for measuring the output-to-input efficiency of a system, robust optimization is highly appropriate for modelling the resilience of a system after output-and-input disruptions. RDEA allows firms to determine how strong efficiency is "penalized" when implementing resilience activities. Based on the theoretical arguments provided above, we argue that augmenting human resources with AI resources for decision-making can influence the trade-off as it might influence the amounts of inputs or outputs related to resilience activities.

2.2 Human adjustment of algorithm prescriptions

The integration of AI-based technologies into business operations is becoming more prevalent to gain competitive advantages. Such technologies facilitate the generation of massive amounts of data and enable the analysis of this data with high accuracy and speed allowing the optimal use for data-driven decision-making (Agrawal et al., 2019). Thus, AI-based data analytics are highly suitable for operational decision-making in the retail context allowing to improve the quality of decision-making outcomes, resulting in increased operational efficiency (Belhadi et al., 2024). For instance, algorithm prescriptions are used regarding picking processes to achieve efficient picking operations (Sun et al., 2021) or transportation processes to optimize delivery cycles (Kuhn et al., 2021). In particular, for store supply strategies, prescriptions for delivery frequencies, (e.g., three deliveries per week) as well as delivery patterns (e.g., Monday-Wednesday-Friday) are the most prevalent forms of algorithm prescriptions. These delivery-related decisions require a consideration of many fluctuating and competitive factors (e.g., personnel, demand, truck utilization, etc.) that store employees might struggle to fully grasp and incorporate into their decision-making process due to their limited cognitive capabilities. Hence, algorithm prescriptions are an increasingly popular form of decision-making configurations that involve AI to support employees. Such prescriptions can be adhered to or adjusted by humans which can lead to different outcomes. Therefore, researchers have just recently started to investigate the impact of human adjustments of algorithm prescriptions on operational efficiency in retail contexts (Revilla et al., 2023; Loske and Klumpp, 2021). However, no study so far has examined whether such adjustments of AI solutions through deviating from algorithm prescriptions can change the efficiency losses associated with resilience activities. Moreover, recent studies highlight that organizational boundary conditions determine the (beneficial or detrimental) impact of AI-based technologies. However, research is needed regarding the conditions that can leverage the benefits of human-AI teams, especially in retail contexts. This is why we explore two critical boundary conditions: organizational experience and product differentiation.

Regarding experience, Jia et al. (2023) show that the effect of human-AI collaboration in a telemarketing context is dependent on employee experience. This impact extends beyond individual experience to encompass team experience, a dimension that is unexplored in current literature (Nyberg et al., 2014; Krakowski et al., 2022). In retail contexts, where store operations are conducted by teams of store employees orchestrated by store managers, the collective experience plays a crucial role in the effectiveness of human adjustments of AI solutions, highlighting a significant gap in understanding the moderating effect of the experience on the team level.

Regarding product differentiation as the second boundary condition, research has shown that different consumer-driven aspects may severely shape the impact of human-AI collaboration but has provided mixed results. On the one hand, a higher variety of product assortments increase complexity which yields negative moderating effects on the impact of human deviation in bin packing processes on performance due to humans limited cognitive capabilities (Boyacı et al., 2023; Sun et al., 2021). Resilience studies also suggest the negative moderating effects of complex and dynamic conditions on the impact of AI on operational efficiency (Wamba et al., 2020). On the other hand, product variability has been found to positively moderate the impact of human adjustments in product planning contexts due to the adaptability in the fulfilment of customer needs (Elmaghraby et al., 2015; Khosrowabadi et al., 2022). Due to the stronger integration of online and offline channels, grocery retail entails increasing assortment variability which could increase the flexibility of responding to changes in customer demands. Therefore, we also explore the moderating role of product differentiation for the impact of algorithm adjustments.

3 Hypotheses Development

3.1 The effect of adjusting algorithm prescriptions on the trade-off

According to the latest view of the RBV, a competitive advantage can be achieved when humans use their augmentation capabilities in collaboration with AI so that new unique bundles of resources are created (Krakowski et al., 2022). This augmentation capability view of the RBV suggests that humans need to recognize situations in which they could complement their cognitive capabilities by relying on algorithm prescriptions. For example, situation-specific decisions of retail stores about the optimal frequency and pattern of delivery of goods to the stores are settings where the (limited) cognitive capabilities of employees can be augmented by AI-based data analytics (Belhadi et al., 2024). Specifically, employees could reduce efficiency losses due to resilience activities by using AI capabilities to quickly and accurately identify the most effective response strategies that firms should realize, thereby minimizing the response time and avoiding wasting additional (unnecessary) inputs such as personnel and logistics costs on less effective activities. Therefore, if employees deviate from algorithm prescriptions for delivery frequency and delivery pattern, the costs of resilience may increase due to a loss of optimality in input and output levels. For example, a downward deviation from the optimal delivery frequency could decrease generated outputs (e.g., sales) due to missing products. In contrast, too high delivery frequency or an unfavorable delivery cycle can mean that employees in the stores cannot handle the amount of delivered goods and thus too many goods cannot be offered on time to customers or may even be lost. Additionally, as algorithm prescriptions perform independent of humans' physical and emotional conditions, a deviation from such prescriptions would disturb a constant allocation of personnel resources hindering firms from stabilizing operational processes in the face of disruptions and making it more difficult to achieve both efficient and resilient systems. Hence, as a baseline, we expect:

H1: *Human adjustments of algorithm prescriptions for* ***(a)*** *delivery frequency and* ***(b)*** *delivery pattern worsen the resilience-efficiency trade-off.*

3.2 The moderating role of organizational experience

A current discourse within the RBV framework centers around how augmentation capabilities manifest in human-AI collaboration settings (Krakowski et al., 2022). However, so far, this perspective does not fully account for the nuanced manifestations of these capabilities. Specifically, it overlooks the dual pathways through which augmentation can unfold: First, the augmentation can be reflected in the conscious decision to let AI substitute human (limited) cognitive capabilities if humans adhere to the algorithm prescription. Second, the augmentation can occur if humans deviate from algorithm prescription and complement AI capabilities with human capabilities as prescriptions are used as a baseline but adjusted through human discretion (Khosrowabadi et al., 2022; Sun et al., 2021). As literature highlights the relevance of boundary conditions, we assume that the effectiveness of these different forms of augmentation capabilities depends on organizational contingencies, an aspect yet unexplored in the augmentation capability view of the RBV. Therefore, we advance the augmentation capability approach by investigating how organizational conditions shape human-AI augmentation's success.

In H1 we have proposed that substituting human decisions through AI prescriptions (and *not* adjusting these prescriptions) is desirable for mitigating the trade-off. In the case of high organizational experience, however, we suggest that adjusting the algorithm prescription will be less detrimental or even beneficial. We argue that employee teams can complement AI capabilities with their idiosyncratic knowledge, especially in understanding the intricacies of customer behavior and preferences, that AI does not have in the decision-making process (Fügener et al., 2021). Organizational experience plays a pivotal role in this process, as it reflects the organizational level of knowledge and skills created through repeatedly performing tasks during a specific period (Argote et al., 2021). This metric is often captured by the overall duration of employment of the members belonging to a store team. Hence, by adjusting algorithm prescriptions, highly experienced employee teams can create superior resource bundles (Sirmon et al., 2007) that can be leveraged to create the most efficient solution in the presence of disruptions. Their deep, accumulated knowledge enables them to early identify critical processes and suitable changes needed and allows them to replace suboptimal algorithm prescriptions with more feasible solutions for responding to disruptions which can reduce failures and wasted resources. Consequently, adjusting AI solutions can better avoid increased inputs (e.g., logistic costs) and output losses (e.g., sales drops) leading to lower efficiency losses through resilience activities. Accordingly, we expect that the undesirable impact of humans' adjustments of AI prescriptions (i.e., for delivery frequency and delivery pattern) on the resilience-efficiency trade-off is alleviated in stores with higher organizational experience. Therefore, we hypothesize:

H2: *Human adjustments of algorithm prescriptions for* ***(a)*** *delivery frequency and* ***(b)*** *delivery pattern have a less detrimental effect on the resilience-efficiency trade-off in stores with higher organizational experience than in stores with lower organizational experience.*

3.3 The moderating role of product differentiation

While high organizational experience might ensure that adjustments of algorithm prescriptions may lead to better outcomes that alleviate the resilience-efficiency conflict, we next identify conditions that make an adjustment leading to suboptimal solutions less problematic. Specifically, we suggest that in the case of higher product differentiation, the detrimental impact of adjusting optimal algorithm prescriptions (for delivery frequency and delivery pattern) can be bolstered. Retail stores with highly differentiated assortments can serve different and volatile customer demands (Besbes and Sauré, 2016). With a higher number of variants within product categories, customers have more opportunities to substitute products (if a product is not available due to disruptions). In addition, stores with larger and more differentiated assortments are typically patronized by households with higher income and hence lower price sensitivity in times of economic shocks (Wakefield and Inman, 2003). Consequently, in such stores, suboptimal delivery frequency and delivery patterns due to adjustments of algorithm prescriptions are less detrimental as a store's output (e.g., sales) can still be increased due to higher flexibility in satisfying customer needs and responding to demand fluctuations through a large choice of (premium) products. We, therefore, hypothesize the following:

H3: *Human adjustments of algorithm prescription for **(a)** delivery frequency and **(b)** delivery pattern have a less detrimental effect on the resilience-efficiency trade-off in stores with higher product differentiation than in stores with lower product differentiation.*

Figure 1 presents our research framework.

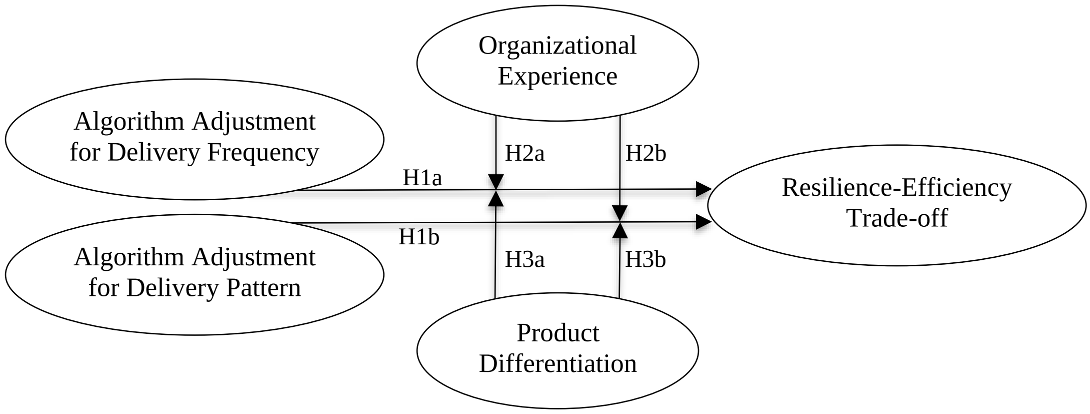

Figure 1. Research framework.

4 Methodology

4.1 Data description and algorithm deployment

We cooperate with a large brick-and-mortar grocery retailer in Europe and our focal units of analysis are individual grocery stores that operate as relatively independent business units. We use a real-world dataset of the retailer to gain deeper insights into algorithm deployment within actual operational settings, offering a comprehensive and authentic view that goes beyond the controlled setting and limited scope of experiments or simulations based on artificial datasets. This dataset contains store and sales data from the retailer's management system "AIMS" for a random selection of 341 grocery stores for a two-month time window (August and September 2022), a period without public holidays. To alleviate concerns of reverse causality we apply a time lag and use the August data (t_1) for measuring our independent variables (e.g., frequency and pattern adjustments) and September data (t_2) to measure the dependent variable resilience-efficiency trade-off. Note that we tested different lag structures (e.g., the first two weeks of August vs. the last two weeks of September) and the results remained unchanged. The retailer has implemented AI-based analytics to support stores in making optimal delivery-related decisions. This tool utilizes machine learning approaches based on a large amount of diverse historical and real-time data with great speed and accuracy (e.g., sales, customer frequency, store, assortment, and store employee data), to calculate the optimal store supply strategy for the non-cooled product categories. The retailer applies this tool to all grocery stores. A store receives a weekly prescription for the delivery frequency and delivery pattern for items of non-cooled products required during the week. For each store, the team is responsible for delivery-related decisions and has the autonomy to decide whether to precisely execute the algorithmic prescriptions or to deviate and adjust them. The single stores implement the algorithm prescriptions to varying degrees with a substantial number of stores deviating from the prescription at least in one week during the focal month (August 2022). Tweaking algorithm prescriptions occurs, for example, to account for store-individual factors or unexpected events that AI-based tools cannot recognize, e.g., rigid work times of employees due to personal issues. Moreover, allowing discretion to deviate leads to higher acceptance and adoption of the tool. Using the AI-based tool, the stores can only determine the delivery frequency and delivery pattern, they cannot change the quantities (e.g., due to truck capacity utilization and route optimization). If the stores need extra items of non-cooled products that are not considered by the AI-based tool, they have to order manually via another system.

4.2 Measuring the resilience-efficiency trade-off

4.2.1 Robust data envelopment analysis (RDEA)

We calculate our dependent variable resilience-efficiency trade-off by using RDEA for the input and output data from September 2022. DEA is a non-parametric method for the measurement of the relative efficiencies of peer decision systems, in our case retail stores, which transform multiple inputs into multiple outputs. DEA identifies the best-practice frontier that defines the most efficient transformation of inputs into outputs and then measures the efficiency of all stores against this frontier instead of considering average performance. Hence, DEA results are based on comparisons with the most efficient stores that operate under similar situations and scales. A store is efficient (i.e., receives an efficiency score of 1 or 100%) if it cannot reduce any input while holding the same level of outputs. Otherwise, a store is not efficient and receives an efficiency score smaller than 1.

DEA is a common method in operations research, and in recent years it has also become important in IS contexts (Ayabakan et al., 2017). Consider n DMUs indexed as $\mathrm{DMU}_j(j = 1, \dots, n)$ (stores) where each unit consumes m inputs $\boldsymbol{x}_j = (\dots, x_{ij}, \dots); i \in I = \{1, \dots, m\}$ to produce s outputs $\boldsymbol{y}_j = (\dots, y_{rj}, \dots); r \in R = \{1, \dots, s\}$. If the input and output data are subject to potential disruptions (and hence to uncertainty) to which a store responds through resilience activities, then employing deterministic DEA models (i.e., DEA without accounting for disruptions) for measuring the efficiency is inappropriate. In this case, decision-makers need to apply a so-called robust DEA approach that extends the common DEA framework by incorporating fluctuations in inputs and outputs. Thus, RDEA allows to model a system's resilience in terms of its robustness after input-and-output disruptions. Therefore, this study uses RDEA as a state-of-the-art approach for considering disruptions in the inputs and outputs of stores and measuring reliable efficiency values that account for these disruptions (Arabmaldar et al., 2024; Klumpp et al., 2023; Toloo et al., 2022). By considering different levels of possible disruptions as a common approach for modelling disruption effects (e.g., Aldrighetti et al., 2023), RDEA shows the efficiency losses associated with keeping the system robust despite these disruptions (i.e., the efficiency losses incurred for being resilient). Formally, the RDEA model can be written as follows (Toloo et al., 2022):

$$
\begin{aligned}
&\theta_R^*(\Gamma_j^x, \Gamma_j^y) = \max \textstyle\sum_{r=1}^{s} u_r y_{ro} - p_o^y \Gamma_o^y - \sum_{r=1}^{s} q_{ro} \\
&s.t. \\
&\textstyle\sum_{i=1}^{m} v_i x_{io} - p_o^x \Gamma_o^x - \sum_{i=1}^{m} w_{io} \leq 1 \\
&\textstyle\sum_{r=1}^{s} u_r y_{ro} - \sum_{i=1}^{m} v_i x_{io} - p_o^x \Gamma_o^x - p_o^y \Gamma_o^y - \sum_{r=1}^{s} q_{ro} - \sum_{i=1}^{m} w_{io} \leq 0 \\
&\textstyle\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + p_j^x \Gamma_j^x + p_j^y \Gamma_j^y + \sum_{r=1}^{s} q_{rj} + \sum_{i=1}^{m} w_{ij} \leq 0 \qquad \forall j \neq o \\
&u_r \hat{y}_{rj} - p_j^y - q_{rj} \leq 0 \qquad \forall j, \forall r \\
&v_i \hat{x}_{ij} - p_j^x - w_{ij} \leq 0 \qquad \forall j, \forall i \\
&q_{rj}, w_{ij}, p_j^y, p_j^x, v_i, u_r \geq 0 \qquad \forall i, \forall r, \forall j
\end{aligned}
\tag{1}
$$

where θ_R^* is the efficiency score which informs about the portion of inputs that can be saved while holding the same level of outputs; v_i and u_r are the weights of the i^{th} input and r^{th} output, respectively. In Model (1) $\hat{x}_{ij} = e x_{ij}$ and $\hat{y}_{rj} = e \tilde{y}_{rj}$ are the deviations of inputs and outputs, respectively, in which e represents the percentage of deviations of the uncertain data from their nominal values due to disruptions. Hence e represents the disruption level of a store. Model (1) measures the robust efficiency of a focal store (store_o) and specifies the level of disruptions with the robust parameters Γ_j^x and Γ_j^y

associated with inputs and outputs data. Model (1) contains variables that protect the objective function and the constraints against disruptions and measures the robust efficiency of the DMUs. For example, the variables (p_j^x, p_j^y) and (q_{rj}, w_{ij}) quantify the sensitivity of the inputs and outputs data when the level of disruptions changes. Besides, the quantities $p_j^x \Gamma_j^x + \sum_{i=1}^{m} w_{ij}$, $j = 1, .., n$ and $p_j^y \Gamma_j^y + \sum_{r=1}^{s} q_{rj}$ leverage the worst-case deviations of the inputs and outputs from their nominal values. Furthermore, the pre-defined robust parameters $\Gamma_j^x \left(\Gamma_j^y\right)$ reflect the maximal number of uncertain inputs (outputs) that are subject to disruptions (i.e., can fluctuate due to disruptions). In addition, to protect the system against input and output disruptions, the objective function value of the robust model is penalized by a loss of efficiency compared to the deterministic model. This comparison informs the managers about the resilience-efficiency trade-off which is defined in the following part.

4.2.2 The resilience-efficiency trade-off

The resilience-efficiency trade-off represents the difference between the deterministic efficiency (i.e., efficiency without disruptions) and the robust efficiency (i.e., efficiency after responding to disruptions) and can be calculated as follows (Arabmaldar et al., 2024; Klumpp et al., 2023):

$$\text{Resilience-Efficiency Trade-off } = \frac{\theta_R^*(0,0) - \theta_R^*(\Gamma_j^x, \Gamma_j^y)}{\theta_R^*(0,0)}, \qquad \forall \Gamma_j^x, \Gamma_j^y > 0 \tag{2}$$

where $\theta_R^*(0,0)$ is the deterministic efficiency measure of a store, and $\theta_R^*(\Gamma_j^x, \Gamma_j^y)$ is the robust efficiency measure of a store for varying levels of Γ_j^x, Γ_j^y. The trade-off metric provides a clear-cut image of the resilience impact on efficiency. For example, let us assume the level of disruption is 5% meaning that inputs and outputs fluctuate by 5%. If the resulting resilience-efficiency trade-off is 10%, this means that if a store responds to this deviation to keep the system robust, the resulting efficiency loss will be 10%.

4.2.3 Inputs and outputs for RDEA and descriptive results

The following five inputs (I) and two outputs (O) are widely used in the DEA literature for investigations of grocery store efficiency (e.g., Neves et al., 2018) and are therefore used in this study for calculating efficiency measures:

Personnel costs (I_1) is the salary paid to store employees in the focal month (September 2022). *Logistics costs* (I_2) is the store-level costs for retail warehouse order picking and transportation in the focal month. Order-picking costs depend on the number of products picked for the store multiplied by a firm-wide unified cost rate. Transport costs depend on the number of transport units delivered to the store multiplied by a uniform transfer price per transport unit. *Frontend space* (I_3) is the space in square meters of a store dedicated for customers to make purchases, excluding the backroom's square, checkout area, and entrance/exit areas. *Backend space* (I_4) is the space in square meters made available for backroom operations. It is the space that is separated from the sales area and used to buffer inventory for shelf replenishment. *Population* (I_5) depicts store neighborhood characteristics and hence this input is considered as a proxy for demand size. For measuring this variable, we combine archival company data on the postal code of each store with secondary data from the Federal Statistical Office (2023) covering the number of inhabitants living in the catchment area. *Sales* (O_1) is the store sales without further adjustments as the circumstances (e.g., taxes) are equal for all observed stores. *Number of different products* (O_2) in the store reflects the variety of products offered to customers. Given that all products sold through cash desk counters are recorded by the retailers' merchandise management system, the number of products sold is provided by counting unique article numbers passing the cash desk.

The robust and deterministic efficiency measures are calculated using the above-mentioned inputs and outputs. Table 1 shows the results (Min, Max, Mean, SD) for the deterministic DEA models, the RDEA model (setting the disruption level to 5%) and the resilience-efficiency trade-off. For the deterministic

DEA and RDEA model, we give the number of efficient stores (No. Eff. Stores) reflecting the number of stores with an efficiency score of one (i.e., maximum efficiency score). Table 1 shows that the average efficiency loss for maintaining the resilience of a store is 15.67%. It also shows that some stores can achieve resilience without efficiency loss (i.e., exhibit a zero trade-off).

	Min	**Max**	**Mean**	**SD**	**No. Eff. Stores**
Deterministic	0.6315	1	0.8894	0.0876	50
Robust (5% disruption)	0.5319	1	0.7515	0.0974	9
Resilience-efficiency trade-off	0	18.23%	15.67%	4.10%	-

Table 1. Efficiency measures and resilience-efficiency trade-off.

4.3 Model development for hypothesis testing

Our dependent variable resilience-efficiency trade-off of a grocery store i is censored, i.e., it is observed within a certain range and observations below or above that range do not exist. In our case, the trade-off metric is right censored in the range of $\{y^* | \, 0 \leq y \leq 1\}$. We therefore use Tobit regression as it has the key advantage of being able to handle censored data.

We define two key independent variables, namely Frequency_Adjustment$_{t1,i}$ and Pattern_Adjustment$_{t1,i}$. In line with Sun et al. (2021), we measure Frequency_Adjustment$_{t1,i}$ as a binary variable that equals one if the delivery frequency of store *i* deviates from the algorithm prescription at least in one week of the focal month (t_1) and zero otherwise. Consider as an example, a grocery store with an algorithm-prescribed frequency of three delivery days per week that decides for only two delivery days.

Pattern_Adjustment$_{t1,i}$ is a binary variable that equals one if the delivery pattern of store *i* deviates from the algorithm prescription at least once in t_1 and zero otherwise. We take delivery pattern adjustment into account, as a store can change the delivery pattern without adjusting delivery frequency. As the low correlation between both variables shows, this is a regular occurrence. For example, the algorithm for a grocery store prescribes a delivery on Mondays, Wednesdays, and Thursdays but the store deviates and decides for a Monday-Wednesday-Friday delivery pattern.

In addition to the independent variables of interest, we consider two moderator variables. Organizational experience is captured by the average number of years the employees of a store have been with the retailing company (i.e., employee tenure) which reflects the volume of accumulated experience of the entire employee team. Product differentiation in the store assortment is captured by the number of product variants within product categories adjusted by the prices of each product variant.

Moreover, we use several control variables to avoid unobserved variance and to isolate the effect of algorithm adjustment on the resilience-efficiency trade-off. Failing to control for systematic variance can lead to biased estimates and incorrect conclusions. As a first control we consider privatization capturing whether a focal retail store is privately owned (=1) by individual merchants or company-owned (=0) as in the context of grocery retailing, the performance of stores varies according to this characteristic. This variability may arise due to differences in management styles, resources, incentives, and other factors related to ownership structure. As a second control, we use customer density measured as the number of customers present in a store *i* per sqm of frontend store space on average in the focal month. To quantify the number of customers that are present in the store, we use data on the average number of sales receipts printed per hour and day. Finally, we incorporate a store-fixed effect $\sum_{i=1}^{n} \gamma_i Store_i$ to control for unobserved differences between stores that can influence the dependent variable, such as differences in customer demographics or characteristics of the area in which the store is located, and isolate the effect of other variables on the dependent variable. Finally, ε is the error term of our Tobit regression model. The full model is denoted as follows:

$$\text{Resilience-Efficiency Trade-off}^{*}_{t2,i} = \beta_0 + \beta_1 Frequency\_Adjustment_{t1,i} + \beta_2 Pattern\_Adjustment_{\,t1,i} + \beta_3 Frequency\_Adjustment_{\,t1,i} \times Organizational\_Experience_{t1,i} + \tag{3}$$

$\beta_4 Frequency\_Adjustment_{t1,i} \times Product\_Differentiation_{t1,i} +$
$\beta_5 Pattern\_Adjustment_{t1,i} \times Organizational\_Experience_{t1,i} +$
$\beta_6 Pattern\_Adjustment_{t1,i} \times Product\_Differentiation_{t1,i} +$
$\beta_7 Controls + \sum_{i=1}^{n} \gamma_i Store_i + \varepsilon$

where,

$$\text{Resilience-Efficiency Trade-off}_{t2,i} = \begin{cases} 0 & Resilience - efficiency\ trade - off_{t2,i} \leq 0 \\ y^* & 0 < Resilience - efficiency\ trade - off_{t2,i} < 1 \\ 1 & Resilience - efficiency\ trade - off_{t2,i} \geq 1 \end{cases}$$

We provide insights into the correlations between the variables of the Tobit regression model (see Table 2) to indicate that no multicollinearity issues are present.

	1.	2.	3.	4.	5.	6.	7.
1. Resilience-efficiency trade-off (t_2)	1						
2. Frequency adjustment (t_1)	0.15**	1					
3. Pattern adjustment (t_1)	0.27***	-0.12*	1				
4. Experience (t_1)	0.28***	0.02	-0.2***	1			
5. Differentiation (t_1)	0.12*	-0.08	-0.04	0.07	1		
6. Privatization (t_1)	-0.03	-0.05	0.02	-0.05	-0.13*	1	
7. Customer density (t_1)	-0.02	-0.05	0.04	0.08	0.05	0.12*	1
Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$							

Table 2. Cross-correlation matrix.

5 Empirical Analysis and Results

Table 3 presents the results of Tobit regression for the impact of human adjustments of algorithm prescription (i.e., adjustments of delivery frequency and delivery pattern prescriptions) on resilience-efficiency trade-off. Note that negative estimates are associated with a lower resilience-efficiency conflict (i.e., lower efficiency losses) which is desirable for the retail stores, while positive estimates are associated with higher efficiency losses meaning undesirable implications. We include our independent variables in Model 1 and add the interaction terms separated for organizational experience in Model 2 and for product differentiation in Model 3. The final Model 4 to test our hypotheses includes all independent variables, interaction terms, controls and fixed effects. The results are highly robust across all models.

In Hypothesis 1, we predict that human adjustment of algorithm prescriptions for (a) delivery frequency and (b) for delivery pattern enhances the resilience-efficiency trade-off. Here, we draw the readers' attention to the estimates of frequency adjustment and pattern adjustment in Model 4. Our results indicate that we find support for Hypotheses 1 given that the estimator for delivery frequency adjustment is positive and significant ($\beta_1 = 0.014$, $p < 0.01$). We find similar results for delivery pattern adjustment with a positive and significant estimator ($\beta_2 = 0.026$, $p < 0.01$). Therefore, human deviation from AI algorithm prescription has unfavorable consequences and these positive estimates reflect higher additional inputs (and lower outputs) associated with resilience activities leading to the undesirable effect. In other words, the wasted inputs and sacrificed outputs related to the response to disruptions could have been prevented if stores had followed the algorithm's prescription. As a robustness check, we used a more fine-grained measurement of frequency adjustment by accounting for upward adjustments (more deliveries than prescribed) and downward adjustments (fewer deliveries than prescribed) and found similar effects in direction and strength. Thus, frequency deviations enhance the costs of resilience no matter in which direction they occur.

In Hypothesis 2, we predict that human adjustments of algorithm prescriptions for (a) delivery frequency and (b) for delivery pattern have a weaker detrimental effect on the resilience-efficiency trade-off in stores with higher experience (vs. lower experience). In Model 4 we find support for this hypothesis as the estimates for the interaction terms frequency adjustment x experience (β_3 = -0.013, $p < 0.01$) and pattern adjustment x experience (β_4 = -0.030, $p < 0.01$) are negative and significant. Importantly, this negative interaction effect indicates that with higher team experience, the undesirable effect of deviations from algorithm prescriptions is mitigated. In other words, while less knowledgeable employees should precisely adhere to prescriptions (as otherwise suboptimal decisions will result), deviations of highly experienced employees can be advisable as they might help to better adjust the AI solution to store-specific circumstances related to a disruption which experienced employees are able to comprehend. Finally, in Hypothesis 3 we predict that human adjustments of algorithm prescriptions for (a) delivery frequency and (b) for delivery pattern have a less detrimental effect on resilience-efficiency trade-off in stores with more differentiated assortments than in stores with lower differentiation. In Model 4 we do not find support for this hypothesis for frequency adjustments (H3a) as the estimate is not significant. However, we find support for this hypothesis in the interaction with pattern adjustment (H3b) (β_6 = -0.010, $p < 0.05$). Hence, a deviation from the prescribed delivery pattern has a less deleterious effect on the resilience-efficiency trade-off in highly differentiated stores.

	Dependent variable: Resilience-efficiency trade-off				***Hypothesis supported?***
	Model 1	**Model 2**	**Model 3**	**Model 4**	
Independent variables					
Frequency adjustment (FA)	0.017^{***}(0.004)	0.014^{***}(0.004)	0.017^{***}(0.004)	0.014^{***}(0.004)	H1a✓
Pattern adjustment (PA)	0.032^{***}(0.005)	0.023^{***}(0.004)	0.032^{***}(0.005)	0.026^{***}(0.004)	H1b✓
Interactions					
FA × Experience		-0.012^{***}(0.004)		-0.013^{***}(0.004)	H2a✓
PA × Experience		-0.030^{***}(0.004)		-0.030^{***}(0.004)	H2b✓
FA × Differentiation			-0.001(0.004)	-0.003(0.004)	H3a×
PA × Differentiation			-0.010^{**}(0.005)	-0.010^{**}(0.004)	H3b✓
Moderators					
Experience	0.015^{***}(0.002)	0.032^{***}(0.003)	0.014^{***}(0.002)	0.031^{***}(0.003)	
Differentiation	0.006^{**}(0.002)	0.005^{**}(0.002)	0.010^{***}(0.003)	0.009^{***}(0.003)	
Controls					
Privatization	-1.013(0.994)	-1.809^{**}(0.917)	-1.171(0.990)	-1.975^{**}(0.913)	
Customer density	-0.002(0.002)	-0.003(0.002)	-0.003(0.002)	-0.003(0.002)	
Store-fixed effects	included	included	included	included	
Wald test	96.43^{***}	170.05^{***}	102.39^{***}	177.98^{***}	
Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$					

Table 3. Tobit regression results.

6 Discussion

Firms face the challenge of enhancing resilience in an efficient way by relying on AI, especially on the integration of algorithm prescriptions for decision-making. In this study, we use a large real-world dataset of a European grocery retail group to provide empirical insights on how human-AI collaboration impacts the efficiency losses associated with resilience activities and under which crucial retail boundary conditions the effect of human adjustments is beneficial.

First of all, we find that employees' discretionary changes of algorithm prescriptions enhance the conflict between resilience and efficiency. This deleterious impact is consistent for both types of adjustments (i.e., adjustments of delivery frequency and delivery pattern). In general, these findings are supported by studies in literature stating that AI can outperform humans (Jussupow et al., 2024) and hence firms profit from conforming to algorithm prescriptions. However, since it is not realistic in the future for AI to fully supersede human decisions in all situations and humans may not accept AI applications if they do not have a voice (Dietvorst et al., 2018), it is important to know in which real-world settings close interaction between human and algorithm prescription can outperform AI-alone or human-alone. We show that humans in the retail context use augmentation capabilities in different ways: for determining the optimal delivery frequency and optimal delivery pattern. While several studies revealed that in highly controlled environments such as chess games augmenting human capabilities through AI capabilities is successful (Jain et al., 2021; Krakowski et al., 2022), we show that also in less controlled environments like retail businesses, augmentation of capabilities is possible and effective. Additionally, humans can take algorithm prescriptions as a baseline and adjust them or execute the prescribed solutions; our results show that the latter might be more promising. Thus, we contribute to the extension of the RBV by demonstrating that AI can create a competitive advantage through human capabilities to assess and accept algorithm prescriptions.

Secondly, we also contribute to resilience research. In the resilience context, it is important to know which processes in firms make resilience even more costly. While AI-based technologies are seen in the literature as a promising driver for resilient systems (e.g., Gupta et al., 2023), our results show that the benefit of these technologies occurs if humans closely collaborate with these technologies.

Furthermore, we investigated different boundary conditions that can alleviate the detrimental effect of human deviations from algorithm prescription in terms of higher resilience costs. First, our results show that high organizational experience empowers employee capabilities to assess the outcomes of AI (akin to AI literacy) and this can mitigate the detrimental effect of human deviations from algorithm prescriptions. Thus, our results show that human capital remains important in terms of competitive advantage. However, we also confirm that in environments with inexperienced employees, changing AI solutions backfires, and humans should execute algorithm prescriptions. Finally, we find that firms with high product differentiation can also alleviate the unfavorable effects of deviations from algorithm prescription and reduce the costs of resilience activities. If firms have the flexibility to satisfy customer needs with a large choice of product variants (e.g., with deep assortments in grocery stores), human violations of optimal algorithm prescriptions are less harmful as the detrimental effects can be bolstered through these flexible responses to customer needs.

7 Implications, Limitations, and Future Research

Our study provides several important implications at the intersection of IS and resilience research, with a keen focus on the theoretical and practical implications of AI-driven strategies.

From a theoretical standpoint, we underscore the importance of examining AI-based technologies – which are treated as drivers for resilience in an efficient way (e.g., Belhadi et al., 2024) – within the context of human interactions. Specifically, our study is among the first ones to understand how human-AI collaboration affects efficiency losses associated with resilience activities empirically. By adopting the RBV, our exploration aids in discerning the nuances between complementing and substituting human capabilities with AI solutions. Through this lens, we provide insights into which forms of human-AI collaboration lead to competitive advantages and hence which augmentation capabilities matter most. Thereby, we shift the traditional RBV focus, highlighting the relevance of novel important human capabilities (e.g., augmenting human resources through AI outcomes) (Helfat et al., 2023; Krakowski et al., 2022). Second, our study contributes to the advancements of RBV through contingencies that reveal when which form of augmentation capabilities is most effective. Therefore, we provide empirical insights into various boundary conditions. Specifically, we highlight the beneficial moderating effects of organizational experience and product differentiation on shaping the impact of human-AI collaboration on the efficiency of resilience activities. By doing so, we are the first to highlight that not only the human capital of individual AI users is relevant but also the collective human capital of entire teams (e.g., service teams in retail stores). Thus, we advocate for more attention to be paid to the collective human capital within both IS and resilience research domains. Additionally, we demonstrate that characteristics of the product portfolio, such as product differentiation, play a significant role in determining the impact of human-AI collaboration on the efficiency of resilience activities.

From a practical standpoint, we offer several implications for managerial practice concerning resilience management. First, retail managers should develop human augmentation capabilities (e.g., in terms of AI literacy capabilities) to improve resilience without additional efficiency losses by training employees on making data-informed decisions that support organizational objectives. Our findings highlight those adjustments of algorithmic prescriptions by humans are significant sources of efficiency loss in the pursuit of resilience. By implementing feedback mechanisms to monitor the impact of these decisions and refine training, managers can minimize these efficiency losses associated with resilience activities. Second, our study highlights the significance of organizational experience and product differentiation in empowering employees to effectively interact with AI systems to reduce efficiency losses due to resilience activities. Thus, managers in retail stores with a rich team experience should leverage this asset by facilitating knowledge sharing and promoting AI literacy across the board. For organizations with less experience, investing in AI training and development programs becomes paramount to enhance the workforce's capability to engage effectively with AI-based technologies. Lastly, retail stores with a high level of product differentiation have an opportunity to mitigate the negative impacts of deviations from AI prescriptions. Managers should thus exploit this flexibility to meet diverse customer needs, using it as a buffer to absorb potential inefficiencies arising from human-AI collaboration discrepancies.

This paper has specific limitations that spark strong interest in future research. While examining employee experience as a moderating factor, the impact of the experience of managers supervising their teams on AI-augmented decisions remains unexplored, presenting a fruitful area for further investigation. Second, the quantitative design of our study limits the depth of understanding regarding why employees might deviate from algorithmic recommendations, pointing to the need for qualitative studies to explore the potential influence of algorithm aversion (Dietvorst et al., 2015). Third, although we explicitly position our work as industry-specific research for the retail sector, our industry focus also raises questions about the generalizability of our findings to different business contexts, suggesting a broader examination of AI's utility in various industries for future research. Furthermore, although time-invariant store-related characteristics are captured by the store-fixed effects, our discussion lacks an in-depth consideration of how organizational factors like culture or technology infrastructure might influence the resilience-efficiency trade-off. Future studies could also benefit from incorporating more controls for confounding variables to deepen the exploration of these observed relationships. Importantly, our research does not capture the longitudinal effects of resilience activities on efficiency losses, which may evolve due to varying disruptions over time. Future studies should thus consider longitudinal designs to assess the dynamic impacts of efficiency losses associated with resilience activities. Altogether, we believe the presented research has the potential to open up a relevant new research stream investigating the role of decision support systems (e.g., AI-based tools) in the context of resilience management.

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