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Clarifying supply chain disruption and operational resilience relationship from a threat-rigidity perspective: Evidence from small and medium-sized enterprises

Felix Kissi Dankyira[a], Dominic Essuman[b,c,*], Nathaniel Boso[c,d], Henry Ataburo[d], Emmanuel Quansah[e]

[a] Department of Supply Chain and Information Systems, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana
[b] Sheffield University Management School, The University of Sheffield, Conduit Road, Sheffield, S10 1FL, United Kingdom
[c] Gordon Institute of Business Science, University of Pretoria, 26 Melville Rd, Illovo, Johannesburg, 2196, South Africa
[d] Center for Applied Research and Innovation in Supply Chain-Africa, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana
[e] Business and Law, Solent University, United Kingdom

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ABSTRACT

Given the significant risk supply chain disruptions pose to businesses, scholars and experts presume such events encourage resilience-building efforts. This study uses the threat-rigidity theory to question this normative assumption by proposing that supply chain disruption can trigger threat interpretation bias, which undermines operational resilience. Specifically, the study contends that threat interpretation bias negatively mediates the relationship between supply chain disruption and operational resilience, particularly in low disruption orientation circumstances. An empirical analysis of survey data from 259 small and medium-sized enterprises in Ghana using covariance-based structural equation modeling supports these theoretical predictions. The results indicate that supply chain disruption increases threat interpretation bias, which in turn reduces operational resilience. The negative effect of threat interpretation bias on operational resilience is stronger when disruption orientation is low than when it is high. These results offer an enhanced understanding of the supply chain disruption–resilience link while shedding light on how firms can manage threat interpretation bias to improve operational resilience.

1. Introduction

Operational resilience, defined as the ability of a firm's operations and production systems to absorb and recover from supply chain disruptions, is vital for business survival, competitiveness, and growth (Liu et al., 2023; Li et al., 2022). Thus, there is a growing interest among scholars and practitioners in understanding the antecedents of operational resilience (Xi et al., 2024; Essuman et al., 2023a). While it is assumed that supply chain disruption is the primary driver of firms' efforts to build resilience (Huang et al., 2023; Zhao et al., 2023), only a few studies have attempted to explain how different manifestations of supply chain disruption, particularly disruption impact and intensity, affect operational resilience (Appendix A). However, despite recognizing that firms vary in how they interpret and respond to supply chain disruptions (Obłój and Voronovska, 2023; Nikiforou et al., 2023; Mithani et al., 2021), it is unclear how and when this behavior explains the relationship between supply chain disruption and resilience in specific settings.

Accordingly, this study applies the threat rigidity theory to develop and test a conceptual model to address this question in the context of small and medium-sized enterprises (SMEs)*: how does threat interpretation bias mediate the relationship between supply chain disruption and operational resilience under different conditions of disruption orientation?* Because supply chain disruption threatens firm survival, the threat-rigidity theory suggests it can induce threat interpretation bias (Obłój and Voronovska, 2023; Pérez-Nordtvedt et al., 2014), especially in resource-scarce settings (Kreiser et al., 2020), such as SMEs (Nikiforou et al., 2023). Threat interpretation bias refers to the degree to which top

* Corresponding author. Sheffield University Management School, The University of Sheffield, Conduit Road, Sheffield, S10 1FL, United Kingdom.
E-mail addresses: denkyira.kissi.98@gmail.com (F.K. Dankyira), d.essuman@sheffield.ac.uk (D. Essuman), nboso@knust.edu.gh (N. Boso), hataburo@carisca.knust.edu.gh (H. Ataburo), emmanuel.quansah@solent.ac.uk (E. Quansah).

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managers frame disruptive events as threats instead of opportunities (Pérez-Nordtvedt et al., 2014; Sharma, 2000). Threat interpretation bias encourages firms to resort to existing and well-learned organizational routines while restricting information search and adaptation behaviors to conserve resources (Kreiser et al., 2020; Staw et al., 1981). Thus, we argue that threat interpretation bias is an important mechanism that explains how supply chain disruption reduces operational resilience (Vogus and Sutcliffe, 2007).

The threat-rigidity literature suggests that threat interpretation bias can have less detrimental consequences when organizations are knowledgeable about disruption situations and have clear coping mechanisms (Staw et al., 1981). Accordingly, we further propose disruption orientation as a moderator of the effect of threat interpretation bias on operational resilience. Disruption orientation reflects a firm's general awareness and consciousness of, concerns about, attitude toward, and recognition of the opportunity to learn from disruptions (Parker and Ameen, 2018). We argue that disruption-oriented firms are more likely to possess greater existing disruption knowledge resources and stronger coping mechanisms (Bode et al., 2011), which can mitigate the negative effect of threat-interpretation bias on operational resilience (Obłój and Voronovska, 2023).

The study provides two key contributions to extant literature. First, it contributes to the literature on the determinants of operational resilience (e.g., Jiang et al., 2023; Liu et al., 2023). Specifically, its conceptual model and empirical analysis reveal how threat interpretation bias and disruption orientation explain how supply chain disruption affects operational resilience differently. These insights improve understanding of the relationships between supply chain disruption and resilience capabilities. Second, the study contributes to the literature on the contingencies in the threat-rigidity thesis (Kreiser et al., 2020; Pérez-Nordtvedt et al., 2014) by identifying disruption orientation as a critical variable that clarifies when the threat-rigidity theory better predicts resilience outcomes (Obłój and Voronovska, 2023; Vogus and Sutcliffe, 2007).

2. Theoretical development and hypotheses

2.1. Threat-rigidity perspective

The threat-rigidity theory argues that negatively framed events produce threat-rigidity responses, manifesting in risk avoidance and maladaptive behaviors (Obłój and Voronovska, 2023; Linnenluecke, 2015). These behaviors discourage a tendency to accommodate new ideas or alternative courses of action for managing disruptive events (Kreiser et al., 2020; Sharma, 2000). The rationale is that when threat interpretation bias increases, firms are likely to resort to existing knowledge and methods of responding to disruptions (Staw et al., 1981). Top managers may further centralize decisions to ensure control while reducing expenses (Staw et al., 1981). Extant literature indicates that these behaviors can undermine adaptation outcomes (Obłój and Voronovska, 2023; Jeong et al., 2023) and resilience (Linnenluecke, 2015; Vogus and Sutcliffe, 2007).

Notwithstanding, prior research suggests that contextual factors moderate the effects of threat-rigidity responses (Kreiser et al., 2020; Pérez-Nordtvedt et al., 2014). The threat-rigidity thesis acknowledges that threat-rigidity responses can be functional or detrimental to building resilience depending on prevailing organizational conditions (Staw et al., 1981). An argument is that threat-rigidity responses can "… certainly be functional when the parameters of the environment are well known and coping mechanisms clear" (Staw et al., 1981, p. 519). Therefore, it is essential to account for relevant organizational circumstances under which threat interpretation bias occurs to capture its net effect on operational resilience (Staw et al., 1981).

In applying this theory, we develop and test a conceptual model that details how threat interpretation bias mediates the relationship between supply chain disruption and operational resilience at different levels of disruption orientation. As illustrated in Fig. 1, we propose that supply chain disruption induces threat interpretation bias, which lowers operational resilience, especially among firms with low (as opposed to high) levels of disruption orientation.

2.2. The mediating role of threat interpretation bias

Threat interpretation bias occurs when top managers interpret ambiguous or uncertain information negatively or as a threat (Pérez-Nordtvedt et al., 2014; Sharma, 2000). The primary managerial concerns regarding supply chain disruptions are that these events are unplanned, difficult to anticipate, and often result in significant losses (El Baz and Ruel, 2021). Therefore, consistent with the threat-rigidity thesis, we expect increases in supply chain disruption to trigger threat interpretation bias (Olson et al., 2020; Linnenluecke, 2015; Staw et al., 1981). This theoretical prediction is consistent with the evidence that greater exposure to or salience of disruptive events tends to increase threat interpretation bias (Pérez-Nordtvedt et al., 2014) and rigidity responses, such as a propensity to centralize decision-making (Obłój and Voronovska, 2023). As a result, threat interpretation bias can be expected to undermine operational resilience for three reasons.

Firstly, high-threat interpretation bias firms may engage less in information processing due to their tendency to rely on existing experiences and knowledge (Staw et al., 1981). However, previous studies have shown that information search and processing activities and resources enhance resilience capabilities (e.g., Essuman et al., 2022; Gu et al., 2021; Brandon-Jones et al., 2014). The reason is that continuous information search and processing helps firms gain visibility in their task environment, swiftly detect looming disruptions, and analyze and prioritize risks and response measures to avert, weather, or recover rapidly from impacts (Brandon-Jones et al., 2014; Gu et al., 2021). Therefore, threat interpretation bias firms are likely to be caught off guard by unexpected events, which may undermine time-to-survive and increase time-to-recover from disruptions (Essuman et al., 2023a).

Secondly, threat interpretation bias firms will likely centralize authority and formalize structures and processes (Garretsen et al., 2022; Staw et al., 1981), relying on a short-term disruption mitigation strategy while blocking the autonomy and flexibility (Garretsen et al., 2022) necessary for employees to initiate creative solutions to manage disruptions (van de Van der Vegt et al., 2015). Because disruptive events may be unique and dynamic, novel solutions might prove helpful for organizations to mitigate and recover from disruption impacts (Essuman et al., 2023a).

Thirdly, high-threat interpretation bias firms have efficiency motives and thus are inclined to conserve resources (Garretsen et al., 2022; Staw et al., 1981). This behavioral tendency may reduce investment in redundancies or exploratory and experimental initiatives (e.g., environmental scanning and learning) (Sharma, 2000; Dewald and Bowen, 2010) necessary for attaining operational resilience (Ambulkar et al., 2023; Essuman et al., 2023b).

In sum, we posit that how supply chain disruption affects operational resilience may be indirect (El Baz and Ruel, 2021), channeled through threat interpretation bias (Linnenluecke, 2015; Pérez-Nordtvedt et al., 2014). The overarching argument is that greater exposure to supply chain disruption can overwhelm firms, which may lead them into a threat interpretation bias trap (Pérez-Nordtvedt et al., 2014; Olson et al., 2020), reducing avenues and options necessary for effective disruption management (Vogus and Sutcliffe, 2007). As organizations grapple with disruptions in their supply chain, the ensuing threat interpretation bias is expected to increase organizational stiffness and vulnerability, ultimately compromising their capacity to build operational resilience. Therefore, we test this hypothesis:

H1. *Threat interpretation bias negatively mediates the relationship between supply chain disruption and operational resilience.*

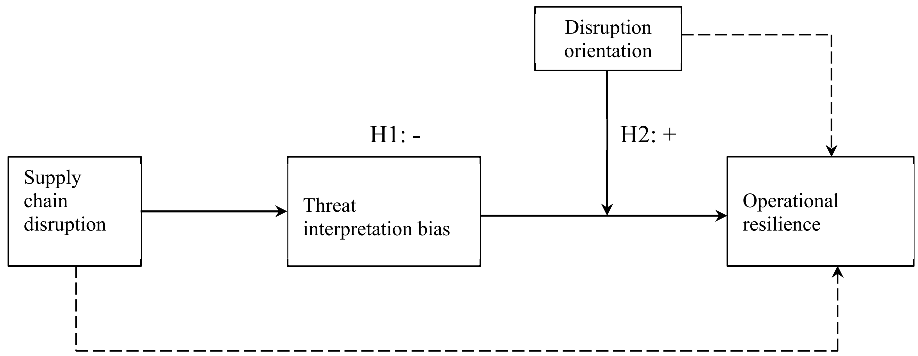

Fig. 1. Conceptual model of resilience. Note: Broken paths represent past studies and are controlled in the current study.

2.3. The moderating role of disruption orientation

Disruption orientation reflects a firm's general awareness and consciousness of, concerns about, attitude toward, and recognition of the opportunity to learn from disruptions (Parker and Ameen, 2018). Disruption orientation enables firms to engage in ongoing information search and learning about disruptions. These information search and learning behaviors can broaden firms' understanding and knowledge of supply chain disruptions (Yang et al., 2021; Yu et al., 2019). While threat interpretation bias may lower firms' tendency to search for new knowledge in the face of increasing supply chain disruptions, the enhanced disruption-specific understanding and knowledge base embedded in disruption-oriented contexts can help firms navigate their operational activities during supply chain disruptions effectively. On the other hand, under conditions of weak disruption orientation, firms with high threat interpretation bias may have a limited range of existing disruption-specific insights for designing and implementing solutions to absorb and recover from supply chain disruptions.

Additionally, a strong disruption orientation can help firms formulate appropriate schemas to decide when, what, and how much response may be relevant in different disruption scenarios (Bode et al., 2011). Again, disruption orientation can enrich firms' ability to interpret complex issues more quickly and formulate alternative scenarios and response actions (Ambulkar et al., 2015). Therefore, while threat interpretation bias may drive firms to be cautious and passive with their responses, the improved disruption knowledge benefits of disruption orientation may increase the likelihood of firms enacting measured reactive responses to new disruptions. Besides, containing and recovering from supply chain disruptions may entail complex processes (Lu et al., 2023), and firms may err in their initial reactions (Essuman et al., 2023a), which may amplify for firms with more threat interpretation bias when disruption orientation is low. We posit that under conditions of strong disruption orientation, firms are better positioned to correct such errors while finding alternative disruption management solutions (Kreiser et al., 2020). For example, in their study of how Ukrainian firms reacted to the disruptions caused by the Russia-Ukraine conflict, Obłój and Voronovska (2023) found that some firms leveraged their experience in emergency management from the COVID-19 pandemic to adapt to the conflict after their initial rigid response. Conversely, we expect that because high-threat interpretation bias firms can be overwhelmed with supply chain disruptions, a weak disruption orientation condition may trigger haphazard response tendencies that may worsen disruption impacts on operational resilience. Accordingly, we hypothesize that.

H2. *Disruption orientation moderates the threat interpretation bias – operational resilience link, such that the negative indirect relationship between supply chain disruption and operational resilience* via *threat interpretation bias is weakened when disruption orientation is stronger.*

3. Research methods

3.1. Sample and research design

We used survey data from SMEs in a developing country, Ghana, to test the research hypotheses for several reasons. As in many developing countries (Munir et al., 2022), SMEs in Ghana are prone to various supply chain disruptions and require strong operational resilience to thrive (Essuman et al., 2023a). The value of operational resilience transcends SMEs or firms in developing countries (Business Continuity Institute, 2022). However, the severe resource scarcity challenges and extreme conditions of environmental hostility in developing countries may complicate the efforts of SMEs to build operational resilience (Essuman et al., 2023a). The threat-rigidity literature suggests these contextual issues may create conditions for developing economy SME managers to activate threat interpretation bias in the face of supply chain disruptions (Nikiforou et al., 2023; Pérez-Nordtvedt et al., 2014). Moreover, SME owner-managers and senior managers have greater discretion and control in resource allocation decisions and are heavily involved in operational activities. Therefore, their threat interpretation bias can substantially affect their firms' operational resilience (Hambrick, 2007). Thus, data from these firms are suitable for testing the research hypotheses.

Using managers' contact information on Ghana Yellow Pages, we approached a sample of 750 SMEs operating in two major commercial/industrial areas in Ghana, namely Greater Accra and Kumasi Metropolis, with questionnaires (Essuman et al., 2023a). The sampling criteria used included firms that had been in operation for at least three years and had informants meeting our key informant requirement: knowledgeable, experienced, and literate top/senior managers (e.g., CEOs, managing directors, and operations managers) who consented to participate in the study (Yu et al., 2019). Given that the sample comprised SMEs (Flynn et al., 2018), we followed the approach used in previous resilience studies (e.g., Munir et al., 2022; Gu et al., 2021; Yu et al., 2019) to identify one key informant per firm to gather the data. We trained and supervised a team of fieldworkers to deliver and retrieve the questionnaires (Essuman et al., 2023a). After several follow-ups, the team retrieved 284 questionnaires. Twenty-five questionnaires with incomplete responses were discarded, leaving 259 useable questionnaires. Table 1 details the characteristics of the firms that fully participated in the study and the key informants involved. On average, a firm in the sample had 41 full-time employees (standard deviation $\approx$ 61) and had been operating for 15.60 years (standard deviation = 10.39), with most of the firms operating in the service sector (73%), which is reflective of the Ghanaian economy (Ghana Statistical Service, 2016).

3.2. Measure and questionnaire development

The study adhered to recommended protocols for measure and questionnaire development to ensure data reliability and validity (e.g.,

Table 1
Sample and informant profile.

Variable	Category	Frequency	Percentage
Firm industry	Manufacturing	70	27.0
	Service	189	73.0
Respondent position	CEO	32	12.4
	General Manager	55	21.2
	Managing Director	31	12.0
	Operations Manager	62	23.9
	Other Middle-level Managerial Positions	79	30.5
Firm age (number of years of operation)	3–10	95	36.7
	10.01–20	104	40.2
	20.1–60	60	23.2
Firm size (number of full-time employees)	5 to 30	165	63.7
	31 to 99	70	27.0
	100 to 500	24	9.3
Variable		Mean	SD
Respondent's years in current position		7.13	5.58
Firm size (number of full-time employees		40.5	60.59
firm age (number of years in operations)		15.6	10.39

MacKenzie et al., 2011; Podsakoff et al., 2003). First, we reviewed relevant literature to clarify the conceptual meaning and domains of the study's constructs. This process allowed us to develop an operational definition for each construct. Subsequently, we employed the operational definitions to survey a pool of relevant measurement indicators. In cases where direct indicators were unavailable, we developed new ones by drawing insights from related previous studies and field interviews with senior managers. For instance, we combined insights from Sharma's (2000) measures for managerial interpretations and Pérez-Nordtvedt et al.'s (2014) measures for SME owners' perceived threats to develop indicators of threat interpretation bias. Additionally, we augmented the literature on supply chain disruption types (e.g., Ambulkar et al., 2015) with interview responses to identify context-specific indicators for supply chain disruption. During the third stage, we incorporated feedback from three supply chain and strategy researchers with an adequate understanding of the study's constructs. This feedback informed revisions to the indicators and their measurement scales before the development and piloting of the questionnaire. In the fourth stage, we finalized the questionnaire based on feedback and results from a pilot study involving 30 senior managers (e.g., CEOs and supply chain managers) participating in an executive MBA program.

3.2.1. Substantive constructs

The indicators for the latent variables and their reliability and validity results are presented in Appendix B. The study used a seven-point scale ranging from "strongly disagree (=1)" to "strongly agree (=7)" to evaluate the indicators for the substantive constructs.

Supply chain disruption: We operationalized supply chain disruption as the frequency of exposure to unexpected events that interrupt the smooth flow of products, materials, and processes in a firm's internal and external supply chains (Wong et al., 2020; Bode et al., 2011). A multiplicity of unexpected events underlies the concept of supply chain disruption (e.g., Iyengar et al., 2021; Wong et al., 2020). Moreover, disruptive events originate from diverse sources; therefore, there is little theoretical reason to expect that supply chain disruptive events would have one underlying factor. For instance, unforeseen supplier failures, transportation breakdowns, and technology downtimes can each independently lead to supply chain disruptions without necessarily being correlated. Essentially, these events collectively contribute to supply chain disruption. Additionally, while empirical research should consider many such events to better capture the concept, removing any can alter the domain of the concept (Jarvis et al., 2003). In line with measurement theory literature, these considerations suggest that supply chain disruption should be viewed as a formative construct (Cadogan and Lee, 2013; Jarvis et al., 2003). Thus, we integrated insights from fieldwork interviews with senior managers and existing literature (e.g., Ambulkar et al., 2015) to identify nine formative indicators to capture supply chain disruption. The indicators measure the extent to which firms have experienced supply chain disruption in the last three years.

Operational resilience: We measured operational resilience using reflective indicators that tap its two core dimensions: disruption absorption and recovery capabilities (Essuman et al., 2023a). Disruption absorption capability refers to the ability of firms' operations to maintain structure and normal function during disruptions. In contrast, disruption recovery capability refers to the ability of firms to restore operations following a disruption (Jiang et al., 2023; Essuman et al., 2023a). Drawing on Brandon-Jones et al. (2014) and Buyl et al. (2019), we generated five indicators to capture the extent of firms' disruption recovery in the last three years. Six indicators were adapted from Wieland and Wallenburg (2012) and Brandon-Jones et al. (2014) to measure the extent of the firms' disruption absorption in the last three years.

Threat interpretation bias: We drew on past studies on threat-opportunity interpretations and threat-rigidity literature (e.g., Pérez-Nordtvedt et al., 2014; Sharma, 2000; Jackson and Dutton, 1988) to develop indicators to measure the degree to which the firms' top managers demonstrated threat interpretation bias in the last three years. Pérez-Nordtvedt et al.'s (2014) study, for example, captures threat interpretation as the extent to which business owners perceive a disruptive event as primarily a threat to their firm's interest, make their business worse off in the future and put competitive pressure on their firms' goods/services. Accordingly, we followed the above-described measurement procedures to generate four reflective indicators to measure threat interpretation bias as the degree to which top managers frame disruptive events as threats instead of opportunities (Sharma, 2000; Pérez-Nordtvedt et al., 2014).

Disruption orientation: We measured disruption orientation with four indicators adapted from Bode et al. (2011) and Ambulkar et al. (2015). The indicators reflect the degree to which firms are concerned about disruptions, feel the need to be alert to possible disruptive events, and learn from such events (Bode et al., 2011; Ambulkar et al., 2015).

3.2.2. Control variables

Not only does the resilience literature suggest that internal and external environmental factors affect resilience capabilities (Manhart et al., 2020), but threat-rigidity theory contends that such variables may influence how threat interpretation bias affects operational resilience (Staw et al., 1981; Pérez-Nordtvedt et al., 2014). Therefore, we included resource slack, environmental dynamism, firm size, firm age, and firm industry as covariates in the empirical analysis to mitigate potential confounding results (Lu et al., 2018).

Resource slack refers to the amount of a firm's discretionary resources that can be used to fund organizational initiatives (Atuahene-Gima et al., 2005). Resource slack can enable firms to prepare for disruptions and help them implement solutions for managing disruptions as and when they occur. Therefore, it can increase managerial perceived controllability of threatening events (Sharma, 2000). Moreover, resource slack can buffer firms' impetus to restrict information search, centralize decision-making, and reduce investment in entrepreneurial initiatives in threatening environments (Kreiser et al., 2020). Four reflective indicators were adapted from Atuahene-Gima et al. (2005) to measure resource slack. The indicators were rated on a seven-point scale ranging from "strongly disagree = 1" to "strongly agree = 7".

Environmental dynamism refers to the extent to which firms experience irregular changes in conditions in their environment (Dess and Beard, 1984). High environmental dynamism conditions increase uncertainty and heighten threats to organizational stability (Lu et al., 2023; Enrique et al., 2022; Yu et al., 2019). Thus, from a threat rigidity perspective, greater environmental dynamism can amplify levels and the effects of threat interpretation bias (Kreiser et al., 2020; Staw et al., 1981) and disruption orientation (Yu et al., 2019). We combined insights from fieldwork interviews with senior managers with extant literature (Dess and Beard, 1984) to identify six reflective indicators to measure environmental dynamism. The indicators were rated on a seven-point scale ranging from "strongly disagree = 1" to "strongly agree = 7".

Though we studied SMEs, these firms also vary significantly in size. We operationalized *firm size* as the natural logarithm of the number of full-time employees (Wong et al., 2020). While smaller firms tend to be more entrepreneurial and agile, they often lack critical resources (e.g., financial and human resources) for managing disruptions (Essuman et al., 2023a). *Firm age* was operationalized as the natural logarithm of the years a firm has been in operation. Younger firms tend to lack the industry experience and networks required to access crucial external resources (e.g., institutional support) for managing disruptions (Essuman et al., 2023a). We controlled for *firm industry* using a dummy variable (service industry = 1; manufacturing = 0). Not only may the level of environmental hostility vary across industries, but differences in supply chain and operations setups across industries may determine the efficacy with which firms may contain and recover quickly from disruptions (Essuman et al., 2023a).

3.3. Survey bias assessment

3.3.1. Nonresponse bias

We assessed the presence of nonresponse bias in the sample by comparing the characteristics of the study's sample with those of the target population and the nonresponse sample (Wagner and Kemmerling, 2010). We observed that the average firm size (number of employees) and years of operation in the sample closely resembled those of similar firms reported in a nationwide business establishment survey conducted by the Ghana Statistical Service in 2014 (Ghana Statistical Service, 2016). Additionally, an independent sample *t*-test indicated that the size and age of firms responding early and late to the survey were not statistically different. The difference in firm size for early respondents (questionnaires received within the first 14 working days: $n = 162$) and late respondents (questionnaires received during the next 14 working days: $n = 97$) was 7.09 ($t = 0.91$, $p = 0.36$), while that of firm age was 1.41 ($t = 1.06$, $p = 0.29$). These results, coupled with the emphasis this study places on testing a theory rather than seeking broad generalization, suggest that nonresponse bias is not a major concern (Hulland et al., 2018; Wagner and Kemmerling, 2010).

3.3.2. Common method bias

The study implemented relevant procedural measures to address the issue of common method bias (CMB) (Podsakoff et al., 2003). For instance, as detailed in Section 3.2, we followed recommended guidelines to generate measurement indicators and develop the study's questionnaire. We ensured that the indicator statements were clear and easy to comprehend. Additionally, we utilized a cover letter printed on letterhead from a well-recognized university in the study's setting to assure informants of complete anonymity. In the cover letter, we explained the purpose of the study and how it would benefit practitioners. Furthermore, we ensured temporal separation between the indicators of interest by incorporating additional indicators to increase their physical distance (Podsakoff et al., 2003). Additionally, we gathered data from experienced, knowledgeable, and educated senior managers (Wong et al., 2020). On average, these managers had held their senior positions for 7.13 years. Among them, 76.8% possessed at least a bachelor's degree, 21.6% held a diploma, and 1.5% had senior high school certificates.

We used exploratory and confirmatory factor analysis procedures to assess whether CMB characterized the data (Craighead et al., 2011; Flynn et al., 2010). We first used Harman's one-factor test to check if one factor explains a larger proportion of the variances in the data (Flynn et al., 2010; Wong et al., 2020). Exploratory factor analysis produced six-factor solution with Eigenvalues greater than 1.00, with 76.149% total variance explained. The first factor accounted for 25.775%, which is less than half of the total variance explained. We used confirmatory factor analysis (CFA) to examine this finding further ((Craighead et al., 2011; Flynn et al., 2010). We specifically estimated a one-factor CFA model, which sets the indicators to load onto a common latent factor (Model 1: method-only model) (Flynn et al., 2010). The model returns a poor fit to the data: $\chi^2 = 4583.731$, DF = 405, normed $\chi^2 = 11.318$, RMSEA = 0.200, CFI = 0.321, NNFI = 0.270, SRMR = 0.198, confirming that a single unmeasured factor does not explain the variances in the data.

We also analyzed a method and trait model (Model 2) to assess how much an unmeasured common factor may confound the data (Bode et al., 2011). We compared this model to our theoretically specified CFA model (Model 3) reported above (Bode et al., 2011). Model 2 includes all relationships in Model 1 and Model 3 and sets the factor loadings in Model 1 equal and the covariances between the unmeasured latent factor and the theoretical factors zero (Bode et al., 2011). The results show Model 3 best fits the data: $\chi^2 = 600.666$, DF = 389, normed $\chi^2 = 1.544$, RMSEA = 0.046, CFI = 0.966, NNFI = 0.962, SRMR = 0.041. However, a chi-square test of difference reveals that Model 2 is not significantly superior to Model 3: $\Delta\chi^2 = 0.000$, ΔDF = 1, $p > 0.05$. We further checked whether including the uncommon latent factor deteriorated the factor loadings in Model 2. We found that the magnitude and significance of the factor loadings in Model 2 and Model 3 were identical. Specifically, the factor loadings of the two models correlated perfectly, $r = 1.0$. (Bode et al., 2011). These results indicate that common method bias is unlikely to inflate or deflate the study's results.

4. Results

We used covariance-based confirmatory factor analysis (CFA) and maximum likelihood estimator in Mplus 7.4 to validate the reflective indicators and collinearity analysis to assess the distinctiveness of the formative indicators (Diamantopoulos and Siguaw, 2006). We estimated a six-factor CFA model to evaluate the psychometric properties of the indicators simultaneously (Hair et al., 2019 Bagozzi and Yi, 2012). This model fits the data well: Chi-square (χ^2) = 600.666, degree of freedom (DF) = 390, normed $\chi^2 = 1.540$, root mean square error of approximation (RMSEA) = 0.046, comparative fit index (CFI) = 0.966, non-normed fit index (NNFI) = 0.962, standardized root mean square residual (SRMR) = 0.041 (Bagozzi and Yi, 2012). As shown in Appendix B, additional results reveal that the indicators exhibit convergent validity. For instance, all factor loadings are significant at 1% and greater than 0.60, and the congeneric reliability and average variance extracted are greater than their minimum cut-off values of 0.60 and 0.50, respectively (Bagozzi and Yi, 2012). As shown in Table 2, the indicators further exhibit discriminant validity, given that their average variance extracted values are greater than their shared variances (Voorhees et al., 2016).

We performed a collinearity diagnosis to assess the extent to which formative indicators of supply chain disruption are not redundant (Diamantopoulos and Siguaw, 2006). We regressed all the indicators on one of the indicators for the disruption absorption capability (Bode et al., 2011). The highest variance inflation factor is 1.698, suggesting that indicator redundancy issues do not describe the indicators for supply chain disruption. Accordingly, we used an unweighted linear sum scale to construct a formative index to capture the supply chain disruption construct (Bode et al., 2011).

4.1. Structural model estimating and hypotheses evaluation

Table 2 shows the descriptive statistics and the correlations for the study's variables. The correlations are below 0.60, indicating multicollinearity is not an issue in the structural model analysis. We tested our hypotheses using covariance-based structural equation modeling (SEM) and maximum likelihood estimator in Mplus 7.4. The SEM approach allows for the simultaneous analysis of all hypothesized and control-

Table 2
Correlations and descriptive statistics.

Variables		1	2	3	4	5	6	7	8	9	10
1.	Threat interpretation bias	*0.789*									
2.	Disruption orientation	0.039	*0.578*								
3.	Disruption recovery capability	−0.170**	0.203**	*0.815*							
4.	Disruption absorption capability	−0.185**	0.164**	0.556**	*0.662*						
5.	Supply chain disruption	0.414**	−0.016	−0.119	−0.104	n/a					
6.	Resource slack	0.149*	0.172**	0.145*	0.160*	−0.014	*0.810*				
7.	Environmental dynamism	0.109	0.119	0.194**	0.154*	0.035	0.231**	*0.555*			
8.	Industry (service = 1)	−0.033	−0.022	−0.065	−0.012	−0.061	−0.078	−0.086	n/a		
9.	Firm size (log)	−0.040	0.142*	0.266**	0.233**	−0.062	0.252**	0.251**	−0.107	n/a	
10.	Firm age (log)	−0.105	0.023	0.140*	0.087	−0.067	0.004	0.010	−0.059	0.554**	n/a
Minimum		1	1	1	1	9	1	1	0	2	1
Maximum		7	7	7	7	56	7	7	1	6	4
Mean		3.54	5.43	4.89	5.30	27.27	4.46	4.91	0.73	3.09	2.55
Standard deviation		1.403	1.008	1.434	1.088	9.327	1.450	1.406	0.445	1.013	0.639

Notes: Correlations are below the principal diagonal. Average variance extracted values are presented on the principal diagonal, *$p < 0.05$(2-tailed), **$p < 0.01$(2-tailed), n/a = not applicable.

effect relationships while controlling for measurement error (Bagozzi and Yi, 2012). Using bootstrapping procedures and following Stride et al.'s (2015) guidelines, we estimated a conditional process SEM model to test our hypotheses. This analytical strategy allowed us to generate the bootstrap confidence for the indirect and conditional indirect effects.

Consistent with previous research (Jiang et al., 2023; Essuman et al., 2023a) and our CFA results, we treated the dimensions of operational resilience as distinct constructs in testing the study's hypotheses. Specifically, we predicted two dependent variables: disruption absorption and recovery capabilities. Because our hypothesis includes direct and moderation effect relationships, we mitigated the effects of multicollinearity by creating the moderation term as a product of the mean-centered scales of the direct and the moderating effect variables. Our analysis included the full indicators for the reflective latent constructs (threat interpretation bias, disruption orientation, disruption absorption capability, disruption recovery capability, resource slack, and environmental dynamism). We used single indicants to represent the moderation term (Miocevic et al., 2022), supply chain disruption

Table 3
Structural equation modeling results.

Direct and interaction effects:	Threat interpretation bias			Disruption absorption			Disruption recovery			VIF
	β	SE	p	β	SE	p	β	SE	p	
Hypothesized paths:										
Supply chain disruption	0.051	0.009	<0.001	−0.003	0.010	0.791	−0.005	0.008	0.567	1.227
Threat interpretation bias (TIB)				−0.211	0.083	0.010	−0.183	0.080	0.021	1.265
TIB × DO				0.181	0.054	0.001	0.108	0.048	0.025	1.014
Non-hypothesized paths:										
Disruption orientation (DO)				0.209	0.100	0.036	0.227	0.078	0.003	1.157
Resource slack				0.113	0.081	0.163	0.066	0.082	0.420	1.136
Environmental dynamism				0.115	0.093	0.218	0.148	0.092	0.109	1.025
Industry				0.075	0.142	0.596	−0.064	0.143	0.653	1.696
Firm size				0.216	0.079	0.006	0.192	0.075	0.011	1.522
Firm age				−0.048	0.125	0.701	0.051	0.131	0.699	1.157

Conditional direct effects:	Levels of moderator	β	95% Bootstrap CI
TIB → DA	Low (-1SD of mean)	−0.394	[-0.554, −0.222]
	High (+1SD of mean)	−0.029	[-0.200, 0.124]
TIB → DR	Low (-1SD of mean)	−0.292	[-0.436, −0.143]
	High (+1SD of mean)	−0.075	[-0.232, 0.086]
Indirect effects:	Indirect β		95% Bootstrap CI
SCD → TIB → DA	−0.011	[-0.019, −0.004]	
SCD → TIB → DR	−0.009	[-0.016, −0.003]	
Conditional indirect effects:	Levels of moderator	Indirect β	95% Bootstrap CI
SCD → TIB → DA	Low (-1SD of mean)	−0.020	[-0.031, −0.011]
	High (+1SD of mean)	−0.001	[-0.010, 0.007]
SCD → TIB → DR	Low (-1SD of mean)	−0.015	[-0.024, −0.007]
	High (+1SD of mean)	−0.004	[-0.011, 0.004]

Model fit indices:
χ^2 = 851.243, DF = 532, Normed χ^2 = 1.600, RMSEA = 0.048, NNFI = 0.944, CFI = 0.950, SRMR = 0.061.
R^2 for model of threat rigidity bias = 0.181, R^2 for model of disruption absorption = 0.210, R^2 for model of disruption recovery = 0.182

Notes.
1. SCD = supply chain disruption; TIB = threat interpretation bias; DA = disruption absorption, DR = disruption recovery.
2. VIF = variance inflation factor. These factors were estimated by regressing disruption absorption on the predictors in the model.
3. All relationships were estimated simultaneously in Mplus 7.4.
4. Bootstrap sample = 5000.
5. Unstandardized estimates are reported.
6. p = p-value (2-tailed).

(Bode et al., 2011), firm industry, firm size, and firm age. The SEM model shows a good fit to the data: $\chi^2 = 851.243$, DF = 532. Normed $\chi^2 = 1.600$, RMSEA = 0.048, NNFI = 0.944, CFI = 0.950, SRMR = 0.061. Table 3 details the results for the hypothesized relationships. It shows the variables in the model do not violate multicollinearity assumptions since all the variance inflation factors are below 2.0.

The results show that supply chain disruption has a significant positive relationship with threat interpretation bias: $\beta = 0.051$, $p < 0.001$. Additional results show threat interpretation has significant negative relationships with disruption absorption capability ($\beta = -0.211$, $p = 0.010$) and disruption recovery capability ($\beta = -0.183$, $p = 0.021$). Importantly, the mediation test reveals supply chain disruption has significant negative indirect relationships, through threat interpretation bias, with disruption absorption capability (indirect $\beta = -0.011$, 95% CI [−0.019, −0.004]) and disruption recovery capability (indirect $\beta = -0.009$, 95% CI [−0.016, −0.003]). These results support H1.

Additionally, the results reveal that the interaction between threat interpretation bias and disruption orientation has significant positive relationships with disruption absorption capability ($\beta = 0.181$, $p = <0.001$) and disruption recovery capability ($\beta = 0.108$, $p = 0.025$). Given these results, we conducted simple slope analyses of the direct effects of threat interpretation bias and the indirect effects of supply chain disruption through threat interpretation bias at *low* (−1 standard deviation) and *high* (+1 standard deviation) levels of the disruption orientation scale.

The results show that at a low level of disruption orientation, threat interpretation bias has stronger negative relationships with both disruption absorption capability ($\beta = -0.394$, 95% CI [−0.554, −0.022]) and disruption recovery capability ($\beta = -0.292$, 95% CI [−0.436, −0.143]). However, at a high disruption orientation level, threat interpretation has insignificant associations with disruption absorption capability ($\beta = -0.029$, 95% CI [−0.200, 0.124]) and disruption recovery capability ($\beta = -0.075$, 95% CI [−0.232, 0.086]). As illustrated in Fig. 2, these results demonstrate that disruption orientation significantly attenuates the negative relationship between threat interpretation bias and both disruption absorption capability (Panel A) and disruption recovery capability (Panel B) dimensions of operational resilience.

The slope analysis further reveals that the indirect effect of supply chain disruption on disruption absorption capability, through threat interpretation bias, is negative and strong in a low disruption orientation condition (indirect $\beta = -0.020$, 95% CI [−0.019, −0.011]) but insignificant in a high disruption orientation condition (indirect $\beta = -0.001$, 95% CI [−0.010, 0.007]). Similarly, the indirect effect of supply chain disruption on disruption recovery capability, through threat interpretation bias, is negative and strong in a low disruption orientation condition (indirect $\beta = -0.015$, 95% CI [−0.024, −0.007]) but insignificant in a high disruption orientation condition (indirect $\beta = -0.004$, 95% CI [−0.011, 0.004]). These results, therefore, provide support for H2.

5. Discussion and implications

5.1. Discussion of key findings

This study reveals two main findings. Firstly, as theorized, the results confirm the negative mediating role of threat interpretation bias in the relationship between supply chain disruption and operational resilience. Specifically, the results indicate that a unit increase in supply chain disruption increases threat interpretation bias by 0.051. However, increasing threat interpretation bias by one unit reduces disruption absorption and recovery capabilities by −0.211 and −0.183, respectively. The logic behind these results is that while supply chain disruption inherently threatens business survival and profitability, threat interpretation bias will likely increase as supply chain disruption increases (Pérez-Nordtvedt et al., 2014). Such threat-rigidity response to supply chain disruption, which manifests in reduced information and new idea search and heightened resource conservation behaviors, reduces firms' options for building operational resilience (Gu et al., 2021; Essuman et al., 2023a; Vogus and Sutcliffe, 2007).

The above results broadly align with past studies that show that threatening events affect organizational outcomes indirectly through firm-level or managerial responses, such as issue interpretation (Pérez-Nordtvedt et al., 2014), risk management (El Baz and Ruel, 2021), and information technology-related internal controls (Gong et al., 2023). More specifically, the finding reinforces past evidence suggesting that the closer SME owners are to a disruption source, the more likely they are to interpret such a disruptive event as a threat to their business survival and profitability, subsequently reducing their adaptation intention (Pérez-Nordtvedt et al., 2014). Overall, the finding supports the threat-rigidity theory's argument that disruptive and hostile conditions can induce threat interpretation bias among top managers (Obłój and Voronovska, 2023; Garretsen et al., 2022; Pérez-Nordtvedt et al., 2014), which, in turn, can limit SMEs' chances to gain operational resilience advantages (Pérez-Nordtvedt et al., 2014; Vogus and Sutcliffe, 2007).

Secondly, the results support the study's arguments that disruption orientation reduces the negative effect of threat interpretation bias on operational resilience. Specifically, the results show that disruption orientation changes the magnitude of the negative impact of threat interpretation bias on operational resilience (see Fig. 2). The slope analysis reveals that a unit increase in threat interpretation bias significantly reduces disruption absorption and recovery dimensions of operational resilience by −0.394 and −0.292, where disruption orientation is one standard deviation below the mean level. In contrast, a unit

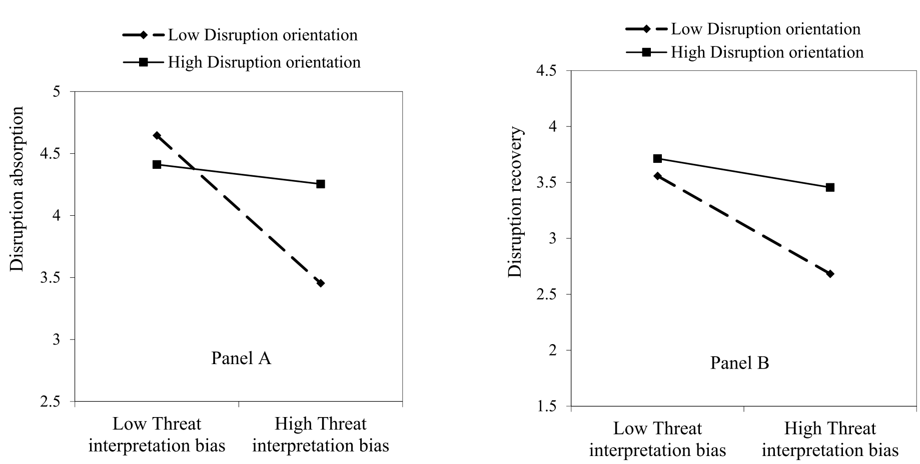

Fig. 2. Moderating effects of disruption orientation.

increase in threat interpretation bias marginally reduces these operational resilience dimensions by −0.029 and −0.075, where disruption orientation is one standard deviation above the mean level (see Table 3). Accordingly, the study further finds that the negative indirect effect of supply chain disruption on operational resilience via threat rigidity bias is stronger and more significant for low disruption-oriented firms than for high disruption-oriented firms.

A plausible explanation for these findings is that while a high disruption orientation enables firms to develop richer knowledge and coping mechanisms for dealing with disruptions (Yu et al., 2019), firms that emphasize threat rigidity bias can capitalize on these benefits, thereby improving their ability to build resilience (Obłój and Voronovska, 2023). Conversely, when disruption orientation is low, firms may have limited knowledge and mechanisms for dealing with disruptions. In such environments, an emphasis on threat interpretation bias can result in poor and haphazard decisions, potentially leading to costly consequences, including worsening disruption impact and increased recovery time (Essuman et al., 2023a).

The study's findings broadly support the contention that the extent to which threat rigidity responses may be dysfunctional depends on the extent of firms' relevant knowledge and coping mechanisms (Staw et al., 1981). The negative consequences of threat interpretation bias on operational resilience are likely to be lower in firms with richer disruption-specific knowledge resources (Kreiser et al., 2020; Staw et al., 1981). Overall, the study's findings align with research that focuses on the contingencies in the threat-rigidity thesis (Kreiser et al., 2020; Pérez-Nordtvedt et al., 2014; Chattopadhyay et al., 2001).

5.2. Theoretical implications

The study's implications for research on supply chain disruption and resilience are twofold. First, the study reveals threat interpretation bias as a significant conduit through which supply chain disruption reduces operational resilience and that disruption orientation suppresses this negative indirect effect. Top executives and, for that matter, firms interpret supply chain disruption differently (Obłój and Voronovska, 2023; Nikiforou et al., 2023). In ignoring this important phenomenon, past studies generally presume that supply chain disruptions would drive resilience-building efforts (Xi et al., 2024; Huang et al., 2023; Zhao et al., 2023). This study demonstrates that variability in top executives' disruption interpretation matters in understanding SMEs' success or failure in building operational resilience (Pérez-Nordtvedt et al., 2014; Obłój and Voronovska, 2023). The study theorizes and empirically shows that supply chain disruption can impact operational resilience differently depending on how SMEs' top executives interpret disruptions and their firms' disruption orientation level. These insights clarify the limited literature on how supply chain disruption concepts affect resilience capabilities (e.g., Essuman et al., 2023b; El Baz and Ruel, 2021; Parker and Ameen, 2018).

Second, the study contributes to existing theoretical perspectives on resilience-building. In strengthening existing literature on the significance of the threat-rigidity thesis for resilience theorization (Obłój and Voronovska, 2023; Linnenluecke, 2015; Pérez-Nordtvedt et al., 2014; Vogus and Sutcliffe, 2007), this study demonstrates the empirical value of accounting for specific threat-rigidity responses and contexts (Staw et al., 1981). The manifestation of threat rigidity responses (e.g., threat interpretation bias) and the context under which they occur (e.g., disruption orientation) vary in intensity. The major implication of the study's results is that the explanatory power and accuracy of the threat-rigidity thesis improve when research models and analyzes specific threat-rigidity responses and their boundary conditions.

5.3. Implications for SME managers

The study's findings have important implications for top managers in SMEs in a developing country. Due to resource scarcity problems, these managers are likely to frame supply chain disruption as a threat to the survival of their business. The results from this study serve as a reminder to these managers that the lenses through which they interpret disruptive events determine the operational resilience of their firms. The study's findings suggest that SME managers should minimize the tendencies towards consistently interpreting disruptive events as threats. The Covid-19 pandemic reveals how disruptive circumstances create conditions that foster business opportunity exploration and exploitation, which drives organizational resilience and survival in the long run. The dangers of consistently interpreting disruptions as threats are that it prevents managers from recognizing the opportunities that the disruptive event may present and further limits investments in resources and capabilities to build more resilient operations and supply chains.

Several measures can help organizations to effectively interpret disruptions and reduce the chances and negative consequences of threat interpretation bias. First, managers should encourage participative decision-making and tolerate diversity. Participative decision-making can improve decision quality. Also, encouraging diversity and inclusivity in the workplace can help reduce bias by exposing employees to different perspectives and backgrounds. These initiatives can help organizations better diagnose issues and reach effective conclusions. Second, instead of relying on past experiences and intuition alone, managers should institute formal procedures for searching, analyzing, and interpreting information about disruptions. A lack of broad and pertinent information can obscure managers' understanding of the magnitude of the threat that accompanies specific disruptions. Finally, instead of consistently adopting a short-term approach to responding to disruptions, managers should focus on lasting solutions that involve opportunity exploitation. Specifically, managers should be proactive in responding to disruptions, recognizing them as avenues for learning and improvement. Such orientation is useful for implementing measured responses to supply chain disruptions.

6. Conclusion and limitations

Supply chain disruption is central to resilience literature and application, yet there is limited theoretical and empirical analysis of its effect on resilience capabilities. This research sheds new light by identifying threat interpretation bias and disruption orientation as important variables determining how and when supply chain disruption affects operational resilience in SMEs in a developing country. The study's findings, however, must interpreted within the context of some theoretical and empirical limitations.

Firstly, we operationalized supply chain disruption as the frequency of unexpected events that interrupt a firm's supply chain operations. Such events differ in terms of their scope and scale of impact. Future studies can explore the effects of these different aspects of the construct on threat interpretation bias and operational resilience.

Secondly, our analysis of disruption interpretation is limited to threat interpretation bias. Some scholars suggest opportunity interpretation bias as a distinct construct (e.g., Pérez-Nordtvedt et al., 2014). Threat and opportunity interpretation biases can affect operational resilience differently (Pérez-Nordtvedt et al., 2014; Chattopadhyay et al., 2001). Thus, future studies can expand on our conceptual model by analyzing the potential competing mediating roles of threat and opportunity interpretation biases in the relationship between supply chain disruption and operational resilience.

Thirdly, the study's model incorporates one moderating variable. Threat-rigidity literature highlights other factors that can moderate the effects of threat interpretation bias. Examples of such factors that future research can explore are slack resources, the magnitude, proximity, or salience of disruption, strategic orientations, and cultural factors (see, e.g., Obłój and Voronovska, 2023; Garretsen et al., 2022; Kreiser et al., 2020; Pérez-Nordtvedt et al., 2014).

Finally, although the research design adopted and data used to test our conceptual model are consistent with previous resilience studies (e.

g., Munir et al., 2022; Wong et al., 2020), there is potential for improvement. For example, cross-sectional survey data limits our ability to draw causal inferences from the findings. Future research can use longitudinal survey design to address this shortcoming. Again, the study's results based on data from SMEs in a single country lack broad generalizations. We encourage future research to replicate our research in large firms and other SME settings to assess the robustness of our findings.

CRediT authorship contribution statement

Felix Kissi Dankyira: Writing – review & editing, Writing – original draft, Conceptualization. **Dominic Essuman:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Nathaniel Boso:** Writing – review & editing, Supervision, Conceptualization. **Henry Ataburo:** Writing – review & editing, Writing – original draft. **Emmanuel Quansah:** Writing – review & editing, Writing – original draft.

Data availability

Data will be made available on request.

Appendix A. Indicative empirical evidence on the relationship between disruption concepts and resilience outcomes

Authors (year)	Disruption form/type	Resilience type/form	Theoretical perspective	Empirical context and data	Key findings
Essuman et al. (2023b)	Supply chain disruption (i.e., frequency or intensity of disruption)	Firm resilience (i.e., firms' ability to absorb, recover from, adapt to, or transform during disruptions)	Organizational information processing theory	Disruptions in international supply chain contexts. Survey data from 272 SME exporters from Ghana.	There is evidence that supply chain disruption has a negative effect on firm resilience ($\beta = -0.158$, $p = 0.001$). Moreover, there is evidence that supply chain disruption positively moderates the effect of foreign market scanning on firm resilience ($\beta = 0.105$, $p = 0.010$).
El Baz and Ruel (2021)	Disruption impacts (i.e., negative impact of the Covid-19 pandemic)	Supply chain resilience (i.e., the ability of a firm's supply chain to maintain situational awareness of, react to, cope with, and adapt to supply chain disruption). Supply chain robustness (i.e., the ability of a firm's supply chain to maintain functionality and performance during supply chain disruption).	Resource-based/dynamic capabilities theory and organizational information processing theory	Covid-19 induced supply chain disruption context. Survey data from 470 firms in France.	There is no evidence that disruption impact affects supply chain resilience directly ($\beta = -0.060$, $t = 1.276$). In contrast, there is evidence that disruption impact has a significant negative effect on supply chain robustness ($\beta = -0.264$, $t = 5.686$). There is also evidence that supply chain risk assessment practices negatively mediate the relationship between disruption impact and supply chain resilience ($\beta = -0.094$, $t = 3.079$) but not the relationship between disruption impact and supply chain robustness ($\beta = -0.040$, $t = 1.758$).
Wong et al. (2020)	Supply chain disruptions (i.e., frequency or intensity of disruptions): Supply-side disruption, infrastructure disruption, and catastrophic disruption	Supply chain resilience (i.e., the ability of a firm's supply chain to absorb and recover from disruptions).	Organizational information processing theory	No specific supply chain disruption setting. Survey data from 236 manufacturing firms in Taiwan.	There is evidence that supply-side disruption has a significant negative correlation with supply chain resilience ($r = -0.173$, $p < 0.01$). However, there is no evidence that infrastructure disruption ($r = -0.109$, $p > 0.05$) or catastrophic disruption ($r = -0.037$, $p > 0.05$) is correlated with supply chain resilience.
Yang et al. (2021)	Disruption impact	Supply chain risk management capabilities (i.e., firms' capability to prevent, detect, respond to, and restore from operational risks). Supply chain resilience (i.e., the ability of a firm to react to, minimize negative impacts, maintain normal operations during, and restore from supply chain disruptions)	Organizational information processing theory	Covid-19 induced supply chain disruption context. One hundred ninety-five manufacturing firms in China.	There is evidence that disruption impact has a significant positive effect on supply chain risk management capabilities ($\beta = 0.14$, $t = 2.42$), which in turn has a significant positive effect on supply chain resilience ($\beta = 0.52$, $t = 9.13$).
Parker and Ameen (2018)	Disruption impact (i.e., impact of power supply disruption).	Firm resilience (i.e., firms' ability to maintain awareness of, react to, cope with, and adapt to supply disruption).	Resource dependence theory	Power supply disruptions. Survey data from 150 firms in South Africa.	There is no evidence that disruption impact affects firm resilience ($\beta = 0.08$, $p > 0.05$). Again, there is no evidence that the interaction between disruption impact and resource reconfiguration positively affects firm resilience ($\beta = 0.04$, $p > 0.05$).

Appendix B. Reliability and validity results

Construct/indicator	Loadings	T-values
Threat interpretation bias [a] ($\rho_C = 0.937$; AVE = 0.789). *When we faced threatening events in the last three years,*		
our top management often saw problems rather than opportunities	0.873	17.538
our top management worried more about the losses from the events than the benefits	0.903	18.528
our top management tended to lose focus on the potential bright side of the events	0.893	18.210
our top management became quite worried about the fate of the company	0.884	17.899
Disruption orientation [a] ($\rho_C = 0.845$; AVE = 0.578).		
We always feel the need to be alert to possible disruptive events	0.773	13.738
Previous unplanned disruptions show us where we can help improve our company's operations	0.832	15.162
We think a lot about how threatening events could have been avoided	0.739	12.826
After an unplanned operational disruption has occurred, our management lead in analyzing it thoroughly	0.691	11.721
Disruption absorption [a] ($\rho_C = 0.921$; AVE = 0.662). *For the past 3 years, whenever disruptive events occur,*		
our company is able to carry out its regular functions	0.827	16.001
our company grants us much time to consider a reasonable response	0.711	12.858
our company is able to carry out its functions despite some damage done to it	0.832	16.158
without much deviation, we are able to meet normal operational and market needs	0.866	17.235
without adaptations being necessary, our company performs well over a wide variety of possible scenarios	0.847	16.626
our company's operations retain the same stable situation as it had before disruptions occur for a long time	0.788	14.880
Disruption recovery [a] ($\rho_C = 0.957$; AVE = 0.815). *Over the past 3 years, whenever our operations breakdown due to a disruption event,*		
it does not take long for us to restore normal operation	0.888	18.146
our company reliably recovers to its normal operating state	0.880	17.889
our company easily recovers to its normal operating state	0.913	19.056
our company effectively restores operations back to normal quickly	0.917	19.186
we are able to resume operations within the shortest possible time	0.915	19.136
Resource slack [a] ($\rho_C = 0.955$; AVE = 0.810).		
Our company often has uncommitted resources that can quickly be used to fund new strategic initiatives	0.871	17.587
Our company usually has adequate resources available in the short run to fund its initiatives	0.902	18.657
We are often able to obtain resources at short notice to support new strategic initiatives	0.910	18.953
We often have substantial resources at the discretion of management for funding strategic initiatives	0.924	19.442
Our company usually has a reasonable amount of resources in reserve	0.892	18.315
Environmental dynamism [a] ($\rho_C = 0.881$; AVE = 0.555). *Over the past three years, there have been irregular changes in …*		
the needs and preferences in our demand/customer market	0.772	13.891
the actions of our competitors, in terms of their promotions, innovations, etc.	0.784	14.177
terms, conditions, and structures in our supply markets	0.805	15.017
government policies and programs for our industry	0.778	13.932
laws and regulations governing our industry	0.683	11.535
technological needs and advancement in our industry	0.632	10.777
Supply chain disruption [b]. *Unexpectedly,*		
some of our employees leave their posts (i.e., quit their job)	–	–
some of our suppliers fail to make deliveries	–	–
we experience vehicular breakdowns	–	–
we experience service/product failure	–	–
we run out of cash for running day-to-day operations	–	–
we experience machine/technology downtime/failure	–	–
we experience a shortage of raw materials	–	–
we experience power cuts	–	–
some of our service providers fail to honor their promises	–	–

Notes: a = measured with reflective indicators; [b] = measured with formative indicators and was excluded from the confirmatory factor analysis; ρ_C = congeneric reliability; AVE = average variance extracted.

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