

Digital Sustainable Finance Capability and SME Resilience Under Polycrisis

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Abstract

This study examines how digital sustainable finance capability strengthens small and medium-sized enterprise resilience during polycrisis and whether resource reconfiguration explains this effect under adversity. The analysis uses an event-based firm-year panel of 1,439 United Kingdom AIM-listed firms observed from 2016 to 2025, producing 8,184 observations. Firm- and year-fixed-effects models, confirmatory factor analysis, mediation tests, moderated mediation, block-bootstrap inference, and robustness checks support the design. Results show that lagged capability improves resilience and intensifies resource reconfiguration. Reconfiguration accounts for about 31 percent of the total capability effect, while the indirect effect increases as adversity intensifies. However, capability does not reduce the risk of delisting. The study contributes an integrated higher-order capability that connects digital execution, sustainability credibility, financing readiness, and adaptive resource movement within dynamic capabilities theory. Its observational setting, annual measurement, disclosure-based indicators, and focus on listed British firms limit causal inference and generalization. In practice, managers should develop digital controls, credible sustainability information, and preauthorized reallocation routines before shocks emerge. Lenders and investors should assess these elements jointly rather than treating disclosure quality as sufficient. Socially, stronger adaptive capacity may support business continuity and economic recovery during prolonged disruption.

JEL: G32, L26, M15, O33, Q56

1. Introduction

Small and medium-sized enterprises are now operating in a climate where disruptions overlap, uncertainty lingers, and financing conditions tighten unevenly across firms. Adversity is not only a temporary setback in this environment. It can redirect entrepreneurial trajectories and widen the gap between firms that stabilize and adapt and those that deteriorate or exit (Doern et al., 2019; Eggers, 2020; Belitski et al., 2022). Resilience, then, needs to be treated as more than survival. It reflects a shifting pattern of downside protection, adaptive adjustment, and recovery capacity that varies with context and shock profiles (Conz & Magnani, 2020; Esteve-Pérez et al., 2024; Saezow & Sukhabot, 2025; Koporcic et al., 2026).

Polycrisis thinking sharpens that point by treating shocks as causally entangled rather than isolated events, thereby pushing research to explain repeated adaptation under compounding constraints (Miklian & Hoelscher, 2022; Klyver & McMullen, 2025; Maalouf et al., 2025). Yet much of what we know still sits in parallel lanes. Digitalization, sustainability orientation, and financing constraints are often examined as separate correlates of resilience rather than as a single capability that firms build internally and deploy repeatedly when shock windows open (Amankwah-Amoah et al., 2021; Santos et al., 2023; Sagala & Őri, 2025). This study starts from that disconnect and asks a focused question: How does digital sustainable finance capability strengthen SME resilience under polycrisis, through what internal mechanism, and under what adversity conditions is the effect strongest (Doern et al., 2019; Conz & Magnani, 2020).

Answering that question matters because financing becomes a moving constraint under persistent adversity. As uncertainty rises, information asymmetry becomes more consequential, and financiers tighten screening, thereby raising the value of credible, comparable sustainability signals (Beck, 2023; Bao & Yang, 2025; Palmieri et al., 2025). At the same time, crisis research shows that rapid reorientation becomes central as constraints shift, so firms that can adjust quickly and credibly are more likely to protect stability and support recovery (Kuckertz et al., 2020; Kraus et al., 2020; Shepherd & Williams, 2023). These pressures make it difficult to treat digitalization and sustainability as background features. In polycrisis contexts, they can become part of the core toolkit firms use to secure resources and act quickly when conditions deteriorate (Santos et al., 2023; Sagala & Őri, 2025).

The argument is anchored in dynamic capabilities theory, which explains why firms differ under turbulence through repeated sensing, seizing, and reconfiguring. This lens fits resilience views that emphasize adaptive action and transformation rather than passive endurance, especially when adversity persists (Bullough et al., 2014; Conz & Magnani, 2020; Gianiodis et al., 2022). Digitalization research in crisis contexts reinforces the idea that digitally enabled capabilities can accelerate adjustment and shape survival and stability outcomes (Amankwah-Amoah et al., 2021; Du et al., 2023; Zhou & Sun, 2024). A complementary signaling and legitimacy logic explains why sustainability credibility becomes financing relevant when screening tightens and uncertainty makes trust harder to earn (Beck, 2023; Bao & Yang, 2025; Palmieri et al., 2025).

Bringing these strands together, digital sustainable finance capability is defined here as an internally developed capability that integrates digitalization and sustainability credibility to mobilize sustainable finance in adversity and to rapidly redeploy the resources obtained. The logic is practical and behavioral rather than rhetorical. The capability should matter because it enables stronger, faster resource reconfiguration when shock windows open, and it should matter even more when adversity becomes severe, as the marginal value of rapid reallocation and credible signaling rises as constraints tighten (Cowling et al., 2020; Papanikolaou & Schmidt, 2022; Beck, 2023). Resource reconfiguration intensity sits at the center of this mechanism because dynamic capabilities create value through observable reallocations and reinvestments rather than capability claims alone (Sharma et al., 2020; Breier et al., 2021; Gianiodis et al., 2022).

This framing matters for scholars interested in resilience, digital entrepreneurship, and sustainable finance because it specifies a concrete endogenous capability and ties it to a finance-relevant mechanism that becomes visible during adversity rather than in calm periods. It also matters for managers and finance stakeholders because it implies that resilience is partly built through the capacity to fund and execute timely reallocations, rather than solely through liquidity buffers or generic digital adoption (Beck, 2023; Santos et al., 2023; Raby & Chowdhury, 2025). The empirical focus on listed SMEs and small caps in the United Kingdom supports transparent measurement, reproducibility, and a setting in which annual reports and market data enable observation of resilience through downside exposure and recovery patterns across multiple regimes of adversity (Papanikolaou & Schmidt, 2022; Esteve-Pérez et al., 2024).

2. Literature Review

Polycrisis research reframes adversity as overlapping and mutually reinforcing rather than isolated events with clear boundaries, which means SMEs face repeated adaptation under compounding constraints and the drivers of resilience can shift across phases of deterioration and partial recovery (Miklian & Hoelscher, 2022; Klyver & McMullen, 2025; Maalouf et al., 2025; Audretsch & Kariv, 2025). This view strengthens the case for examining resilience inside adversity windows, because what appears resilient in a single episode can look fragile when disruptions persist and interact (Miklian & Hoelscher, 2022; Maalouf et al., 2025). Recent evidence also shows that grit and community belonging can sustain entrepreneurial persistence during polycrisis, while ecosystem routines and resourcing configurations can organize sustainable entrepreneurial action (Audretsch, Fiedler, et al., 2026; Audretsch & Kariv, 2026).

In that context, SME resilience research has moved beyond survival to a richer view that includes downside protection, adaptive adjustment, and recovery capacity, while emphasizing that the same shock can stabilize some firms and push others toward deterioration or exit (Doern et al., 2019; Eggers, 2020; Belitski et al., 2022; Zakaria et al., 2023). Reviews further emphasize that resilience unfolds differently across settings and shock profiles, making generalization risky unless studies clearly specify the conditions of adversity and measurement choices (Conz & Magnani, 2020; Esteve-Pérez et al., 2024; Saezow & Sukhabot, 2025).

Entrepreneurship under crisis research converges on rapid reorientation as a core feature of resilient responses, since firms that revise priorities, reallocate resources, and act quickly can protect stability and improve recovery prospects (Kuckertz et al., 2020; Kraus et al., 2020; Campagnolo et al., 2022; Shepherd & Williams, 2023). Yet the SME crisis literature remains fragmented because many studies isolate single levers such as digital adoption, sustainability orientation, or financing constraints, without explaining how they combine inside the firm as a repeatable capability deployed when shock windows open (Amankwah-Amoah et al., 2021; Santos et al., 2023; Sagala & Őri, 2025). Knowledge collaboration is another part of this process because relational similarity can influence innovative outcomes, while knowledge spillovers help explain why entrepreneurial responses differ across firms and places (Audretsch & Belitski, 2026; Audretsch, Belitski, et al., 2026).

Digitalization and fintech research offers a strong reason to expect digital enablement to matter for resilience because digitally enabled adaptation has been tied to survival and stability during disruption, and fintech has been discussed as support for SME continuity when traditional channels tighten (Du et al., 2023; Santos et al., 2023; Zhou & Sun, 2024; Li & Xie, 2025). At the same time, digital resilience is not automatic, as governance and infrastructure constraints can impede the translation of tools into downside protection, shifting attention from adoption to capability (Zirar et al., 2024; Oo & Rakthin, 2025). Technological ambidexterity introduces a related mechanism, as firms can combine the exploitation and exploration of technological knowledge, while science and cluster policy mixes shape the knowledge environment in which entrepreneurship develops (Audretsch, Lehmann, et al., 2026; Martínez-Román et al., 2026).

Sustainable finance and SME finance research complements this by clarifying why sustainability credibility becomes strategically relevant in the face of adversity. When uncertainty rises, information asymmetry

becomes more consequential and financiers tighten screening, increasing the value of credible, comparable disclosure (Beck, 2023; Palmieri et al., 2025). Evidence linking ESG disclosure and sustainability practices to stakeholder responses and performance-relevant conditions in SME-related contexts supports the view that sustainability signals can shape financing feasibility and perceived risk under constraints (Skýpalová et al., 2023; Shou et al., 2024; Bao & Yang, 2025; Xiao et al., 2026).

The missing link is therefore not whether digitalization or sustainability matter, but how they jointly become a finance-relevant capability that translates into observable adaptive action during shock windows. Treating finance as background context can obscure the mechanism through which firms move from intent to reallocation, especially when resources are scarce, and the ability to fund adaptive investment becomes decisive (Cowling et al., 2020; Beck, 2023; Raby & Chowdhury, 2025). This study addresses that gap by focusing on digital sustainable finance capability as an integrated capability built internally and deployed repeatedly under polycrisis to mobilize sustainable finance and support timely resource redeployment.

The empirical focus on UK listed SMEs and small caps supports this objective because standardized disclosures and consistent market and accounting coverage allow downside exposure, operating stability, and recovery to be observed within a consistent firm year structure, which is essential when the goal is to separate digitalization signals, sustainability credibility, and financing relevant outcomes (Papanikolaou & Schmidt, 2022; Beck, 2023; Esteve-Pérez et al., 2024). This setting also aligns with the argument that financing constraints and liquidity buffers shape crisis endurance and adaptive investment, making a finance-visible context well-suited to testing a resource reconfiguration mechanism (Cowling et al., 2020; Raby & Chowdhury, 2025).

2.1 Theoretical framework

Dynamic capabilities theory provides the primary lens because it explains performance differences amid turbulence through repeated sensing, seizing, and reconfiguring, rather than through static resource endowments. This perspective is especially relevant for SMEs facing tight constraints because it centers on how firms build and redeploy competencies to respond to rapidly changing conditions (Teece et al., 1997; Winter, 2003; Teece, 2007). The lens also aligns with resilience work that emphasizes adaptive action and transformation rather than passive endurance in the face of persistent adversity (Bullough et al., 2014; Conz & Magnani, 2020; Gianiodis et al., 2022). This adaptive capacity is also shaped by the community ties and ecosystem routines that help entrepreneurs persist and mobilize resources as crises compound (Audretsch, Fiedler, et al., 2026; Audretsch & Kariv, 2026).

Within this framing, digital sustainable finance capability is treated as a higher-order capability integrating two essential pillars. The digitalization pillar captures sensing and execution speed enabled by digital resources and routines, while the sustainability credibility pillar captures the firm's ability to present credible, comparable signals that support resource access as screening tightens. Capability matters because it links the identification and mobilization of financing options to the reconfiguration of the resource base in the face of adversity, which is the behavioral route through which dynamic capabilities

generate value (Teece, 2007; Du et al., 2023; Zhou & Sun, 2024; Li & Xie, 2025). The same logic suggests that knowledge collaboration and innovation spillovers can strengthen sensing and seizing, although their benefits remain uneven across entrepreneurial settings (Audretsch & Belitski, 2026; Audretsch, Belitski, et al., 2026).

A complementary signaling and legitimacy logic explains why sustainability credibility becomes relevant to financing under adversity. As uncertainty rises and financiers tighten screening, credible disclosure can reduce perceived risk and improve access to capital needed for adaptive investment (Beck, 2023; Bao & Yang, 2025; Palmieri et al., 2025). In this model, signaling strengthens the seizing component rather than replacing dynamic capabilities, as it improves the feasibility of mobilizing finance when resources are needed for adaptation and recovery.

The core mechanism linking capability to resilience is resource reconfiguration intensity during shock windows, captured by the intensity of adaptive reinvestment and asset-mix change. Dynamic capabilities create advantage through realized reallocation actions, so the mechanism focuses on observable redeployment and reinvestment rather than stated intentions (Sharma et al., 2020; Breier et al., 2021; Gianiodis et al., 2022). The boundary condition is adversity severity. As adversity intensifies, the marginal value of fast reallocation increases, and access to finance becomes more consequential for executing adaptive investment, implying a stronger indirect effect through reconfiguration in high-adversity shock windows (Papanikolaou & Schmidt, 2022; Beck, 2023; Shou et al., 2024; Palmieri et al., 2025).

Reconfiguration may therefore reflect both technological ambidexterity within the firm and the wider science and cluster policy conditions that influence how knowledge translates into entrepreneurial action and growth (Audretsch, Lehmann, et al., 2026; Martínez-Román et al., 2026).

2.2 Hypothesis development

Digital sustainable finance capability should strengthen SME resilience during shock windows by coupling rapid digital adjustment with sustainability credibility, which becomes decisive when uncertainty rises and screening tightens. In polycrisis conditions, where shocks interact and constraints compound, this combination should help firms limit downside exposure while sustaining recovery capacity (Doern et al., 2019; Eggers, 2020; Miklian & Hoelscher, 2022; Santos et al., 2023; Beck, 2023). Dynamic capabilities logic supports this expectation because resilience under turbulence depends on what firms can repeatedly do, especially sensing change, seizing resource options, and reconfiguring the resource base toward adaptive investment (Teece, 2007; Conz & Magnani, 2020; Gianiodis et al., 2022).

Hypothesis 1

Digital sustainable finance capability is positively associated with SME resilience during shock windows.

If digital sustainable finance capability is effective, it should also be visible in crisis time behavior through stronger resource reconfiguration intensity. Digital enablement improves the speed of coordination and execution amid disruption, while sustainability credibility enhances the feasibility of mobilizing finance as lenders and investors become more selective. Together, these elements should support stronger

redeployment toward adaptive investments during adverse periods (Du et al., 2023; Beck, 2023; Zhou & Sun, 2024; Bao & Yang, 2025).

Hypothesis 2

Digital sustainable finance capability is positively associated with resource reconfiguration intensity during shock windows.

Resource reconfiguration intensity should then explain why the capability translates into resilience. Under turbulence, advantage is realized through tangible reallocations and reinvestments rather than capability claims, so capability should primarily raise resilience by enabling firms to shift resources more forcefully toward adaptation during shock windows. This places reconfiguration at the center of the pathway from capability to downside protection and recovery outcomes (Sharma et al., 2020; Conz & Magnani, 2020; Breier et al., 2021; Gianiodis et al., 2022).

Hypothesis 3

Resource reconfiguration intensity mediates the relationship between digital sustainable finance capability and SME resilience during shock windows.

The strength of this mediated pathway should depend on the severity of adversity. As adversity intensifies, constraints tighten, external finance becomes more consequential for funding adaptive investment, and credible sustainability signals become more valuable as screening escalates. Under these conditions, the capability should produce larger increases in reconfiguration intensity, and reconfiguration should contribute more strongly to resilience, yielding a stronger conditional indirect effect at higher adversity severity (Cowling et al., 2020; Papanikolaou & Schmidt, 2022; Beck, 2023; Shou et al., 2024; Palmieri et al., 2025).

Hypothesis 4

The indirect effect of digital sustainable finance capability on SME resilience through resource reconfiguration intensity is stronger when adversity severity is higher.

Figure 1 presents the study's conceptual model, illustrating the theorized relationships among the core variables and clarifying the logical structure through which the proposed effects are expected to unfold.

3. Methodology

3.1 Research design, setting, and sample

This study uses a secondary-data, event-based firm-year panel of UK AIM-listed SMEs and small caps observed from 2016 through 2025. The final panel contains 8,184 firm-year observations for 1,439 firms. LSEG (formerly Refinitiv) provides the consistent firm identifiers, market data, accounting data, and ESG

disclosure fields used across the panel. Publicly available annual reports provide the text used to construct the digitalization indicators. The firm-year is the unit of analysis.

The sample includes UK AIM firms that meet the study's SME or small-cap criteria and the stated eligibility and traceability rules. Each retained firm-year requires LSEG market and fundamentals coverage for the resilience outcomes. ESG disclosure fields and annual-report text are matched where available and may remain missing at the firm-year level; eligible missing predictors are handled through the multiple-imputation procedure described below. Capability is lagged by one year to preserve the build-then-deploy sequence and reduce simultaneity between capability measurement and shock-window outcomes (Teece, 2007; Conz & Magnani, 2020; Gianiodis et al., 2022).

Adversity is measured with a prespecified annual severity index based on CPI inflation, the absolute magnitude of Bank Rate changes, and UK policy uncertainty. These components capture cost pressures, shifts in financing conditions, and uncertainty that raise screening intensity and the value of credible information (Beck, 2023). The index is a narrow macro-financial pressure measure rather than a comprehensive chronology of crisis intensity because it does not include lockdown severity, mortality, or output disruption. Its year ranking is interpreted only within the three included components. Years in the top quartile of the index define the high-adversity shock windows. Adjacent years remain in the panel so that the study can distinguish exposure during the shock from subsequent stabilization and recovery (Conz & Magnani, 2020; Esteve-Pérez et al., 2024).

Data provenance is maintained by variable family. Provider-origin market, accounting, cash-flow, security-status, and ESG fields come from LSEG. Digitalization indicators are calculated from annual-report text. Factor scores, ratios, year-to-year changes, adversity measures, and market-based resilience outcomes are derived from those source fields. Only eligible missing predictors are completed through multiple imputation; outcome variables are not multiply imputed in the primary specifications.

3.2 Measures, data origin, and construct operationalization

All focal constructs are modeled using five indicators to reduce reliance on any single proxy and to align with the multidimensional definitions of capability, reconfiguration, and resilience. Indicators are scaled for cross-firm comparability and standardized within the year when market conditions or disclosure practices could mechanically shift their levels. Vulnerability measures are reverse-oriented so that higher latent scores consistently indicate stronger resilience. Table 1 reports the operational definition, measurement class, data source, and theoretical justification for every indicator.

Digital sustainable finance capability is specified as a second-order construct with digitalization and sustainability-credibility pillars. The digitalization pillar uses three annual-report indicators: normalized disclosure intensity for digital operations, digital finance, and data and analytics. These measures capture visible routines that can support sensing and execution under disruption (Amankwah-Amoah et al., 2021; Santos et al., 2023; Du et al., 2023; Li et al., 2025). The sustainability-credibility pillar uses LSEG ESG disclosure and transparency fields because comparable disclosure becomes more consequential when financing screens tighten and information frictions rise (Beck, 2023; Palmieri et al., 2025). An ESG

combined-score construction is retained as a sensitivity test rather than added to the five-item measurement model (Skýpalová et al., 2023; Bao & Yang, 2025; Xiao et al., 2026).

Resource reconfiguration intensity is modeled as a latent mediator using five change-based archival indicators: changes in intangible-asset intensity, capital-expenditure intensity, research-and-development intensity, divestiture and asset-redeployment intensity, and investing-cash-flow intensity. The indicators are calculated from LSEG accounting and cash-flow fields. Their change-based form matches the theoretical claim that capability affects resilience through realized shifts in the resource base rather than through static asset stocks (Sharma et al., 2020; Breier et al., 2021; Gianiodis et al., 2022).

SME resilience is modeled as a latent outcome with five indicators spanning market and operating dimensions. Downside semivariance, lower-tail risk, and maximum drawdown are calculated from the daily-market analytical series. Operating stability and recovery speed are calculated from annual accounting outcomes. Recovery speed is defined as the improvement in operating margin or ROA from the preceding fiscal year to the focal fiscal year, so the 2025 observation does not require FY2026 accounts. This structure separates protection during adversity from contemporaneous stabilization and recovery (Conz & Magnani, 2020; Papanikolaou & Schmidt, 2022; Esteve-Pérez et al., 2024).

Table 1 consolidates the construct definitions, exact calculations, field classifications, data origins, and supporting references used in the measurement model.

Table 1
Constructs, Indicators and Measurement

Construct (latent variable)	Indicator	Measurement	Data Origin	Embedded Justification
Digital sustainable finance capability (independent)	Digital operations disclosure intensity	Digital operations terms count in annual report ÷ total word count, standardized within year	Annual reports matched to LSEG identifiers	Digitalization of operations supports crisis adaptation and resilience, so disclosure-based intensity captures a scalable capability signal (Amankwah-Amoah et al., 2021; Santos et al., 2023; Du et al., 2023; Li et al., 2025)
Digital sustainable finance capability (independent)	Digital finance disclosure intensity	Digital finance and fintech terms count in annual report ÷ total word count, standardized within year	Annual reports matched to LSEG identifiers	Digitally enabled finance supports SME continuity when traditional channels tighten (Du et al., 2023; Zhou & Sun, 2024)
Digital sustainable finance capability (independent)	Data and analytics disclosure intensity	Data and analytics terms count in annual report ÷ total word count, standardized within year	Annual reports matched to LSEG identifiers	Data-driven sensing supports rapid adjustment under disruption, distinguishing capability from generic tool adoption (Santos et al., 2023; Zirar et al., 2024)
Digital sustainable finance capability (independent)	Sustainability credibility disclosure indicator	LSEG ESG disclosure score (or equivalent disclosure indicator), standardized within year	LSEG ESG	Under tighter screening, credible disclosure becomes financing relevant (Beck, 2023; Palmieri et al., 2025)
Digital sustainable finance capability (independent)	Sustainability credibility transparency indicator	LSEG ESG transparency score (or equivalent transparency indicator), standardized within year	LSEG ESG	Broader transparency strengthens legibility and comparability under information frictions (Beck, 2023)

Construct (latent variable)	Indicator	Measurement	Data Origin	Embedded Justification
Resource reconfiguration intensity (mediator)	Change in intangible assets intensity (primary proxy)	Year-to-year change in intangible assets ÷ total assets	LSEG fundamentals	Reconfiguration is expressed through redeployment and reinvestment actions (Sharma et al., 2020; Breier et al., 2021; Gianiodis et al., 2022)
Resource reconfiguration intensity (mediator)	Change in capex intensity	Year-to-year change in capital expenditures ÷ total assets	LSEG fundamentals	Captures shifts in adaptive investment pace under adversity
Resource reconfiguration intensity (mediator)	Change in R and D intensity (where available)	Year-to-year change in R and D ÷ sales	LSEG fundamentals	Captures adaptive renewal through innovation investment, used as complementary proxy
Resource reconfiguration intensity (mediator)	Divestiture and asset redeployment intensity	Proceeds from sales of fixed assets and businesses ÷ total assets	LSEG cash-flow statements	Captures the resource release side of reconfiguration, complementing the reinvestment-based indicators (Sharma et al., 2020; Gianiodis et al., 2022)
Resource reconfiguration intensity (mediator)	Change in investing cash flow intensity (where available)	Year-to-year change in net cash used in investing ÷ total assets	LSEG cash-flow statements	Broadens reconfiguration beyond capex to wider investment redeployment
SME resilience during shock windows (dependent)	Downside semivariance	Downside semivariance of returns in the shock window, reverse oriented so higher indicates greater resilience	LSEG market data	Captures downside protection dimension during adversity (Papanikolaou & Schmidt, 2022; Esteve-Pérez et al., 2024)
SME resilience during shock windows (dependent)	Lower tail risk proxy	Left-tail percentile loss from shock window return distribution, reverse oriented	LSEG market data	Complements semi variance by targeting extreme downside in adversity windows
SME resilience during shock windows (dependent)	Maximum drawdown	Maximum peak-to-trough decline in cumulative return path during shock window, reverse oriented	LSEG market data	Captures depth of deterioration inside the shock window

Construct (latent variable)	Indicator	Measurement	Data Origin	Embedded Justification
SME resilience during shock windows (dependent)	Operating stability	Absolute deviation of shock-year operating margin or ROA from its three-year pre-shock average, reverse oriented	LSEG fundamentals	Captures operational stability as resistance to deterioration relative to the pre-shock baseline, computable within an annual reporting structure (Esteve-Pérez et al., 2024)
SME resilience during shock windows (dependent)	Recovery speed	Improvement in operating margin or ROA from the preceding fiscal year to the focal fiscal year	LSEG fundamentals	Captures recovery capacity dimension of resilience (Conz & Magnani, 2020; Esteve-Pérez et al., 2024)

3.3 Empirical models and estimation

Estimation uses firm fixed effects and year fixed effects panel regressions with firm-clustered standard errors. Firm fixed effects absorb time-invariant heterogeneity in business quality, sector position, and governance that could confound capability measures. Year fixed effects absorb macro-level shocks common to all firms in a given year. The capability index is entered one year lagged to align with the build-then-deploy logic and reduce simultaneity.

Mediation is tested with two fixed-effects equations. The first estimates resource reconfiguration intensity from lagged digital sustainable finance capability and the controls. The second estimates resilience from lagged capability, resource reconfiguration, and the same controls. The indirect effect is the product of the two estimated paths and is evaluated with firm-level block-bootstrap confidence intervals that preserve the within-firm panel structure (Preacher & Hayes, 2008).

Moderated mediation is estimated using conditional indirect effects across levels of adversity severity. This is implemented by interacting adversity severity with the capability to reconfigure the path, then computing the indirect effect at representative severity values, including the top-quartile high-adversity threshold defined by the severity index. This operationalizes the claim that the mechanism strengthens when constraints tighten, and financing access becomes more consequential (Cowling et al., 2020; Beck, 2023).

3.4 Data treatment, validity checks, and controls

Controls are selected to separate the focal capability pathway from baseline financial capacity and shock sensitivity. Firm size, leverage, profitability, liquidity, firm age (when available), industry fixed effects, year fixed effects, and ESG controversy proxies (when available) are included as stated in the extended abstract. Liquidity is especially important because crisis endurance is shaped by cash buffers and reserve policy, as evidenced by SMEs (Cowling et al., 2020).

The panel retains delisted and failed firms via LSEG coverage of dead and inactive securities, so that their exit remains observable rather than being removed by survivorship. Attrition is profiled by year and industry, and a Cox model tests whether lagged capability predicts delisting during shock windows (Esteve-Pérez et al., 2024). Because traceability requirements can favor larger and more transparent firms, selection into ESG coverage is modeled using a first-stage probit that includes firm size, index membership, and trading liquidity. The resulting inverse Mills ratio enters the outcome models, and inverse-probability weighting provides a separate reweighting check (Heckman, 1979).

Missing data are treated as an explicit modeling task rather than a reporting footnote. Missingness is first mapped by variable family, year, and industry, and Little's (1988) test assesses whether values are missing completely at random. Under the resulting missing-at-random working assumption, multiple imputation by chained equations with predictive mean matching generates 30 completed datasets, with imputation models that include all analysis variables, the fixed-effects structure, and auxiliary predictors of disclosure coverage (Rubin, 1987; White et al., 2011). Estimates are pooled using Rubin's rules and benchmarked against complete-case results; outcome values are not multiply imputed in the primary specifications, and R&D intensity receive dedicated handling because nondisclosure is common among SMEs, so a disclosure indicator distinguishes true zeros from unreported values rather than forcing missing values to zero.

Continuous accounting variables are winsorized at the 1st and 99th percentiles within each year to limit crisis-outlier leverage without dropping observations, with sensitivity checks at the 2.5th and 97.5th percentiles and under symmetric trimming. Because winsorization alone cannot guarantee that conclusions are not driven by influential observations, we report robust MM estimation and median regression as estimator-level checks, and use influence diagnostics based on Cook's distance and DFBETA statistics to verify that no small set of firm years determines the focal coefficients.

Construct validity is established through a two-step procedure that separates measurement from structural estimation. Confirmatory factor analysis validates the measurement model before any hypothesis test, reporting standardized loadings, composite reliability, and average variance extracted for each construct, with discriminant validity assessed through the Fornell and Larcker (1981) criterion and the heterotrait-monotrait ratio (Henseler et al., 2015). Digital sustainable finance capability is specified as a second-order construct, with digitalization and sustainability credibility as first-order pillars. The digitalization pillar is further refined by splitting the term dictionary into digital operations, digital finance, and data and analytics subdictionaries, so that each pillar carries multiple indicators. Measurement invariance is tested across high and low adversity windows before pooling; standardized factor scores are then exported to the panel models, and equal-weighted composites and first principal components are estimated as alternative weightings to demonstrate that conclusions are not weighting-dependent. Because the change-based mediator indicators may behave formatively rather than reflectively, we report a composite specification with variance inflation checks alongside the reflective baseline.

Text-based measures carry their own audit trail. Parsing quality is verified on a random subsample of reports; the dictionary is validated against human coding by two independent raters, with agreement assessed using Cohen's (1960) kappa; boilerplate passages are screened out; and term frequency-inverse

document frequency weighting is estimated as a robustness alternative to raw frequencies. Text measures are normalized by total word count to avoid report-length bias and then standardized within each year to reduce reporting drift, exactly as specified in the extended abstract.

We interpret commercial ESG measures as disclosure-based credibility signals, not direct ratings of underlying environmental or social performance, because provider methodologies can diverge and change over time (Berg et al., 2022). All ESG variables come from a single LSEG series and are used consistently across the study to avoid mixing scoring systems. The LSEG data vintage and extraction date are recorded for replication.

Inference is protected against the dependence structures typical of firm-year panels under common shocks. Firm-clustered standard errors form the baseline, two-way clustering by firm and year (Cameron et al., 2011) and Driscoll & Kraay (1998) standard errors address cross-sectional dependence induced by shared macro conditions, and the wild cluster bootstrap is applied where the effective number of clusters is modest (Cameron et al., 2008). Serial correlation is examined with the Wooldridge (2010) panel test, groupwise heteroskedasticity with a modified Wald statistic, cross-sectional dependence with the Pesaran (2015) statistic, and multicollinearity with variance inflation factors.

Identification receives safeguards beyond the one-year capability lag. Because year fixed effects absorb the level of the annual severity index, moderation is identified through the interaction term, and a firm-exposure variant interacts industry-level shock sensitivity with the macro index in the spirit of shift-share designs to restore cross-sectional variation in adversity exposure (Goldsmith-Pinkham et al., 2020). Dynamic specifications are estimated by two-step system generalized method of moments with the Windmeijer (2005) finite-sample correction, collapsed instrument sets to discipline instrument proliferation, and standard AR(2) and Hansen diagnostics (Blundell & Bond, 1998; Roodman, 2009). Entropy balancing on pre-shock covariates compares high- and low-capability firms on a reweighted basis (Hainmueller, 2012); coefficient stability under proportional selection on unobservables is assessed following Oster (2019); and lead tests confirm that future capability does not predict current outcomes, thereby complementing the placebo tests in low-adversity years.

Mediation inference follows current best practice for panel settings. Indirect effects are computed using a firm-level block bootstrap that resamples entire firms with replacement across 10,000 draws, and bias-corrected percentile confidence intervals are reported (Preacher & Hayes, 2008). Moderated mediation is summarized using the index of moderated mediation, with conditional indirect effects evaluated at prespecified severity values, including the top-quartile threshold, and Johnson-Neyman regions describing where the conditional indirect effect is distinguishable from zero (Hayes, 2015). Because mediation estimates rest on sequential ignorability, the sensitivity of the indirect effect to unobserved mediator-outcome confounding is quantified following Imai et al. (2010).

Finally, because the design generates a broad battery of specifications, false discovery is controlled within robustness families using the Benjamini & Hochberg (1995) procedure, and the full pipeline is prespecified, versioned, and seed-fixed with the data vintage documented to support replication. Robustness checks

follow the extended abstract and cover alternative resilience metrics, alternative capability constructions, continuous-severity and high-versus-low-adversity checks, placebo tests in low-adversity years, and sensitivity to liquidity buffers (Cowling et al., 2020).

4. Results

4.1 Sample, Descriptive Statistics, and Missing Data

The final panel contains 8,184 firm-year observations for 1,439 UK AIM-listed SMEs and small caps observed between 2016 and 2025. The panel is unbalanced: 312 firms appear in all ten years, and the median firm contributes five. Because firm fixed effects absorb 263 single-year firms, the estimation sample is 7,921 firm-years. The prespecified severity index, built from CPI inflation, the magnitude of Bank Rate changes, and UK policy uncertainty, places 2022, 2023, and 2025 in the top quartile that defines high-adversity shock windows (threshold = 0.32), with 2022 the most severe year in the panel (index = 1.33). This ranking reflects only the three macro-financial components. It is not a general ranking of pandemic or operational severity, so 2020 outside the top quartile and 2021 at the sample minimum should be interpreted within that narrow construction.

Table 2 reports descriptive statistics and pairwise correlations. Lagged capability correlates positively with reconfiguration intensity ($r = .39$) and resilience ($r = .38$), and reconfiguration correlates with resilience ($r = .41$), all $p < .001$, so the raw associations already run in the theorized direction. The adversity index is essentially orthogonal to the construct scores, a consequence of within-year standardization that matters later: severity variation is not mechanically entangled with construct levels. Among the controls, only firm size and trading liquidity are strongly related ($r = .92$); both were retained on theoretical grounds, and the largest variance inflation factor (7.06) remains below conventional thresholds, while the focal predictors are at or below 1.29. The accounting ratios are winsorized within year and expressed as proportions. Their means and standard deviations therefore describe the processed analysis scale, not the raw AIM-wide distribution.

Missing data behaved as the design anticipated. In the analysis input, 7.6% of numeric cells were missing, concentrated in ESG fields (38.0%), annual-report text measures (30.9%), and change-based mediator indicators (19.3%), compared with 4.1% for the controls. Little's test rejected the missing-completely-at-random hypothesis ($p < .001$), so estimation proceeded under the missing-at-random working assumption with chained-equations multiple imputation ($m = 30$, predictive mean matching) and outcomes left unimputed. Pooled and complete-case estimates, reported below, tell the same story.

Table 2
Descriptive Statistics and Pairwise Correlations

Variable	<i>M</i>	<i>SD</i>	1	2	3	4	5	6	7	8	9
1. Capability (t – 1)	–0.00	0.98	–								
2. Reconfiguration intensity	0.00	1.00	.39	–							
3. SME resilience	–0.00	1.00	.38	.41	–						
4. Adversity severity	–0.01	0.58	.00	.00	.00	–					
5. Firm size (ln assets)	3.24	1.05	.06	.02	.04	.02	–				
6. Leverage	0.04	0.05	.03	.03	.00	.16	–.03	–			
7. Profitability (ROA)	–0.00	0.06	.22	.06	.04	–.14	.03	–.03	–		
8. Cash holdings	0.18	0.08	–.25	–.13	–.11	–.13	–.01	–.18	–.15	–	
9. Firm age	11.35	7.55	.01	.00	.00	.06	–.05	.02	–.06	–.06	–
10. Trading liquidity	11.34	1.20	.10	.04	.09	–.04	.92	–.04	.07	.01	–.07

Note. N = 8,184 firm-year observations (1,439 firms, 2016–2025). Capability, reconfiguration, and resilience are standardized factor scores; the capability score is lagged one year. Adversity severity is the annual macro index. Accounting ratios are winsorized within-year and expressed as proportions; their descriptive dispersion is reported on the processed analysis scale rather than the raw AIM-wide scale. Correlations with $|r| \geq .03$ are significant at $p < .01$; entries of $\pm .02$ or smaller are not significant at $p < .05$.

Source: Authors' own elaboration.

4.2 Measurement Model

Table 3 summarizes the measurement diagnostics. Standardized loadings range from .53 (divestiture and asset redeployment) to .98 (digital operations disclosure), all above the .50 threshold, and composite reliabilities run from .83 to .98. Average variance extracted is .94 for the digitalization pillar, .90 for sustainability credibility, and .58 for resilience; for reconfiguration it lands exactly on the conventional boundary (.50), which we consider acceptable given its reliability of .83 and the deliberately heterogeneous mix of reinvestment and resource-release indicators. In the two-pillar specification, the reported inter-pillar correlation of .50 implies second-order loadings of .71 each, with CR = .67 and AVE = .50. The higher-order factor is therefore retained cautiously at the conventional boundary rather than presented as strongly identified.

Discriminant validity is supported on the reported criteria: the largest inter-construct correlation (.50 between the two pillars) is below the square root of the smallest AVE (.71), and the largest HTMT ratio is .53, well under .85. Measurement also holds across regimes. Comparing low- and high-adversity windows, the mean absolute difference in standardized loadings is .02, and the largest is .08, so pooling factor scores across regimes appears safe. The text pipeline passed its audit as well: across 2,448 double-coded firm-year-dimension cases, the two independent raters agreed 79.7% of the time, with Cohen's kappa between .56 and .62 across the three subdictionaries, in the moderate-to-substantial range.

Table 3

Measurement Model: Standardized Loadings, Composite Reliability, and Average Variance Extracted

Construct	Indicator	λ	CR	AVE
Digitalization (first-order pillar)	Digital operations disclosure intensity	.98	.98	.94
	Digital finance disclosure intensity	.96		
	Data and analytics disclosure intensity	.97		
Sustainability credibility (first-order pillar)	ESG disclosure score	.95	.95	.90
	ESG transparency score	.95		
Digital sustainable finance capability (second-order, implied)	Digitalization pillar	.71	.67	.50
	Sustainability credibility pillar	.71		
Resource reconfiguration intensity	Δ Intangible assets intensity	.78	.83	.50
	Δ Capex intensity	.74		
	Δ R&D intensity	.68		
	Divestiture and asset redeployment intensity	.53		
	Δ Investing cash-flow intensity	.78		
SME resilience	Downside semivariance (rev.)	.78	.87	.58
	Lower-tail risk (rev.)	.90		
	Maximum drawdown (rev.)	.74		
	Operating stability (rev.)	.68		
	Recovery speed	.69		

Note. λ = standardized loading; CR = composite reliability; AVE = average variance extracted; rev. = reverse-oriented so that higher values indicate greater resilience; Δ = year-to-year change. Discriminant validity: the largest inter-construct correlation (.50) is below the smallest $\sqrt{\text{AVE}}$ (.71), and the maximum HTMT ratio is .53. Across low- versus high-adversity windows, the largest absolute loading difference is .08 ($M = .02$). For the two-pillar second-order factor, loadings of .71 are implied by the reported .50 pillar correlation; CR and AVE are algebraic transformations of the loadings. Dictionary audit: 2,448 double-coded cases, 79.7% agreement, Cohen's $\kappa = .56-.62$.

Source: Authors' own elaboration.

4.3 Hypothesis Tests

Table 4 reports Rubin-pooled firm- and year-fixed-effects estimates across 30 imputed datasets with firm-clustered standard errors; continuous variables are standardized, so coefficients are interpreted as within-firm standard-deviation effects. Model 3 estimates the total effect: a one-standard-deviation increase in lagged capability is associated with a 0.309-standard-deviation improvement in resilience during the same window ($SE = 0.019, p < .001$). Hypothesis 1 is supported, and the estimate survives the removal of everything time-invariant about the firm and everything common to a given year.

Hypothesis 2

concerns the first stage. In Model 1, lagged capability predicts reconfiguration intensity ($b = 0.304, SE = 0.020, p < .001$): firms that enter a window with stronger capability reallocate more forcefully once it opens. Model 4 then adds reconfiguration to the resilience equation. Reconfiguration enters at 0.311 ($SE = 0.011, p < .001$) while the capability coefficient falls from 0.309 to 0.215. The indirect effect, bootstrapped by resampling entire firms across 10,000 draws, is .095 with a bias-corrected 95% CI of [.082, .109]. Hypothesis 3 is therefore supported, with roughly 31% of the total effect flowing through reconfiguration. The sizeable residual direct effect indicates partial mediation and leaves room for channels that our mediator battery does not capture, with financing terms and demand-side stabilization as possible candidates. The indirect effect and percentage mediated are algebraic transformations of the estimated paths rather than independent estimates.

Hypothesis 4

asks whether the pathway strengthens as conditions worsen. In Model 2, the capability-by-adversity interaction on the first stage is positive ($b = 0.081, SE = 0.017, p < .001$); year effects absorb the severity level, so identification comes from the interaction itself. Table 5 translates this into conditional indirect effects, which rise monotonically from .075 [.060, .090] in the calmest observed year to .089 at the median, .103 at the top-quartile threshold, and .129 [.108, .149] at the 2022 peak, about 72% larger than at the sample minimum. The index of moderated mediation is .025 [.015, .036]. A Johnson-Neyman inspection shows that the conditional indirect effect is distinguishable from zero across the entire observed severity range, with the implied sign change occurring at a severity of -3.79 , far outside the observed range. Severity amplifies an already present mechanism; it does not switch one on. Split samples agree: the first-stage coefficient is 0.350 in high-adversity years versus 0.284 in low-adversity placebo years, with path products of 0.106 and 0.093, respectively. The top-30-percent rule is not treated as an alternative shock-window test because it selects the same three years as the top-quartile rule in this ten-year panel. Adding the interaction to the outcome equation shows that the direct path strengthens with severity as well ($0.065, p < .001$).

Table 4
Fixed-Effects Panel Estimates: Mediator and Outcome Equations

Predictor	Reconfiguration intensity		SME resilience	
	Model 1	Model 2	Model 3	Model 4
Capability (t – 1)	0.304 (0.020)***	0.306 (0.020)***	0.309 (0.019)***	0.215 (0.018)***
Capability × Adversity severity		0.081 (0.017)***		
Reconfiguration intensity				0.311 (0.011)***
Firm size (ln assets)	0.073 (0.036)*	0.073 (0.035)*	-0.241 (0.035)***	-0.264 (0.033)***
Leverage	-0.517 (0.357)	-0.509 (0.354)	-0.772 (0.339)*	-0.612 (0.316)
Profitability (ROA)	0.055 (0.309)	0.059 (0.308)	-2.181 (0.318)***	-2.198 (0.304)***
Cash holdings	0.377 (0.313)	0.360 (0.312)	0.514 (0.278)	0.396 (0.273)
Firm age	-0.006 (0.012)	-0.005 (0.012)	0.023 (0.015)	0.025 (0.015)
Trading liquidity	-0.040 (0.028)	-0.037 (0.028)	0.256 (0.028)***	0.268 (0.026)***
Firm and year fixed effects	Yes	Yes	Yes	Yes
Within R ²	.033	.036	.058	.157
N (firm-years)	7,921	7,921	7,921	7,921
<i>Note.</i> Cell entries are Rubin-pooled coefficients with firm-clustered standard errors in parentheses. All continuous variables are standardized. The common analysis row count is 7,921 after excluding 263 single-year firms, as they provide no within-firm variation. Year fixed effects absorb the level of adversity severity, so the moderation in Model 2 is identified by the interaction term. Capability is the second-order factor score lagged one year. Table 4 reports within R²; the robustness analysis reports overall R² where stated. *p < .05. **p < .01. ***p < .001.				

Source: Authors' own elaboration.

Table 5
Indirect Effects, Conditional Indirect Effects, and Moderated Mediation

Quantity	Adversity value	Estimate	BC 95% CI
Unconditional indirect effect ($a \times b$)	—	.095	[.082, .109]
Conditional indirect effect at:			
Sample minimum (2021)	-0.81	.075	[.060, .090]
25th percentile	-0.48	.083	[.069, .098]
Median	-0.26	.089	[.075, .103]
High-adversity threshold (top quartile)	0.32	.103	[.089, .118]
75th percentile	0.41	.106	[.091, .121]
Sample maximum (2022)	1.33	.129	[.108, .149]
Index of moderated mediation ($a_3 \times b$)	—	.025	[.015, .036]
<i>Note.</i> First-stage paths are taken from Model 2 and the second-stage path from Model 4 (Table 4). Confidence intervals are bias-corrected percentile intervals from a firm-level block bootstrap with 10,000 draws, resampling entire firms with replacement. Adversity values are on the severity-index scale (sample range = 0.81 to 1.33); the high-adversity threshold (0.32) is the prespecified top-quartile cutoff. The Johnson-Neyman region covers the full observed range: the conditional indirect effect is distinguishable from zero at every observed severity value, with the implied zero crossing at - 3.79. Conditional indirect effects, the index of moderated mediation, and the zero crossing are algebraic transformations of the estimated paths and severity values.			

Source: Authors' own elaboration.

4.4 Robustness and Identification

Inference remains stable across the reported error structures. Two-way clustering by firm and year, along with Driscoll-Kraay standard errors, leaves the focal coefficients significant at $p < .001$. With 10 year-level clusters, the wild-cluster bootstrap has 1,024 sign patterns; its smallest rounded p value is .001, which is reported at the method's resolution floor. The Wooldridge test finds no first-order serial correlation, $F(1, 1051) = 0.17, p = .68$, whereas the Pesaran statistic detects cross-sectional dependence ($CD = -3.86, p < .001$), which is exactly why the Driscoll-Kraay results matter.

Table 4 reports Rubin-pooled estimates across the thirty completed datasets. The complete-case benchmark ($N = 4,132$) returns a direct effect of 0.213 and a second-stage effect of 0.301, close to the pooled values of 0.215 and 0.311. Selection into ESG coverage appears benign as well: the inverse Mills ratio enters at 0.001 ($p = .94$) without altering the focal estimates, and inverse-probability weighting yields 0.209 and 0.311.

Survivorship remains relevant because the panel deliberately keeps delisted and failed firms in view. The Cox model, however, supplies a boundary rather than a confirmation: lagged capability does not predict the delisting hazard (835 events among 1,439 firms; hazard ratio = 0.998, $p = .96$). The capability protects firms

on the intensive margin, limiting drawdowns, stabilizing operations, and speeding recovery, but we find no evidence that it shifts the probability of leaving the market altogether. We flag this asymmetry rather than smooth it over; AIM delistings mix distress with acquisitions and voluntary moves, and separating those routes is a task for data we do not have here.

Falsification and construction checks behave as they should. Future capability does not predict current resilience once the lag is included (lead coefficient = 0.013, $p = .55$). Equal-weighted composites (first stage 0.269, second stage 0.338) and a TF-IDF-weighted capability measure (0.394 and 0.314) reproduce the pattern, so conclusions are not hostage to factor weighting or raw term frequencies. Huber-type robust regression and median regression on within-transformed data return direct and second-stage estimates between 0.209 and 0.312, ruling out a handful of crisis outliers as the source. On omitted variables, adding the full control set moves the capability coefficient only from 0.316 to 0.309, while overall R^2 rises from .339 to .354; the implied Oster delta of 6.7 indicates that unobservables would need to be almost seven times as influential as the observed controls to erase the effect. Table 4 reports within R^2 , whereas these values are the overall R^2 used for the Oster calculation. Applying the Benjamini-Hochberg procedure at $q = .05$ within the robustness family leaves every focal result intact.

Across the reported specifications, the coefficient pattern is consistent with all four hypotheses, subject to the data and specification limits stated above. Capability built before a shock window predicts stronger reallocation inside it, reallocation predicts downside protection and recovery, and the pathway strengthens as adversity deepens. The estimates remain stable across the reported error structures, imputation, selection, weighting, and influence checks. In this sample, however, capability does not keep firms listed.

5. Discussion

The results clarify how digital sustainable finance capability operates during polycrisis rather than merely establishing a positive association with resilience. A one-standard-deviation increase in lagged capability is associated with a 0.309-standard-deviation improvement in resilience, of which 0.095 is attributable to resource reconfiguration. The remaining direct effect is 0.215. Mediation is therefore meaningful but partial, indicating that realized resource shifts account for a substantial share of the relationship without exhausting it.

Dynamic capabilities theory is strengthened by evidence that a capability measured before the shock window predicts an observable change in the firm's resource base. Lagged capability predicts reconfiguration by 0.304 standard deviations, and reconfiguration predicts resilience by 0.311 standard deviations after capability and controls are included. These estimates place changes in investment, intangible assets, research and development, divestiture, and investing cash flow between capability and resilience. They also support the theoretical requirement that sensing and seizing create value only when firms alter resource commitments in time (Teece et al., 1997; Winter, 2003; Teece, 2007; Gianiodis et al., 2022).

The measurement results add a second point of precision by showing that digitalization and sustainability credibility constitute a single higher-order capability in this setting. The reported pillar correlation of .50 implies second-order loadings of 0.71 each. The resulting CR of .67 and AVE of .50 support only a cautious, boundary-level higher-order interpretation, while the underlying indicators meet the reported first-order reliability and discriminant validity tests. Prior studies often examine digitalization, ESG practices, and financing conditions as parallel explanations (Amankwah-Amoah et al., 2021; Beck, 2023; Santos et al., 2023; Sagala & Őri, 2025). The current evidence permits their joint treatment when credible information and digital execution are used to mobilize and redirect resources. The residual direct effect shows that reconfiguration is not the only possible channel, but the present design does not identify the others.

Adversity materially changes the strength of the mechanism. The capability-by-adversity coefficient is 0.081, and the conditional indirect effect increases from 0.075 in the least severe observed year to 0.129 in 2022, the panel's most severe year. At the prespecified high-adversity threshold, the indirect effect is 0.103, compared with 0.089 at the median. This pattern is consistent with polycrisis research that treats disruption as a persistent, interacting condition rather than an isolated interruption (Miklian & Hoelscher, 2022; Klyver & McMullen, 2025; Maalouf et al., 2025). It also complements Audretsch & Kariv's (2025) evidence that entrepreneurial performance during a permanent crisis depends on the ongoing mobilization of internal and community-based resources.

The delisting analysis defines an important boundary around the resilience claim. Lagged capability does not predict the delisting hazard (hazard ratio = 0.998, $p = .96$), even though it predicts lower downside exposure, stronger operating stability, and faster recovery. Resilience should therefore be interpreted here as improved adaptive functioning on intensive margins, not as a guarantee of continued listing. Delisting can also reflect acquisition, privatization, strategic migration, or financial distress, so a single exit indicator cannot identify the underlying route (Doern et al., 2019; Conz & Magnani, 2020; Eggers, 2020; Esteve-Pérez et al., 2024).

Confidence in the central pattern comes from its stability across alternative error structures, missing-data treatments, selection corrections, weighting schemes, estimators, and construct specifications. The future-capability placebo is null, whereas the moderated indirect effect remains positive across the observed range of adversity. These checks narrow several rival explanations, but they do not convert the observational panel into a causal design. The interpretation remains conditional on the timing assumptions, measurement choices, and adequacy of the fixed-effects specifications.

6. Implications

6.1 Theoretical Implications

The study advances dynamic capabilities theory by specifying a finance-relevant higher-order capability that joins digital execution with sustainability credibility. This formulation differs from treating digitalization, sustainability, and finance as independent antecedents because it explains why their joint value depends on how they are used within the firm. Credible disclosure can improve a firm's legibility to

capital providers, while digital routines support faster sensing, analysis, and execution; the capability becomes consequential when these elements support resource movement under constraint (Amankwah-Amoah et al., 2021; Beck, 2023; Santos et al., 2023; Bao & Yang, 2025; Palmieri et al., 2025).

The mediation evidence adds a measurable behavioral conduit to the theory. Resource reconfiguration accounts for about 31 percent of the total capability-resilience association through changes in intangible assets, capital expenditure, research and development, divestiture and asset redeployment, and investing cash flow. This result moves the explanation beyond possession of resources or disclosure quality and toward what firms actually change after conditions deteriorate. The significant residual direct path also prevents an overly narrow interpretation: reconfiguration is an identified mechanism, not the complete theory of how the capability affects resilience.

The moderation result embeds the capability in the conditions under which it is deployed. As adversity increases, the capability-to-reconfiguration path strengthens, and the indirect effect increases across the observed range of severity. Polycrisis, therefore, shifts the return to capability rather than simply lowering average performance. This firm-level mechanism complements work on permanent crisis that emphasizes psychological capital, community belonging, and ecosystem support (Audretsch & Kariv, 2025): external support can expand the resources available to entrepreneurs, whereas the present study explains how an internal capability helps SMEs redirect available resources once pressure intensifies.

The null delisting result further defines the theory's domain. Digital sustainable finance capability improves adaptive performance and recovery margins, but the evidence does not show that it prevents market exit. That distinction separates resilience, as functioning under adversity, from survival, as continued listing, and limits the claim to the outcomes directly measured in the study.

6.2 Managerial Implications

For SME boards, capability development must precede the shock because the predictor in the models is lagged by one year. A quarterly governance review should assign named owners to digital operations, digital finance, data and analytics, ESG disclosure, and ESG transparency. The review should record the current control environment, the financing decision each capability supports, the data used by decision-makers, and any unresolved assurance gaps. Technology investment and sustainability reporting should not be managed as separate compliance projects when neither is connected to financing readiness or capital allocation.

Resource reconfiguration should be governed as a preauthorized process rather than improvised after conditions deteriorate. Management should identify which investments can be accelerated, reduced, deferred, or sold; set approval limits for capital expenditure, research and development, intangible assets, divestitures, and investing cash flow; and specify who can act at each threshold. The trigger dashboard can monitor inflation, Bank Rate changes, and policy uncertainty, as these variables define adversity in this study. The sample cutoff of 0.32 should not be copied into practice; each firm needs thresholds calibrated to its cash runway, covenant headroom, refinancing dates, and sector exposure.

Finance teams should connect sustainability credibility to a specific funding and reallocation case. A lender or investor pack should state the requested amount, use of proceeds, timing of the resource shift, expected effect on operating stability or recovery, covenant capacity, responsible executive, and reporting controls. The study does not estimate approval probability, financing volume, credit spreads, or cost of capital, so credible disclosure should be treated as evidence supporting a financing decision rather than as a guaranteed reduction in financing cost.

Boards should also use outcome measures that match the evidence. The supported benefits concern downside exposure, operating stability, and recovery speed; the models do not show a reduction in delisting risk. Internal targets and external claims should therefore focus on the firm's ability to absorb a shock, maintain operations, and recover, rather than presenting that capability as protection against every form of exit.

Lenders and investors can translate the results into a three-part review of an SME's preparedness: the reliability of its digital controls and data, the credibility and comparability of its sustainability information, and the existence of an executable resource-reconfiguration plan. These elements should be evaluated jointly with cash flow, collateral, leverage, covenant headroom, and management quality. A disclosure score alone is not a substitute for credit analysis.

7. Conclusion

This study reports a positive association between lagged digital sustainable finance capability and SME resilience among UK AIM firms observed from 2016 to 2025. Resource reconfiguration accounts for part of the reported association, and the mediated pathway strengthens as adversity becomes more severe. The coefficient pattern is consistent with all four hypotheses across the stated robustness checks.

The supported effect concerns downside protection, operating stability, and recovery when digital execution and sustainability credibility enable firms to redirect resources during shock windows. It does not extend to delisting probability. The study therefore identifies a bounded, finance-relevant mechanism within dynamic capabilities theory without claiming that capability guarantees survival.

The scope of inference is constrained by the UK AIM setting, where listed SMEs and small caps provide relatively rich public disclosure. Private SMEs, microenterprises, and firms operating in weaker disclosure environments may build or reveal the capability differently. Replication should examine bank-dependent firms, private firms, and economies where adversity is more persistent and institutional support is less stable.

Measurement remains a limitation because digitalization is inferred from annual-report language and sustainability credibility from LSEG ESG disclosure fields. These indicators capture disclosed capability and may not represent every enacted routine. Missingness is concentrated in the ESG fields (38.0%), thereby increasing reliance on the missing-at-random assumption. Multiple imputation, complete-case analysis, selection correction, and alternative construct specifications leave the estimates materially unchanged, but none removes measurement error. Future studies should link the archival indicators to

financing transactions, board-approved reallocation decisions, and direct observations of operating routines.

The ten-year annual panel and the narrow macro-financial adversity index also constrain temporal and causal interpretation. Year fixed effects absorb the index level, so moderation is identified through the interaction term. Reproducibility further depends on the archived outputs of extraction, transformation, imputation, and estimation, because the descriptive scales, attrition counts, and mediation quantities cannot be independently verified from the manuscript alone. Quarterly or monthly observations could more precisely identify the timing of reconfiguration and separate national conditions from firm-specific exposure. Natural experiments, matched financing events, or credible instruments would provide stronger evidence about causality.

Resource reconfiguration explains only part of the observed association, while financing access is theorized but not measured as a separate outcome. Future research should test whether loan approval, credit spreads, covenant terms, refinancing capacity, or sustainable-finance proceeds connect capability to reconfiguration. It should also separate distress delistings from acquisitions, privatizations, and strategic market transfers before treating a delisting as an organizational failure.

Declarations

Author Contribution

Charbel Salloum: Conceptualization, Research Design, Methodology, Supervision, Project Administration, Writing (Original Draft, Writing, Review & Editing). Renato Pereira: Conceptualization, Methodology, Theoretical Development, Validation, Writing (Review & Editing). Hajer Jarrar: Literature Review, Investigation, Data Curation, Formal Analysis, Writing (Original Draft, Writing, Review & Editing). Andrej Přivara: Methodology, Formal Analysis, Validation, Robustness Checks, Interpretation of Results, Writing (Original Draft, Writing, Review & Editing). All authors have read and approved the final version of the manuscript.

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N/A

Data Availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

References

1. Amankwah-Amoah, J., Khan, Z., Wood, G., & Knight, G. (2021). COVID-19 and digitalization: The great acceleration. *Journal of Business Research*, 136, 602–611.
<https://doi.org/10.1016/j.jbusres.2021.08.011>
2. Audretsch, D. B., & Belitski, M. (2026). Knowledge spillover of innovation: Entrepreneurial difference. *Research Policy*, 55(1), Article 105362. <https://doi.org/10.1016/j.respol.2025.105362>
3. Audretsch, D. B., Belitski, M., Caiazza, R., & Siegel, D. (2026). Assessing the impact of homophily on knowledge collaboration and innovative outcomes. *Economics of Innovation and New Technology*, 35(5), 797–813. <https://doi.org/10.1080/10438599.2026.2641458>
4. Audretsch, D. B., Fiedler, A., Fath, B., & Verreyne, M.-L. (2026). Entrepreneurial ecosystem playbooks: Configurations of routines and resourcing sustainable entrepreneurship. *Industry and Innovation*, 33(6), 679–699. <https://doi.org/10.1080/13662716.2026.2637176>
5. Audretsch, D. B., & Kariv, D. (2025). Entrepreneurship in the context of permanent crisis: The role of community support. *Review of Managerial Science*, 19(10), 3143–3176.
<https://doi.org/10.1007/s11846-025-00845-6>
6. Audretsch, D. B., & Kariv, D. (2026). Making a miracle: The interplay of grit and community belonging in polycrisis. *Small Business Economics*. Advance online publication. <https://doi.org/10.1007/s11187-026-01222-7>
7. Audretsch, D. B., Lehmann, E. E., Menter, M., & Seitz, N. (2026). More knowledge, more entrepreneurs? An investigation of the science and cluster policy mix in Germany. *Small Business Economics*, 66, 1755–1784. <https://doi.org/10.1007/s11187-026-01175-x>
8. Bao, J., & Yang, L. (2025). Will ESG disclosure affect the green innovation level of SMEs? *Finance Research Letters*, 83, Article 107656. <https://doi.org/10.1016/j.frl.2025.107656>
9. Beck, T. (2023). Access to finance: Adaptability and resilience during a global pandemic. *Accounting and Business Research*, 53(5), 565–579. <https://doi.org/10.1080/00014788.2023.2219153>
10. Belitski, M., Guenther, C., Kritikos, A. S., & Thurik, R. (2022). Economic effects of the COVID-19 pandemic on entrepreneurship and small businesses. *Small Business Economics*, 58(2), 593–609.
<https://doi.org/10.1007/s11187-021-00544-y>
11. Benjamini, Y., & Hochberg, Y. (1995). Controlling the false discovery rate: A practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society: Series B (Methodological)*, 57(1), 289–300.
12. Berg, F., Kölbel, J. F., & Rigobon, R. (2022). Aggregate confusion: The divergence of ESG ratings. *Review of Finance*, 26(6), 1315–1344.
13. Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87(1), 115–143.
14. Breier, M., Kallmuenzer, A., Clauss, T., Gast, J., Kraus, S., & Tiberius, V. (2021). The role of business model innovation in the hospitality industry during the COVID-19 crisis. *International Journal of Hospitality Management*, 92, 102723.

15. Bullough, A., Renko, M., & Myatt, T. (2014). Danger zone entrepreneurs: The importance of resilience and self-efficacy for entrepreneurial intentions. *Entrepreneurship Theory and Practice*, 38(3), 473–499. <https://doi.org/10.1111/etap.12006>
16. Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2008). Bootstrap-based improvements for inference with clustered errors. *The Review of Economics and Statistics*, 90(3), 414–427.
17. Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2011). Robust inference with multiway clustering. *Journal of Business & Economic Statistics*, 29(2), 238–249.
18. Campagnolo, D., Laffineur, C., Leonelli, S., Martiarena, A., Tietz, M. A., & Wishart, M. (2022). Stay alert, save businesses: Planning for adversity among immigrant entrepreneurs. *International Journal of Entrepreneurial Behavior & Research*, 28(7), 1773–1799.
19. Cohen, J. (1960). A coefficient of agreement for nominal scales. *Educational and Psychological Measurement*, 20(1), 37–46.
20. Conz, E., & Magnani, G. (2020). A dynamic perspective on the resilience of firms: A systematic literature review and a framework for future research. *European Management Journal*, 38(3), 400–412. <https://doi.org/10.1016/j.emj.2019.12.004>
21. Cowling, M., Brown, R., & Rocha, A. (2020). Did you save some cash for a rainy COVID-19 day? The crisis and SMEs. *International Small Business Journal*, 38(7), 593–604. <https://doi.org/10.1177/0266242620945102>
22. Doern, R., Williams, N., & Vorley, T. (2019). Special issue on entrepreneurship and crises: Business as usual? An introduction and review of the literature. *Entrepreneurship & Regional Development*, 31(5–6), 400–412. <https://doi.org/10.1080/08985626.2018.1541590>
23. Driscoll, J. C., & Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *The Review of Economics and Statistics*, 80(4), 549–560.
24. Du, Y., Wang, Q., & Zhou, J. (2023). How does digital inclusive finance affect economic resilience? Evidence from 285 cities in China. *International Review of Financial Analysis*, 88, Article 102709. <https://doi.org/10.1016/j.irfa.2023.102709>
25. Eggers, F. (2020). Masters of disasters? Challenges and opportunities for SMEs in times of crisis. *Journal of Business Research*, 116, 199–208. <https://doi.org/10.1016/j.jbusres.2020.05.025>
26. Esteve-Pérez, S., Pieri, F., & Rodriguez, D. (2024). Coping with high decline: Firms' resilience to adversity. *Small Business Economics*, 63, 193–219.
27. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50.
28. Gianiodis, P. T., Lee, S.-H., Zhao, H., Foo, M.-D., & Audretsch, D. B. (2022). Lessons on small business resilience. *Journal of Small Business Management*, 60(5), 1029–1040.
29. Goldsmith-Pinkham, P., Sorkin, I., & Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review*, 110(8), 2586–2624.
30. Hainmueller, J. (2012). Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies. *Political Analysis*, 20(1), 25–46.

31. Hayes, A. F. (2015). An index and test of linear moderated mediation. *Multivariate Behavioral Research*, 50(1), 1–22.
32. Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica*, 47(1), 153–161.
33. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135.
34. Imai, K., Keele, L., & Yamamoto, T. (2010). Identification, inference and sensitivity analysis for causal mediation effects. *Statistical Science*, 25(1), 51–71.
35. Klyver, K., & McMullen, J. S. (2025). Rethinking entrepreneurship in causally entangled crises: A poly-crisis perspective. *Journal of Business Venturing*, 40(1), 106459.
36. Koporcic, N., Kukkamalla, P. K., Markovic, S., & Maran, T. (2026). Resilience of small and medium-sized enterprises in times of crisis: An umbrella review. *Review of Managerial Science*, 20(1), 301–329. <https://doi.org/10.1007/s11846-025-00883-0>
37. Kraus, S., Clauss, T., Breier, M., Gast, J., Zardini, A., & Tiberius, V. (2020). The economics of COVID-19: Initial empirical evidence on how family firms in five European countries cope with the corona crisis. *International Journal of Entrepreneurial Behavior & Research*, 26(5), 1067–1092. <https://doi.org/10.1108/IJEBr-04-2020-0214>
38. Kuckertz, A., Brändle, L., Gaudig, A., Hinderer, S., Morales Reyes, C. A., Prochotta, A., Steinbrink, K. M., & Berger, E. S. C. (2020). Startups in times of crisis: A rapid response to the COVID-19 pandemic. *Journal of Business Venturing Insights*, 13, Article e00169. <https://doi.org/10.1016/j.jbvi.2020.e00169>
39. Li, R., Zahra, K., Najam, H., & Jia, S. (2025). Examining the role of digitalization and ESG strategies in enhancing resilience and sustainable performance of SMEs. *International Entrepreneurship and Management Journal*, 21, Article 108. <https://doi.org/10.1007/s11365-025-01105-5>
40. Li, S., & Xie, N. (2025). The impact of digital finance on firms' digital transformation: Mechanism analysis based on enterprise financing. *International Review of Economics & Finance*, 101, Article 104223.
41. Little, R. J. A. (1988). A test of missing completely at random for multivariate data with missing values. *Journal of the American Statistical Association*, 83(404), 1198–1202.
42. Maalouf, J., Miklian, J., & Hoelscher, K. (2025). Business survival strategies in a polycrisis: SME experiences from Beirut, Lebanon. *Business Horizons*, 68(4), 461–477.
43. Martínez-Román, J. A., Gamero, J., Tamayo, J. A., Delgado-González, M. L., & Audretsch, D. B. (2026). Technological ambidexterity and firm growth: Analyzing synergies between exploitation and exploration of technological knowledge. *International Entrepreneurship and Management Journal*, 22, Article 28. <https://doi.org/10.1007/s11365-026-01160-6>
44. Miklian, J., & Hoelscher, K. (2022). SMEs and exogenous shocks: A conceptual literature review and forward research agenda. *International Small Business Journal*, 40(2), 178–204.
45. Oo, N. C. K. K., & Rakthin, S. (2025). Knowledge-oriented leadership and organizational resilience in SMEs during a crisis: The mediation role of innovation quality. *Journal of Innovation & Knowledge*,

- 10(5), Article 100775. <https://doi.org/10.1016/j.jik.2025.100775>
46. Oster, E. (2019). Unobservable selection and coefficient stability: Theory and evidence. *Journal of Business & Economic Statistics*, 37(2), 187–204.
47. Palmieri, E., Beltrame, F., Zorzi, G., & Geretto, E. F. (2025). The SMEs' financial benefits of going green: Environmental performance, default risk and cost of capital. *Global Business Review*. Advance online publication. <https://doi.org/10.1177/09721509251370588>
48. Papanikolaou, D., & Schmidt, L. D. W. (2022). Working remotely and the supply-side impact of COVID-19. *The Review of Asset Pricing Studies*, 12(1), 53–111.
49. Pesaran, M. H. (2015). Testing weak cross-sectional dependence in large panels. *Econometric Reviews*, 34(6–10), 1089–1117.
50. Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods*, 40(3), 879–891.
51. Raby, S., & Chowdhury, R. H. (2025). Examining the impact of adaptive financial strategies on SME performance: Insights from the COVID-19 pandemic. *Small Business Economics*, 65(2), 895–913. <https://doi.org/10.1007/s11187-025-01011-8>
52. Roodman, D. (2009). A note on the theme of too many instruments. *Oxford Bulletin of Economics and Statistics*, 71(1), 135–158.
53. Rubin, D. B. (1987). Multiple imputation for nonresponse in surveys. John Wiley & Sons.
54. Saezow, K., & Sukhabot, S. (2025). Synthesizing the resilience elements of small and medium enterprises (SMEs) amidst the COVID-19 pandemic crisis: A systematic review. *Cogent Business & Management*, 12(1), Article 2512823. <https://doi.org/10.1080/23311975.2025.2512823>
55. Sagala, G. H., & Őri, D. (2025). Exploring digital transformation strategy to achieve SMEs resilience and antifragility: A systematic literature review. *Journal of Small Business & Entrepreneurship*, 37(3), 495–524. <https://doi.org/10.1080/08276331.2024.2392080>
56. Santos, S. C., Liguori, E. W., & Garvey, E. (2023). How digitalization reinvented entrepreneurial resilience during COVID-19. *Technological Forecasting and Social Change*, 189, Article 122398. <https://doi.org/10.1016/j.techfore.2023.122398>
57. Sharma, P., Leung, T. Y., Kingshott, R. P. J., Davcik, N. S., & Cardinali, S. (2020). Managing uncertainty during a global pandemic: An international business perspective. *Journal of Business Research*, 116, 188–192. <https://doi.org/10.1016/j.jbusres.2020.05.026>
58. Shepherd, D. A., & Williams, T. A. (2023). Different response paths to organizational resilience. *Small Business Economics*, 61(1), 23–58. <https://doi.org/10.1007/s11187-022-00689-4>
59. Shou, Y., Shan, X., Shao, J., Lai, K.-H., & Zhou, Q. (2024). How do foreign SMEs mitigate violent conflict risk by doing good? An instrumental stakeholder theory perspective. *Journal of Business Ethics*, 192(2), 407–422. <https://doi.org/10.1007/s10551-023-05521-x>
60. Skýpalová, R., Kozáková, J., Urbánová, M., & Di Sabato, V. (2023). Corporate social responsibility in business practices of multinational companies: Study of differences between Czech and Slovak.

Business, Management and Economics Engineering, 21(1), 106–123.
<https://doi.org/10.3846/bmee.2023.18942>

61. Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, 28(13), 1319–1350.

62. Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, 18(7), 509–533.

63. White, I. R., Royston, P., & Wood, A. M. (2011). Multiple imputation using chained equations: Issues and guidance for practice. *Statistics in Medicine*, 30(4), 377–399.

64. Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of Econometrics*, 126(1), 25–51.

65. Winter, S. G. (2003). Understanding dynamic capabilities. *Strategic Management Journal*, 24(10), 991–995.

66. Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data* (2nd ed.). MIT Press.

67. Xiao, S., Roh, T., Park, B. I., Al-Tabbaa, O., & Seo, K. (2026). Unpacking the role of digital dynamic capabilities in ESG performance: A social exchange perspective on organizational trust and identification. *Business Strategy and the Environment*, 35(2), 1951–1969.
<https://doi.org/10.1002/bse.70273>

68. Zakaria, N., Sehgal, R., Watson, A., & Kamarudin, K. A. (2023). Staying afloat? Using a reflective cycle approach to examine the effects of crisis on the business resilience of SMEs during COVID-19. *Journal of General Management*, 48(3), 267–281. <https://doi.org/10.1177/03063070221088371>

69. Zhou, N., & Sun, R. (2024). Coping with the storm: The role of fintech in SME survival. *International Review of Financial Analysis*, 93, Article 103157. <https://doi.org/10.1016/j.irfa.2024.103157>

70. Zirar, A., Jabbar, A., Tchouamou Njoya, E., & Amoozad Mahdiraji, H. (2024). Smart contract challenges and drawbacks for SME digital resilience. *Journal of Enterprise Information Management*, 37(5), 1527–1550. <https://doi.org/10.1108/JEIM-02-2023-0082>

Figures

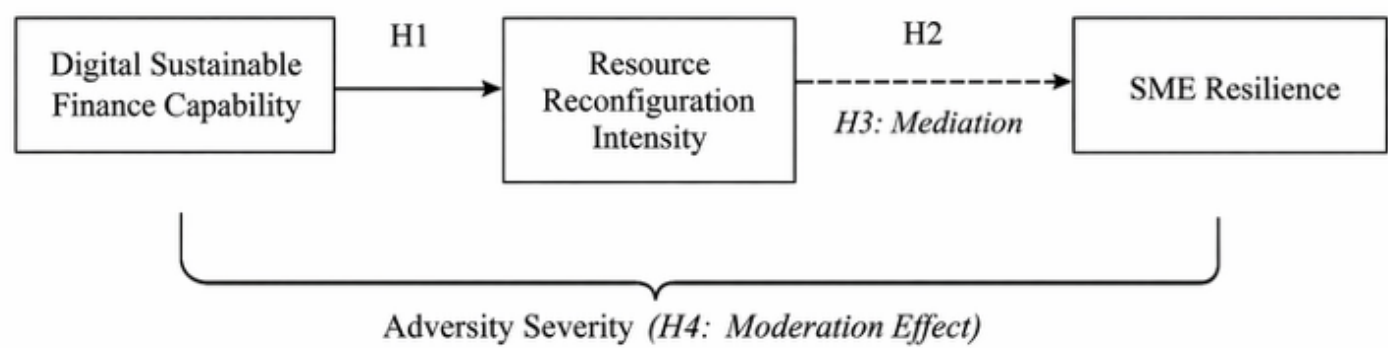


Figure 1

