

Architecting the human-centric factory: analyzing the relationship between cognitive control units and operational antifragility in Industry 5.0

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Abstract

Purpose – This study examines how cognitive control units (CCUs), human-machine mutual trust (HMMT), cognitive load reduction (CLR) and agentic production protocols (APPs) are associated with operational antifragility (OA) in Industry 5.0 manufacturing environments. It also tests CLR as a mediator and APPs as both a direct antecedent and a moderator.

Design/methodology/approach – Cross-sectional survey data were obtained from qualified key informants in 215 large manufacturing firms using Industry 5.0 technologies across five South Asian countries. The hypothesized mediation and moderation relationships were tested with partial least squares structural equation modelling (PLS-SEM). Reliability, convergent and discriminant validity, collinearity, model fit, predictive relevance and effect sizes were assessed.

Findings – CCUs and HMMT were positively associated with CLR but had no significant direct associations with OA. CLR fully mediated both relationships, identifying cognitive optimization as the principal mechanism through which technological and relational capabilities relate to antifragility. APPs were positively associated with OA and strengthened the positive CLR–OA relationship.

Originality/value – Integrating cognitive load theory with sociotechnical systems theory, the study shifts attention from automation intensity to the cognitive and governance mechanisms that enable human-machine systems to benefit from disruption. It identifies cognitive load reduction as the link between cognitive control, calibrated trust, and OA, while showing that structured autonomy converts cognitive benefits into system-level antifragility. Evidence from South Asian manufacturers extends Industry 5.0 research beyond its predominant Western and East Asian settings.

Keywords Industry 5.0, Operational antifragility, Cognitive load reduction, Human–robot collaboration, Agentic production protocols

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1. Introduction

Manufacturing is moving beyond Industry 4.0's efficiency-oriented logic toward the human-centred, adaptive, and collaborative orientation of Industry 5.0. Human cognition, creativity, judgement, and collaborative intelligence are treated as strategic complements to intelligent technologies (Sheikh *et al.*, 2024; Ghobakhloo *et al.*, 2024). Competitiveness therefore depends not only on cost, speed, automation, and digital integration, but also on the capacity to learn and improve amid supply-chain disruption, geopolitical uncertainty, labour shortages, and demand volatility. This capacity reflects operational antifragility (OA): improvement through volatility rather than mere resistance or recovery (Taleb, 2012; Lou *et al.*, 2024; Camarinha-Matos *et al.*, 2024).

Despite extensive research on artificial intelligence, cyber-physical systems, robotics, digital twins, and automation, much of the Industry 4.0 literature remains technology-centred and implicitly equates greater automation with better performance (Villar *et al.*, 2023; Keshmiry and Hassani, 2025; Qadeer *et al.*, 2025; Hussain *et al.*, 2025). Three connected gaps remain. First, resilience and adaptive capability are often conflated with OA, although resilience emphasizes recovery whereas antifragility denotes improvement because of volatility (Taleb, 2012). Second, human cognition is rarely modelled as the mechanism linking intelligent technologies and relational trust to OA, even though digitalization can intensify information overload, attention fragmentation, alert fatigue, and decision pressure (Saniuk *et al.*, 2024). Third, studies seldom examine the governance arrangements that determine whether cognitive benefits become coordinated, system-level responses (Rožanec *et al.*, 2023; Camarinha-Matos *et al.*, 2024).

These gaps motivate three research questions.

RQ1. How are CCUs and HMMT associated with OA in I5MEs?

RQ2. Does CLR mediate the associations of CCUs and HMMT with OA?

RQ3. How are APPs associated with OA, and do they moderate the CLR-OA relationship?

Theoretically, the study integrates CLT and STS by positioning CLR as the cognitive mechanism connecting CCUs and HMMT with OA, and APPs as a sociotechnical governance mechanism that both supports OA and conditions the translation of cognitive efficiency into antifragile performance. Practically, it shows managers and system designers that antifragility requires more than intelligent systems or greater machine autonomy: it also requires cognitively manageable interfaces, calibrated trust, explicit decision rights, and clear escalation procedures. The following sections develop the hypotheses, describe the methods, report the results, and discuss their implications and limitations.

2. Theoretical background

This study integrates CLT and STS to explain how human-centred design mechanisms relate to OA in I5MEs (Bucci *et al.*, 2024; Saniuk *et al.*, 2024). CLT holds that working memory is limited; performance deteriorates when task demands exceed that capacity (Sweller, 1988). This constraint is salient in advanced manufacturing, where operators monitor autonomous systems, interpret algorithmic outputs, and manage exceptions (Ghobakhloo *et al.*, 2023a). CCUs can reduce extraneous load by prioritizing relevant information, while calibrated HMMT can reduce unnecessary monitoring; poorly designed interfaces or miscalibrated trust may instead increase load or encourage automation complacency (Villar *et al.*, 2023; Lou *et al.*, 2024). STS complements CLT by treating organizations as interdependent social and technical subsystems that require joint optimization (Emery and Trist, 1965; Cherns, 1976; Carayon *et al.*, 2014). APPs operationalize this alignment by specifying human and machine decision rights, responsibilities, and escalation rules under uncertainty (Fernández-Miguel *et al.*, 2025a).

2.1 Conceptual boundaries and the theoretical gap in Industry 5.0 research

OA must be distinguished from resilience and adaptive capability. Resilience concerns absorbing disruption and restoring acceptable functioning (Camarinha-Matos *et al.*, 2024), whereas adaptive capability concerns sensing change and reconfiguring resources over time (Rožanec *et al.*, 2023). An antifragile system improves because of disorder rather than merely surviving or adjusting to it (Taleb, 2012). CCUs and APPs are likewise narrower than general human-centred automation or ergonomics. CCUs coordinate information and exceptions at the human-machine interface; APPs govern decision authority and exception handling (Cherns, 1976). This distinction exposes a theoretical gap in technology-first accounts that treat resilience or adaptability as automatic consequences of technological sophistication (Villar *et al.*, 2023). CLT suggests that technological and relational resources affect performance through cognitive demands, while STS suggests that these benefits depend on structural alignment. Evidence from other sociotechnical settings similarly shows that technology alone does not ensure adaptive performance; alignment among work structures, human cognition, and technical processes is decisive (Carayon *et al.*, 2014). Combining CLT and STS therefore provides a mediation-moderation account of OA in which cognitive mechanisms explain how inputs operate and governance structures specify when those mechanisms yield system-level gains.

2.2 CCUs, OA and CLR

From an STS perspective, OA emerges when technical components support adaptive capacity under volatility. CCUs integrate decision support, real-time exception handling, and intelligent feedback to structure information flows and facilitate rapid sensemaking between people and autonomous systems (Villar *et al.*, 2023). Accordingly, CCUs should help manufacturers reconfigure operations and learn from disruption.

Cognitively integrated manufacturing architectures can strengthen learning and adaptability after disturbances (Lou *et al.*, 2024), while intelligent interfaces can accelerate reconfiguration and reduce coordination losses when conditions change (Sheikh *et al.*, 2024). Human-in-the-loop arrangements may also outperform exclusively automated or human-controlled systems during recovery (Rožanec *et al.*, 2023). Nevertheless, added coordination layers can increase cognitive load when they are poorly matched to human processing limits (Saniuk *et al.*, 2024). The net association between CCUs and OA is therefore tested rather than assumed.

H1. CCUs are positively associated with OA.

CLT explains why CCUs should be associated with CLR. When operational demands exceed working-memory capacity, performance declines (Sheikh *et al.*, 2024). In ISMEs, operators must interpret complex data, monitor autonomous systems, and manage exceptions simultaneously. CCUs can reduce extraneous load by filtering irrelevant material, prioritizing urgent signals, and presenting feedback coherently (Bucci *et al.*, 2024). Cognitively transparent human-AI interfaces can consequently reduce perceived workload and improve intervention accuracy during anomalies (Ghobakhloo *et al.*, 2023a; Aldabousi *et al.*, 2025; Shemais *et al.*, 2024).

Evidence from manufacturing dashboards indicates that cognitive load depends strongly on information architecture rather than information volume alone (Fernández-Miguel *et al.*, 2025b). By aligning technical complexity with human capacity, CCUs can reduce coordination strain, role ambiguity, and operator fatigue while sustaining decision quality during disruption (Villar *et al.*, 2023; Sheikh *et al.*, 2024).

H2. CCUs are positively associated with CLR.

2.3 HMMT, OA and CLR

STS identifies effective coordination between human and technological actors as a foundation of adaptive performance under uncertainty (Villar *et al.*, 2023). HMMT, conceptualized as calibrated cognitive trust, enables appropriate reliance on automation, timely human

intervention, and flexible human-machine coordination. Trust in semi-autonomous systems has been associated with faster coordination, fewer errors, and greater flexibility during abnormal events (Rožanec *et al.*, 2023), and high-trust human-machine teams can outperform low-trust teams in dynamic production environments (Camarinha-Matos *et al.*, 2024). Calibrated trust may also release cognitive resources for sensemaking by reducing redundant verification (Fernández-Miguel *et al.*, 2025b). Excessive trust, however, can reduce vigilance and create automation complacency during novel disruptions (Villar *et al.*, 2023). The association between HMMT and OA must therefore be established empirically.

H3. HMMT is positively associated with OA.

CLT provides a direct rationale for the HMMT-CLR association. Low trust compels operators to monitor outputs continuously, justify algorithmic recommendations, and simulate alternative responses, increasing cognitive strain (Lou *et al.*, 2024). Calibrated trust stabilizes expectations and reduces uncertainty about system behaviour. Human-automation research links such trust to lower perceived workload, less intensive monitoring, and greater decision confidence (Priyadarshini *et al.*, 2024). Transparent and trustworthy AI-assisted planning similarly reduces cognitive burden (Merchán-Cruz *et al.*, 2025). From an STS perspective, trust also aligns human and machine agency, reducing role ambiguity and cognitive conflict at the interface (Bucci *et al.*, 2024).

H4. HMMT is positively associated with CLR.

CLT also explains the CLR-OA association. Lower extraneous load frees cognitive resources for problem-solving, learning, and adaptive decisions (Keshmiry and Hassani, 2025). In I5MEs, this capacity helps operators identify weak signals, correct errors, reconfigure operations, and convert disruption into learning (Lou *et al.*, 2024; Saniuk *et al.*, 2024). CLR therefore aligns technical complexity with human capacity and supports coordinated system improvement (Fernández-Miguel *et al.*, 2025b).

H5. CLR is positively associated with OA.

2.4 Moderating role of APPs

STS proposes that individual learning produces system-level effects only when supporting structures are in place. APPs provide adaptable rules for task allocation, decision authority, and the limits of human and machine autonomy (Lou *et al.*, 2024). Clear authority and escalation procedures turn individual cognitive clarity into coordinated responses and distribute learning across decentralized production systems (Saniuk *et al.*, 2024; Ghobakhloo *et al.*, 2023a). APPs should therefore strengthen the extent to which CLR is associated with OA by enabling timely decisions, reconfiguration, and learning during disruption.

H6. APPs positively moderate the relationship between CLR and OA.

APPs may also contribute directly to OA. By defining autonomy levels, decision rights, and escalation procedures, they facilitate rapid reconfiguration and shared agency during disruption (Rožanec *et al.*, 2023; Lou *et al.*, 2024). Rule-based, modular, and decentralized production arrangements support experimentation and learning under uncertainty, while clear autonomy boundaries reduce coordination failures in human-robot collaboration (Keshmiry and Hassani, 2025; Villar *et al.*, 2023; Camarinha-Matos *et al.*, 2024). APPs thus reduce vulnerabilities associated with over-centralization and unstructured automation.

H7. APPs are positively associated with OA.

2.5 Mediating role of CLR

CLT positions CLR as the mechanism linking CCUs to OA. Although CCUs can improve information processing and decision support, poorly designed systems may overload operators

and weaken adaptive performance (Bucci *et al.*, 2024; Camarinha-Matos *et al.*, 2024). Their benefits therefore depend on presenting information in a cognitively accessible form, especially during anomalies (Ghobakhloo *et al.*, 2023a; Keshmiry and Hassani, 2025). By aligning technical complexity with human decision capacity, CLR enables CCUs to support learning and improvement through disruption (Lou *et al.*, 2024).

H8. CLR mediates the relationship between CCUs and OA.

CLR should likewise mediate the HMMT-OA relationship. Mistrust or miscalibrated trust increases uncertainty, monitoring, and verification, weakening adaptive decisions under disruption (Keshmiry and Hassani, 2025; Villar *et al.*, 2023). Calibrated trust reduces workload and mental fatigue, supports cognitive stability (Lou *et al.*, 2024), and coordinates human and technical subsystems (Bucci *et al.*, 2024). HMMT should therefore relate to OA through the cognitive processes required for adaptive learning and coordinated action (Saniuk *et al.*, 2024).

H9. CLR mediates the relationship between HMMT and OA.

Following Figure 1, which shows the conceptual framework:

Figure 1 presents the proposed research model.

3. Methods

3.1 Population and sampling

The study population comprised large manufacturing firms in India, Pakistan, Bangladesh, Sri Lanka, and Nepal. Regional manufacturing directories and industry associations identified a sampling frame of approximately 820 firms with more than 200 employees and advanced production technologies. This setting is appropriate because manufacturers across the region are adopting AI-supported decision systems, human-robot collaboration, and cyber-physical production while facing volatile markets, labour-intensive operations, and infrastructure constraints (Fernández-Miguel *et al.*, 2025a). The organization was the unit of analysis. Firms were selected by a computer-generated simple random sequence, and one qualified key informant from senior management, operations, production systems, or digital transformation represented each participating organization. Six experts (three senior practitioners with more than ten years of Industry 5.0 implementation experience and three manufacturing or operations scholars) pretested the questionnaire for relevance and clarity. Of 520 questionnaires distributed, 215 usable responses were received after follow-up reminders and selected site visits, yielding a usable response rate of 41.35%. Table 1 reports the sample profile. Respondents occupied senior management (28.37%), operations management (26.98%), production/system management (25.58%), and digital-transformation management (19.07%) roles; 84.19% had at least five years of experience and 77.68% held postgraduate qualifications. These characteristics support the key-informant design.

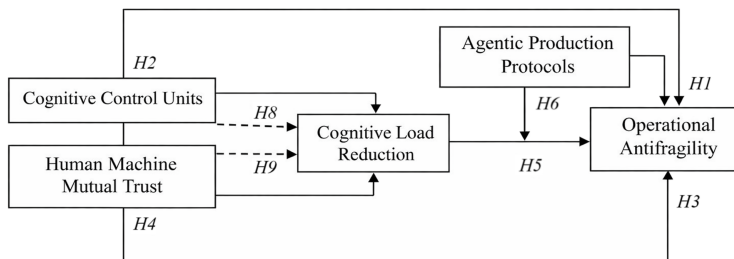


Figure 1. Proposed conceptual framework linking cognitive control units, human-machine mutual trust, cognitive load reduction, agentic production protocols, and operational antifragility. The arrows represent the hypothesized relationships (H1–H9)

Table 1. Demographic profile

Characteristic	Category	<i>n</i>	%
<i>Organizational profile</i>			
Firm size (employees)	201–500	101	46.98
	Other	114	53.02
System/production managers	5–10	78	36.28
	Other	137	63.72
Years in operation	More than 20 years	137	63.72
	20 years or fewer	78	36.28
<i>Respondent profile</i>			
Job position	Senior Manager	61	28.37
	Operations Manager	58	26.98
	Production/System Manager	55	25.58
	Digital Transformation Manager	41	19.07
Years of professional experience	Less than 5 years	34	15.81
	5–10 years	76	35.35
	11–15 years	58	26.98
	More than 15 years	47	21.86
Educational attainment	Bachelor’s Degree	48	22.33
	Master’s Degree	123	57.21
	M.Phil./MS	27	12.56
	Ph.D	17	7.91
Gender	Male	156	72.56
	Female	59	27.44

The sample of 215 also exceeded the PLS-SEM ten-times heuristic. The most complex endogenous specification contained five incoming effects, implying a heuristic minimum of 50 observations; the achieved sample was more than four times that value. It also provided a substantial basis for bootstrapping the mediation and moderation paths, although the estimates remain subject to the limitations of a single-informant cross-sectional design (Hair *et al.*, 2014).

3.2 Questionnaire development

The questionnaire adapted established measures of cognitive systems, human-machine interaction, and advanced manufacturing management. All items used a five-point Likert scale from strongly disagree (1) to strongly agree (5). CCUs were measured with 18 items covering adaptive decision support, information structuring, and exception handling (Sheikh *et al.*, 2024; Lou *et al.*, 2024; Villar *et al.*, 2023). HMMT comprised six items on reliability, predictability, interpretability, and trust in system recommendations (Priyadarshini *et al.*, 2024; Villar *et al.*, 2023). CLR used nine items on mental effort, information overload, and decision clarity (Bucci *et al.*, 2024); APPs used seven items on task ownership, autonomy boundaries, escalation, and flexible authority (Camarinha-Matos *et al.*, 2024); and OA used six items on learning, adaptation, and performance improvement following disruption (Sheikh *et al.*, 2024). Appendix A provides the complete instrument and sources. Table A1 in the Appendix A shows the measurement instrument.

3.3 Common method bias (CMB)

Because exogenous and endogenous variables were reported by the same respondents at one time, common method bias (CMB) was possible (Ghobakhloo *et al.*, 2023b; Bucci *et al.*, 2024). Procedural safeguards were incorporated into the survey design, and Harman’s single-factor test was used as a supplementary diagnostic (Podsakoff *et al.*, 1997). The first unrotated

factor explained 42.87% of the variance, below the conventional 50% warning threshold. This result suggests that no single factor dominated the covariance; however, Harman's test cannot exclude CMB, and this residual risk is acknowledged in the limitations.

3.4 Demographic profile

Table 1 summarizes the participating firms and respondents by firm size, management structure, operating history, position, experience, education, and gender, thereby documenting the context and suitability of the key informants.

The 215 respondents represented experienced decision makers: 63.72% of participating firms had operated for more than 20 years, 84.19% of respondents had at least five years of professional experience, and 77.68% held postgraduate qualifications. The sample was 72.56% male and 27.44% female (Table 1).

4. Results

4.1 Measurement model and statistical analysis

The hypotheses were tested in SmartPLS 3.2.8 using PLS-SEM, which is appropriate for prediction-oriented models containing mediation and moderation and is less restrictive regarding multivariate normality than covariance-based SEM (Götz *et al.*, 2010; Hair *et al.*, 2014). The reflective measurement model was assessed for indicator reliability, internal consistency, convergent validity, and discriminant validity. Standardized loadings ranged from 0.623 to 0.961, exceeding the 0.50 minimum. Composite reliability values were satisfactory, and all average variance extracted values exceeded 0.50 (Hair *et al.*, 2014). Discriminant validity was evaluated using the heterotrait-monotrait ratio (HTMT), applying thresholds of 0.85 for conceptually distinct constructs and 0.90 for closely related constructs (Henseler *et al.*, 2015). All reported HTMT values met the applicable criterion. Variance inflation factors were below 5, indicating no problematic collinearity (Table 2).

Path significance was evaluated by bootstrapping 2,000 subsamples (Table 3). CCUs and HMMT were positively associated with CLR, supporting H2 and H4, and CLR was positively associated with OA, supporting H5. APPs were positively associated with OA and positively moderated the CLR-OA relationship, supporting H7 and H6, respectively. The direct CCUs-OA and HMMT-OA paths were not significant; thus, H1 and H3 were not supported. The indirect effects were significant, and variance accounted for was 85.14% for CCUs → CLR → OA and 83.96% for HMMT → CLR → OA (Table 4). Because both values exceed 80%, the results support full mediation and therefore H8 and H9.

4.2 Structural model and model fit

The model explained 42.6% of the variance in CLR ($R^2 = 0.426$; adjusted $R^2 = 0.418$) and 61.2% of the variance in OA ($R^2 = 0.612$; adjusted $R^2 = 0.605$), as reported in Table 5. The standardized root mean square residual was 0.061, indicating acceptable fit for the PLS-SEM model (Table 6; Hair *et al.*, 2014). Together with the significant indirect effects in Table 4, these results confirm full, rather than partial, mediation.

Table 2. Discriminant validity (HTMT) at second order

Variables	VIF	OA	APPs	CLR	HMMT	CCUs
OA	–					
APPs	1.115	0.841	–			
CLR	2.642	0.667	0.336	–		
HMMT	2.913	0.602	0.320	0.812	–	
CCUs	3.275	0.616	0.309	0.828	0.849	–

Table 3. Hypotheses results

Hypotheses	Path	β	t	p	CI LL	CI UL	Decision
H1	CCUs $\rightarrow$ OA	0.038	0.914	0.361	-0.029	0.094	Not supported
H2	CCUs $\rightarrow$ CLR	0.321	8.743	0.000	0.295	0.432	Supported
H3	HMMT $\rightarrow$ OA	0.034	0.822	0.411	-0.031	0.089	Not supported
H4	HMMT $\rightarrow$ CLR	0.287	7.112	0.000	0.261	0.389	Supported
H5	CLR $\rightarrow$ OA	0.412	11.526	0.000	0.392	0.467	Supported
H6	APPs $\times$ CLR $\rightarrow$ OA	0.128	2.698	0.021	0.021	0.144	Supported
H7	APPs $\rightarrow$ OA	0.359	9.274	0.000	0.321	0.427	Supported
H8	CCUs $\rightarrow$ CLR $\rightarrow$ OA	0.219	6.321	0.000	0.202	0.288	Full mediation
H9	HMMT $\rightarrow$ CLR $\rightarrow$ OA	0.178	5.742	0.000	0.163	0.241	Full mediation

Table 4. Mediation results and variance accounted for

Independent variable	Dependent variable	Mediating variable	Indirect effect	Total effect	VAF (%)
CCUs	OA	CLR	0.219	0.257	85.14
HMMT	OA	CLR	0.178	0.212	83.96

Table 5. Structural model explanatory power

Endogenous construct	R^2	Adjusted R^2
CLR	0.426	0.418
OA	0.612	0.605

Table 6. Model fit

Fit index	Value
SRMR	0.061

4.3 Predictive relevance and effect sizes

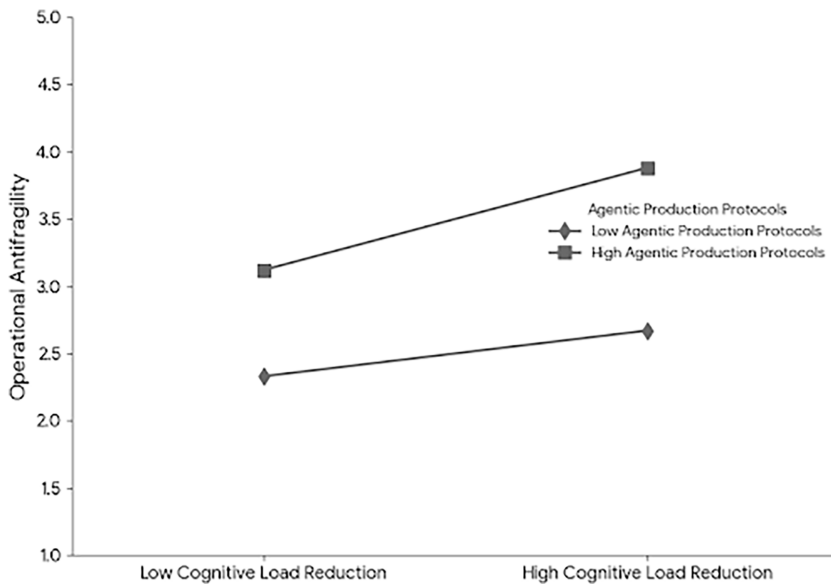
Predictive relevance was medium for OA ($Q^2 = 0.322$) and CLR ($Q^2 = 0.267$), based on the 0.02, 0.15, and 0.35 benchmarks for small, medium, and large values (Cohen *et al.*, 2013). Effect sizes (Table 7) show a large APPs-OA effect ($f^2 = 0.459$), a medium CLR-OA effect ($f^2 = 0.168$), medium CCUs-CLR ($f^2 = 0.341$) and HMMT-CLR ($f^2 = 0.276$) effects, and negligible-to-small direct CCUs-OA and HMMT-OA effects (Cohen, 1988). Figure 2 illustrates the positive interaction: the CLR-OA relationship is stronger when APPs are high.

5. Discussion

The findings support a human-centred, cognition-based explanation of OA in I5MEs. Addressing RQ1 and RQ2, CCUs and HMMT were positively associated with CLR but had no significant direct associations with OA; CLR fully mediated both relationships. Intelligent

Table 7. Effect sizes

Construct	CLR	OA
CCUs	0.341	0.021
HMMT	0.276	0.019
CLR	–	0.168
APPs	–	0.459

**Figure 2.** Moderating effect of APPs on the CLR-OA relationship

coordination and calibrated trust therefore appear to contribute to antifragility by reducing cognitive load rather than by acting as independent performance drivers. CCUs structure complex information and prioritize signals, while calibrated trust stabilizes expectations and reduces unnecessary monitoring. This interpretation accords with evidence that cognitive control systems and calibrated trust reduce workload and improve attentional allocation (Lou *et al.*, 2024; Villar *et al.*, 2023). It also extends prior research by showing that, after CLR is included, the direct CCUs-OA and HMMT-OA paths become negligible. Consistent with CLT (Sweller, 1988), cognitive capacity is not an ancillary ergonomic concern but the mechanism through which technological and relational resources are associated with antifragile performance.

Addressing RQ3, APPs were positively associated with OA and strengthened the CLR-OA relationship. This pattern is consistent with the STS principle of joint optimization (Trist and Bamforth, 1951): APPs align social and technical components by specifying decision rights, escalation routes, and task allocation between humans and machines. Cognitive clarity is therefore more strongly associated with OA when operators also have flexible guidance and clear authority to act. The large APPs-OA effect and medium CLR-OA effect reinforce this interpretation, whereas the direct effects of CCUs and HMMT on OA were negligible. In practical terms, formal governance protocols appear to be the strongest individual lever in the

model, followed by interface and workflow design that reduces cognitive load. Technology and trust investments contribute primarily by improving that cognitive pathway. The findings thus locate antifragility in the alignment of cognition, calibrated trust, and structured agency rather than in automation intensity alone.

5.1 Theoretical contributions

The study makes four theoretical contributions. First, it integrates CLT and STS in a single account of OA, identifying CLR as the mechanism linking CCUs and HMMT to antifragility. Second, it conceptualizes APPs as both an antecedent and a boundary condition, extending STS by treating the allocation of agency as an active governance process. Third, it sharpens the distinction between antifragility, resilience, and adaptability by showing that improvement through disruption depends on aligned cognitive, relational, and structural mechanisms. Fourth, evidence from South Asian manufacturers extends Industry 5.0 research beyond its predominant Western and East Asian settings, while leaving cross-context generalizability for future testing.

5.2 Practical, social, and policy implications

Managers should design Industry 5.0 systems around cognitive usability rather than automation intensity alone. Decision-support interfaces should filter irrelevant information, prioritize critical signals, and explain recommendations. Calibrated trust requires operator training, transparent feedback, and explicit communication of system limits. APPs should formalize task ownership, autonomy boundaries, and escalation routes instead of leaving them as implicit consequences of technology deployment. Technology investment should therefore be paired with workflow simplification, interface design, and workforce development so that operators can interpret outputs and exercise authorized judgement. Regulators and industry associations can support these practices through standards for cognitive workload, interface transparency, explainable AI, and ethical governance of autonomous systems. Such measures can improve productivity and operational antifragility while protecting worker well-being and supporting an inclusive transition to human-centred manufacturing.

6. Conclusion

This study developed and tested an integrated model of OA in I5MEs. In response to [RQ1](#) and [RQ2](#), CCUs and HMMT were not directly associated with OA; instead, CLR fully mediated both relationships. In response to [RQ3](#), APPs were positively associated with OA and strengthened the CLR-OA relationship. Antifragile manufacturing therefore appears to arise from the alignment of cognitive control, calibrated trust, cognitive efficiency, and structured agency rather than from automation intensity alone. The study advances Industry 5.0 theory by integrating cognitive and sociotechnical mechanisms in a mediation-moderation model, and it directs practice toward cognitively manageable interfaces, trust calibration, explicit governance protocols, and workforce development.

Several limitations qualify these findings. First, the cross-sectional design supports associations, not causal inference, and cannot capture the co-evolution of human-machine relationships; longitudinal studies, smart-factory logs, and digital-twin experiments could examine these dynamics. Second, the sample was limited to large manufacturers in five South Asian countries. Replication in small and medium-sized firms, services, and other regions is needed. Third, the study relied on single-informant managerial perceptions. Although procedural safeguards and a statistical diagnostic were applied, common method and social-desirability biases cannot be ruled out; future studies should combine surveys with production logs, downtime, quality outcomes, and real-time workload measures. Finally, research could test leadership, culture, workforce skills, and environmental volatility as additional boundary conditions and examine antifragility at individual and team levels. These extensions would

refine the conditions under which technology, cognition, and sociotechnical governance jointly support human-centred antifragility.

Data availability statement

The data presented in this study are available from the corresponding author upon reasonable request. The data are not publicly available due to confidentiality commitments to participants.

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Supplementary material

The supplementary material for this article can be found online

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