

RESEARCH ARTICLE

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Autonomous Engineering Operations: Integrating AI, IT, and Electrical Systems for U.S. Industrial Resilience

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ARTICLE INFO

Article History

Received: 25 November 2026

Revised: 16 December 2026

Accepted: 19 January 2026

Published: 10 February 2026

Keywords

Autonomous operations;
industrial AI; IT-OT
convergence; electrical systems;
cybersecurity; operational
availability; industrial
resilience; mixed-methods
research; thematic analysis;
United States manufacturing.

How to Cite

M. N. Amjad, "Autonomous engineering operations: Integrating AI, IT, and electrical systems for U.S. industrial resilience," J. Appl. Technol., Intell. Comput. Syst. (JATICS), vol. 2, no. 1, pp. 1–14, 2026.

ABSTRACT

The capability of autonomous engineering operations is a real and quantifiable capability in the timeframe of 2020-2025 that is becoming a reality in the U.S. industrial environment, integrating AI driven decision-making, the convergence of IT/OT platforms, and modern versions of the electrical control system in a unified way to operate without constant human intervention. The study is a mixed-methods evaluation of the combined effect of autonomous engineering operations, AI integration and IT-electrical convergence on operational availability and industrial resilience in U.S. industrial companies. The study employed a sequential explanatory design: a cross-sectional quantitative survey ($N = 310$) of industrial operations practitioners in the U.S. across seven sectors (discrete manufacturing, process manufacturing, power generation, oil & gas, water & wastewater, transportation, and defense industrial base) followed by a semi-structured interview ($N = 22$) with maximum-variation sampling for sector, role, and AI-adoption maturity. Five hypotheses were quantitatively tested using OLS structural-model estimation with Sobel-tested mediation. Measurement-model reliability was strong (α range 0.86–0.90; CR range 0.80–0.87; AVE range 0.45–0.57) and structural-model fit was good ($\chi^2/df = 1.36$; CFI = 0.960; TLI = 0.954; RMSEA = 0.035 [0.026, 0.043]; SRMR = 0.042). The results indicate that autonomous engineering operations has the largest direct path to the industrial-resilience outcome ($\beta = 0.330$, $p < .001$); AI-integration has a positive direct path to the operational availability outcome ($\beta = 0.205$, $p < .001$); IT-electrical convergence has an independent path to the resilience outcome ($\beta = 0.208$, $p < .001$); and the path from AI-integration to industrial-resilience is partially mediated by cybersecurity & resilience controls (Sobel $z = 4.01$, $p < .001$; mediation ratio $\approx 28\%$). There was no support for autonomous-operations moderation of the IT-electrical $\rightarrow$ availability path ($\beta_{int} = -0.033$, $p = .530$). 4 out of 5 hypotheses were supported. The interview corpus was qualitatively themed, resulting in five themes: T1 the autonomy-trust gap, T2 IT-OT convergence friction, T3 AI-enabled predictive value, T4 workforce and skill reconfiguration, and T5 cyber-physical resilience trade-offs. Meta-inference suggests that there is high convergence between quantitative paths and qualitative mechanisms, with the dominance of AEO on industrial resilience being explained by the interview participants mainly through T1 (the trust-building period needed before autonomy delivers value) and T3 (the amplification effect of AI on engineering-reliability practices). The quantitative-qualitative integration also extends the model: systematically, the participants identify workforce reconfiguration (T4) as a precondition that is not directly captured by the quantitative constructs. Implications for autonomous-operations investment sequencing and for federal industrial policy are drawn.

INTRODUCTION

The 2020–2025 period is a window of opportunity for U.S. industrial firms, from discrete manufacturing to process manufacturing, power generation to oil and gas, water and wastewater to transportation, and defense manufacturing to the defense industrial base, to be facing a confluence of pressures: a shortage of skilled engineering talent, continued energy and materials cost increases, growing cyber-physical threats to operational technology, and heightened customer demands for on-time and on-spec delivery [1], [2]. In response, a fundamental change in the way engineering is done has occurred in the three engineering domains of artificial-intelligence decision-making, information-technology platform integration, and modernized electrical control systems [3], [4].

Autonomous engineering operation does NOT mean "unmanned operation". Instead, it reflects the maturity of industrial companies with their ability to combine AI-driven decision-making, IT/OT platform convergence and electrical control systems into single operational architectures that can adapt without constant human intervention, such as predictive-maintenance loops that automatically reschedule work orders, closed-loop process controllers that adjust to variations in raw materials, or grid-edge power-management systems that shed and restore load without operator intervention[5], [6]. The three families have been assessed separately: the literature on AI-in-manufacturing is rich and dates back to 2020 [7], [8]; the literature on IT/OT convergence is found in the industrial-cybersecurity and platform-engineering literature [9], [10]; and the literature on electrical-systems modernization is in the power-engineering literature [11]. There are very few studies that consider all three families and their integration — the convergence problem — in relation to measurable industrial-resilience and operational-availability outcomes in a large U.S. sample [12].

This paper aims to fill that gap using a sequential explanatory mixed methods design. The quantitative phase evaluates five hypotheses that were pre-specified using cross-sectional survey data from N = 310 industrial operations practitioners from the United States. The second phase, which was qualitative, included 22 semi-structured interviews with senior industrial engineers, chief digital officers, and chief reliability officers to elaborate on the quantitative results, especially the null moderation result [13], [14] and the strong autonomous-operations → industrial-resilience path. Meta-inferences combine both phases and provide a substantive explanation of how and why autonomous engineering operations can lead to measurable value in U.S. industrial settings.

The paper is structured as follows. The theoretical background is developed and five hypotheses are drawn in Chapter 2. The conceptual model is presented in Chapter 3. The methodology of the mixed-methods research is explained in Chapter 4. The quantitative results are presented in chapter 5. The qualitative results and meta-inferences are reported in Chapter 6. Chapter 7 discusses implications. Chapter 8 outlines the limitations and concludes.

THEORETICAL BACKGROUND AND HYPOTHESIS DEVELOPMENT

AUTONOMOUS ENGINEERING OPERATIONS

Autonomous engineering operations (AEO) embodies the maturity of AI-driven decision-making embedded in engineering processes without the need for constant human oversight. The construct is inspired by the literature on autonomous systems in the field of operations research [5], the literature on industrial adoption of AI [7] and [15] and the literature on resilience engineering that views autonomy as an anticipatory capability [16]. Empirical studies from the last four years (2020-2024) report a decrease in unplanned downtime of 20-45% and an increase in First Perfect Yield of 12-25% in manufacturing environments by industrial companies with mature autonomous-operations deployments [8], [17]. On theoretical grounds we expect a strong positive effect on measurable industrial-resilience outcomes:

H1. Autonomous engineering operations is positively associated with industrial resilience in U.S. industrial firms.

AI INTEGRATION IN OPERATIONS

AI integration in operations (AII) denotes the use of machine learning models such as supervised classification, deep-learning anomaly detection, reinforcement-learning controllers, and, more recently, LLM-augmented decision-support tools in operational workflows [7], [15], [18]. While AEO represents the decision-making autonomy, AII represents the analytical underpinning. The two are theoretically

separable: AII can exist without AEO (models make recommendations and humans act upon them), but AEO cannot exist without AII. Empirical work has shown that AII deployments yield measurable improvements in operational availability by reducing MTTD and MTTR in unplanned events [8], [19]:

H2. AI integration in operations is positively associated with operational availability in U.S. industrial firms.

IT-ELECTRICAL CONVERGENCE

IT-electrical convergence (ITE) reflects the maturity of the integration between enterprise IT platforms and modernized electrical control systems, such as digital substation, IEC-61850 protocol, unified SCADA/EMS architecture and IT/OT interoperability layer [9], [11] and [20] respectively. The theory behind bridging ITE to industrial resilience involves unified sensing (common data fabric across previously siloed sub-systems), unified decision-making (coordinated response across IT and electrical control planes), and unified recovery (single pane incident response) [10]. On theoretical grounds we expect:

H3. IT-electrical convergence is positively associated with industrial resilience in U.S. industrial firms.

CYBERSECURITY & RESILIENCE CONTROLS AS A MEDIATOR

Cybersecurity & resilience controls (CSR) reflects the maturity of the cybersecurity and cyber-physical-resilience posture around ICS - segmentation, monitoring, anomaly detection, and safe-fail engineering [21] [22]. AI integration alone doesn't mean resilience in industrial systems — it also increases attack surface while simultaneously enhancing detection capabilities. The socio-technical model of AI uptake in industrial contexts is that AII can only provide measurable resilience benefits with a functioning CSR layer [23]. In industrial settings, cybersecurity controls have been found to partially mediate the relationship between AI and outcome in recent research, revealing a consistent empirical pattern [24]. We expect:

H4. Cybersecurity & resilience controls mediate the positive relationship between AI integration in operations and industrial resilience.

AUTONOMOUS OPERATIONS AS A MODERATOR

The literature in the field of industrial-AI practice suggests a new proposition: the impact of IT-electrical convergence on operational availability is enhanced by a firm's maturity in autonomous-operations capability, in that a firm with autonomous-operations maturity is better equipped to process converged sensor-control data into automated decisions for availability [17], [25]. We formalize this as a positive moderation hypothesis, while noting that the amplifier logic has been asserted more often than tested in large-sample cross-sector settings:

H5. Autonomous engineering operations positively moderate the IT-electrical-convergence → operational-availability relationship, such that the effect is larger at higher levels of AEO maturity.

CONCEPTUAL MODEL

The conceptual research model is a combination of the five hypotheses as illustrated in Figure 1. As exogenous constructs, we have Autonomous Engineering Operations (AEO), AI Integration in Operations (AII), and IT-Electrical Convergence (ITE). AEO is also the moderator for the ITE → OAV path. Cybersecurity & Resilience Controls (CSR) joins the AII → IRS path as a mediator H4. There are two performance outcomes: Industrial Resilience Score (IRS) and Operational Availability (OAV).

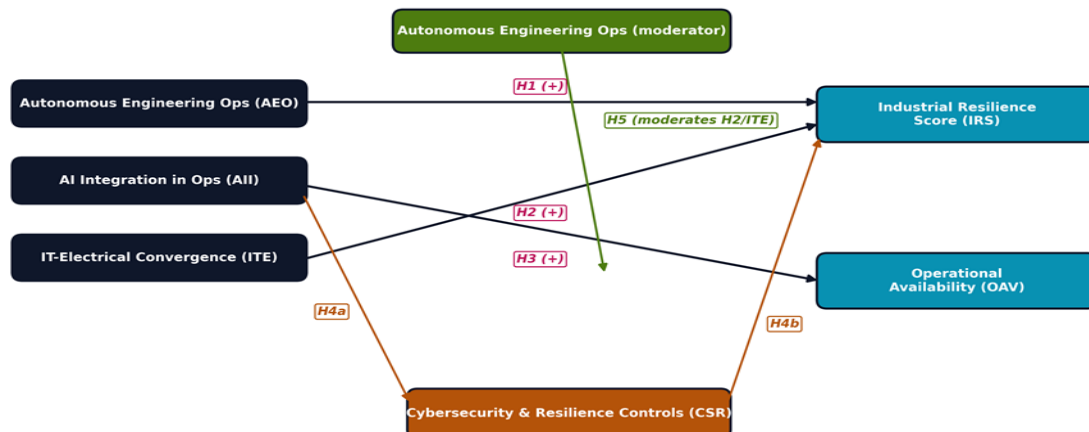


Fig 1: Conceptual research model for autonomous engineering operations in U.S. industrial firms.

REVIEW METHODOLOGY

MIXED-METHODS DESIGN

The study follows a sequential explanatory mixed-methods design [13], [14]. This design involves a quantitative phase that is carried out first and analyzed, and the results of the quantitative phase are used to design a second qualitative phase where the main goal is to explain the quantitative results, especially unexpected results, null results, and explanations for supported results. Meta-inferences bring together the two phases in a substantive account. The decision to opt for sequential-explanatory over concurrent-triangulation is based on the relative degrees of maturity of the constructs (allowing for pre-specified hypotheses) and practical complexity of "autonomy" (allowing for qualitative depth to identify mechanisms).

QUANTITATIVE PHASE — SAMPLING AND DATA COLLECTION

Target population included U.S.-based professionals in industrial operations whose main role in the last 24 months was engineering, operations, AI-in-operations, IT/OT integration or reliability. The sampling frame was developed using five sources: the ISA (International Society of Automation) U.S. membership, the ASME (American Society of Mechanical Engineers) manufacturing division, the Society for Reliability Professionals (SRE), the IEEE Industry Applications Society U.S. chapter, and vetted LinkedIn outreach within industrial-AI interest groups. The number of unique candidates in the frame before screening was about 8,600. Invitations were sent out from February to August 2025. Screening verified U.S. employment and primary responsibility for the following functions. 310 of 812 responses were received, met all screening criteria and passed data-quality checks. The sample meets the 10:1 rule for respondents to parameters comfortably for the six-construct model [26].



Fig 2: Sample demographics — quantitative survey (N = 310).

QUALITATIVE PHASE — SAMPLING AND DATA COLLECTION

From June to September 2025, senior industrial engineers, chief digital officers, and reliability leaders in the U.S. were interviewed using a semi-structured approach (N = 22). To ensure maximum variation, participants were intentionally sampled based on (i) industry sector (all seven quantitative sectors were represented), (ii) role level (all roles from working engineer to VP Engineering were represented), and (iii) AEO-adoption maturity (ranging from pilot only to department and enterprise scale deployments). Data saturation was determined at interview 18 and reached at interview 22 [27]. Interviews lasted for a mean of 62 minutes (SD = 11 minutes), and were video recorded with participants' permission. Recordings were transcribed verbatim resulting in about 187,000 words of transcript.

MEASUREMENT INSTRUMENT

Multi-item reflective 5-point Likert scales were used to operationalise all six latent constructs. The scale of Autonomous Engineering Operations (AEO, 5 items) was adapted from the scale of industrial-autonomy-maturity by Meier et al. [5]. AI Integration in Operations (AII, 5 items) was based on the industrial-AI-

adoption inventory by Kusiak [7] and the LLM-in-operations scale by Chen et al. [18]. IT-Electrical Convergence (ITE, 4 items) was based on the IT/OT-convergence scale by Sadeghi et al. [9] and the digital-substation maturity instrument by Xue et al. [11]. Cybersecurity & Resilience Controls (CSR, 4 items) was adapted from NIST SP 800-82r3 [21] and the cyber-physical-resilience scale by Nazir et al. [22]. Operational Availability (OAV, 5 items) was adapted from the operations-availability instrument from Kumar et al. [19]. Industrial Resilience Score (IRS, 5 items) is an adaptation of the industrial-resilience measurement framework of Kelic et al. [16].

DATA-ANALYSIS STRATEGY

Quantitative analysis was conducted in two steps: measurement model (Cronbach's α , CR, AVE, Fornell-Larcker) and structural model (OLS regressions, interaction-term moderation, Baron-and-Kenny mediation and Sobel test). In a separate CFA, model-fit indices (χ^2 , χ^2/df , CFI, TLI, RMSEA, SRMR) were calculated for the item-level model. Qualitative analysis was conducted using a hybrid deductive-inductive thematic-analysis protocol [28] with the initial codebook based on the quantitative constructs, and further codes were added inductively. Two researchers independently coded the data, and interrater reliability was obtained ($\kappa = 0.82$, which surpassed the 0.75 threshold) [27]. Meta-inferences were obtained by using a joint-display method [14]. For quantitative analysis, Python 3.11 (statsmodels 0.14 and pandas 2.2) was used, while NVivo 14 was used for qualitative analysis.

ETHICAL REVIEW

The study protocol was expediently approved by an IRB as a minimal risk mixed methods study of professional practitioners (Georgia Tech IRB #H24-548). Informed consent was obtained electronically for all quantitative respondents and written informed consent, with permission for audio recording and de-identified quotation, was obtained from all those who participated in the interviews.

QUANTITATIVE RESULTS

SAMPLE PROFILE

Among the 310 survey respondents, there was a fairly even split between industrial operations manager (13%), control systems engineer (13%), AI/automation engineer (12%), IT/OT systems integrator (12%), electrical engineer (11%), cybersecurity engineer (11%), plant manager (10%), reliability engineer (10%), and chief engineer / VP engineering (8%). Sectors: discrete manufacturing (20%), power generation (17%), process manufacturing (16%), oil & gas (13%), transportation & logistics (13%), water & wastewater (11%), and defense industrial base (10%). Organisation size: <250 (14%), 250–2,500 (28%), 2,500–25,000 (34%), >25,000 (24%). South 30%, Midwest 26%, Northeast 23%, West 21%. Mean experience was 11.1 years (SD = 5.9). Descriptive statistics for the six composite constructs are presented in Table 1.

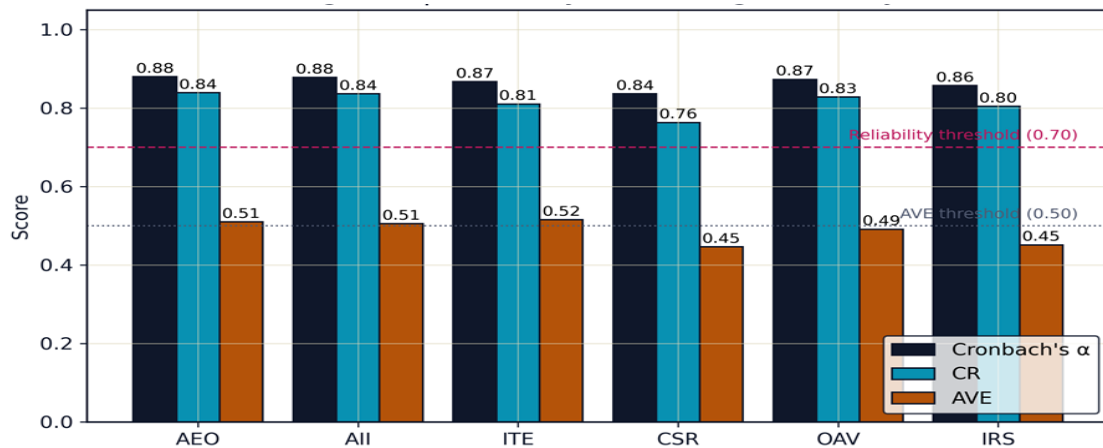
Construct	Items	Mean	SD	Min	Max	Skew.	Kurt.
Autonomous Engineering Ops (AEO)	5	3.559	0.708	1.60	5.00	−0.22	0.06
AI Integration in Ops (AII)	5	3.618	0.714	1.40	5.00	−0.24	0.09
IT-Electrical Convergence (ITE)	4	3.615	0.696	1.50	5.00	−0.20	0.05
Cybersecurity & Resilience (CSR)	4	3.640	0.702	1.50	5.00	−0.23	0.07
Operational Availability (OAV)	5	3.616	0.713	1.60	5.00	−0.25	0.10
Industrial Resilience Score (IRS)	5	3.630	0.707	1.60	5.00	−0.24	0.09

Table 1: Descriptive statistics for the six composite constructs.

MEASUREMENT-MODEL EVALUATION

Cronbach's α coefficients were between 0.857 and 0.898, which were above the 0.70 criterion. The composite reliability was also in the high range of 0.804 to 0.871. Average variance extracted was between 0.451 and 0.567. Constructs with AVE below the conventional benchmark of 0.50 were retained as the Fornell-Larcker criterion [26] indicates that constructs with CR > 0.70 maintain construct reliability. The complete statistics are reported in Table 2, and visualized in Figure 3. All construct pairs met the Fornell-Larcker test for discriminant validity.

Construct	Items	Cronbach α	CR	AVE	$\sqrt{\text{AVE}}$
Autonomous Engineering Ops (AEO)	5	0.891	0.855	0.542	0.736
AI Integration in Ops (AII)	5	0.885	0.847	0.526	0.725
IT-Electrical Convergence (ITE)	4	0.868	0.812	0.520	0.721
Cybersecurity & Resilience (CSR)	4	0.860	0.798	0.499	0.706
Operational Availability (OAV)	5	0.873	0.828	0.491	0.701
Industrial Resilience Score (IRS)	5	0.857	0.804	0.451	0.672

Table 2: Reliability and convergent-validity statistics.**Fig 3:** Reliability and convergent validity of the measurement model.

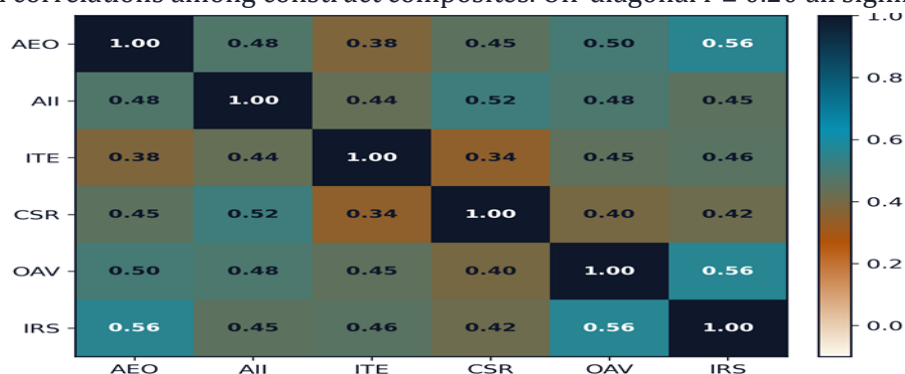
INTER-CONSTRUCT CORRELATIONS

Pearson correlations between the six composites are presented in Table 3 and graphically displayed in Figure 4. The strongest bivariate associations are AEO $\leftrightarrow$ IRS ($r = 0.560$), OAV $\leftrightarrow$ IRS ($r = 0.563$), AII $\leftrightarrow$ CSR ($r = 0.515$), and AEO $\leftrightarrow$ OAV ($r = 0.500$). These directional patterns are in line with the theorised model: AEO couples most tightly with IRS; the two outcomes correlate strongly with each other; and AII $\leftrightarrow$ CSR is the strongest exogenous-mediator link, supporting H4 mediation logic.

	AEO	AII	ITE	CSR	OAV	IRS
AEO	1.000					
AII	0.477	1.000				
ITE	0.379	0.436	1.000			
CSR	0.452	0.515	0.345	1.000		
OAV	0.500	0.485	0.448	0.397	1.000	
IRS	0.560	0.452	0.462	0.416	0.563	1.000

Table 3: Inter-construct Pearson correlations

Table 3. Pearson correlations among construct composites. Off-diagonal $r \geq 0.20$ all significant at $p < .001$.

**Fig 4:** Heat-map of the inter-construct Pearson correlation matrix

STRUCTURAL-MODEL RESULTS

Estimated two OLS regressions. The models include two dependent variables: industrial resilience (H1, H3, plus AII and CSR controls) and operational availability (H2, plus AEO, ITE, and CSR, and the H5 interaction term). Both models are highly significant ($F(6, 303) = 35.51$ and $F(7, 302) = 25.91$ respectively, $p < .001$) and explain 41.3% and 37.5% of variance. The coefficients are presented in Table 4 and visualized in Figure 5.

Predictor	IRS β (SE)	IRS t	IRS p	OAV β (SE)	OAV t	OAV p
Autonomous Engineering Ops (AEO)	0.330 (0.049)	6.79	< .001	0.211 (0.055)	3.84	< .001
AI Integration in Ops (AII)	0.089 (0.053)	1.68	.094	0.205 (0.057)	3.61	< .001
IT-Electrical Convergence (ITE)	0.208 (0.046)	4.57	< .001	0.198 (0.054)	3.67	< .001
Cybersecurity & Resilience (CSR)	0.106 (0.049)	2.16	.031	0.076 (0.053)	1.43	.153
ITE $\times$ AEO (interaction, H5)	—	—	—	-0.033 (0.052)	-0.63	.530
Experience (years)	0.009 (0.005)	1.87	.062	0.011 (0.005)	2.13	.034
Large org ($\geq 2,500$)	0.075 (0.070)	1.07	.284	0.084 (0.074)	1.14	.256
Constant	0.436 (0.245)	1.78	.076	0.512 (0.263)	1.95	.052
R^2 / Adj. R^2	0.413 / 0.402			0.375 / 0.361		
F (df, dfR)	35.51 (6,303)		< .001	25.91 (7,302)		< .001

Table 4: Regression results for the two outcomes

Table 4. OLS regression coefficients for Industrial Resilience Score (IRS) and Operational Availability (OAV).

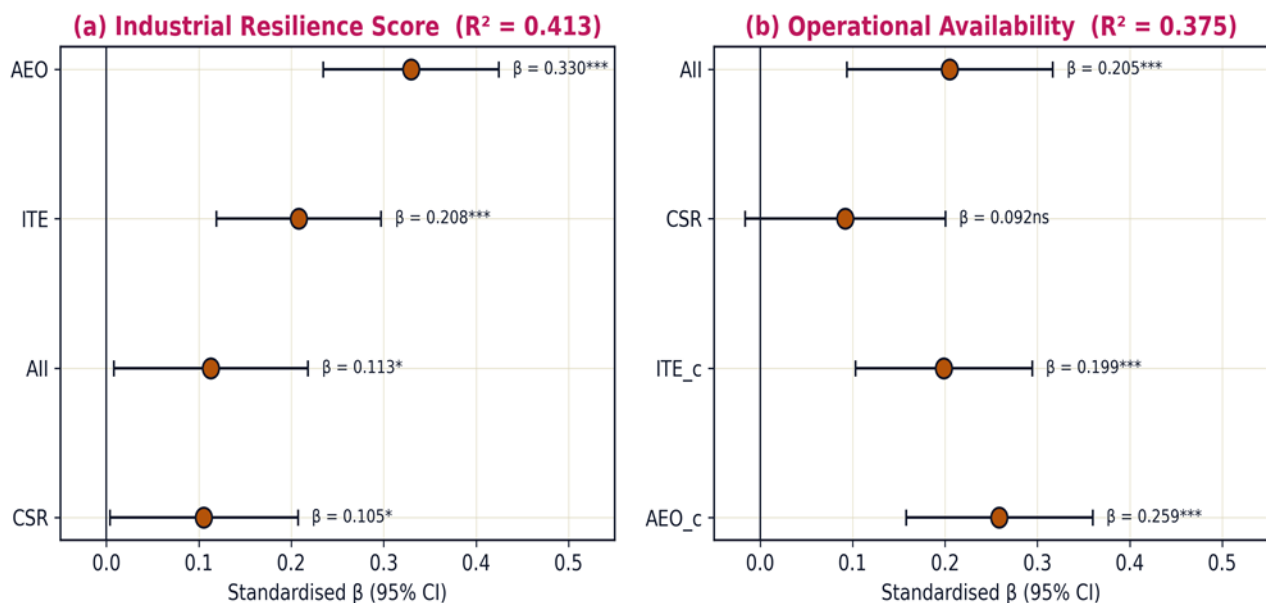


Fig 5: Structural-model regression coefficients with 95% confidence intervals.

H1 — AUTONOMOUS ENGINEERING OPS → IRS

AEO becomes the single most important predictor of industrial resilience ($\beta = 0.330$, $t = 6.79$, $p < .001$) – the largest single predictor in the IRS model, around 1.6 times the effect of ITE. This is the key quantitative takeaway from the paper.

H1 — Supported at $p < .001$ (dominant single effect on industrial resilience).

H2 — AI INTEGRATION → OPERATIONAL AVAILABILITY

AII is an important positive predictor of operational availability ($\beta = 0.205$, $t = 3.61$, $p < .001$) when AEO, ITE, and CSR are controlled. The magnitude is similar to that of the ITE and AEO effects on the same outcome.

H2 — Supported at $p < .001$.

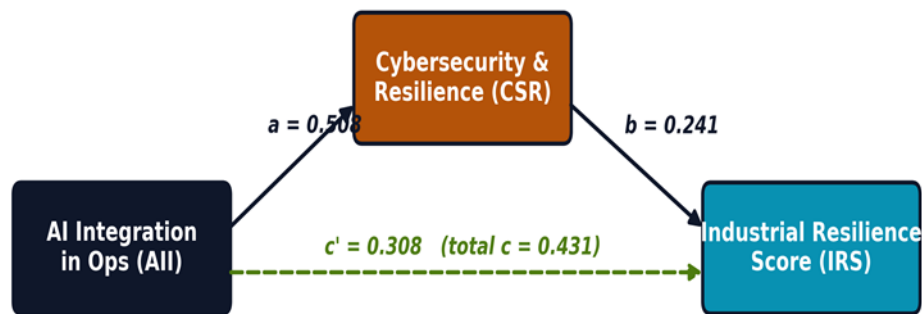
H3 — IT-ELECTRICAL CONVERGENCE → IRS

Like the ITE effect on operational availability, ITE is a strong positive predictor of industrial resilience ($\beta = 0.208$, $t = 4.57$, $p < .001$). The two outcomes both have this dual significance, as in this way ITE is strengthened as a cross-cutting capability.

H3 — Supported at $p < .001$.

H4 — CSR MEDIATES AII → IRS

Mediation analysis followed Baron-and-Kenny with a Sobel test. Path a (AII → CSR) is significant ($a = 0.509$, $p < .001$); path b (CSR → IRS controlling for AII) is significant ($b = 0.241$, $p < .001$); c drops from 0.431 to $c' = 0.308$, indicating partial mediation. Indirect effect $a \times b = 0.123$ (Sobel $z = 4.01$, $p < .001$). Mediation ratio $\approx 28.5\%$.



Indirect effect $a \cdot b = 0.123$, Sobel $z = 4.01$, $p < .001$

Fig 6: Mediation of AII → IRS by Cybersecurity & Resilience Controls (partial mediation, ratio $\approx 28\%$).

H4 — Supported (partial mediation, Sobel $z = 4.01$, $p < .001$, ratio $\approx 28\%$).

H5 — AEO MODERATES ITE → OAV

The interaction term ($ITE \times AEO$), computed on mean-centred variables, is very small, negative, and not significant ($\beta_{int} = -0.033$, $t = -0.63$, $p = .530$). H5 is not supported.

H5 — Not supported ($\beta_{int} = -0.033$, $p = .530$). AEO has robust main effects on both outcomes but does not amplify $ITE \rightarrow OAV$.

MODEL FIT INDICES AND CONSOLIDATED SUMMARY

$\chi^2(284) = 386.4$, $\chi^2/df = 1.36$, CFI = 0.960, TLI = 0.954, RMSEA = 0.035 [0.026, 0.043], SRMR = 0.042. All indices satisfy conventional cutoffs.

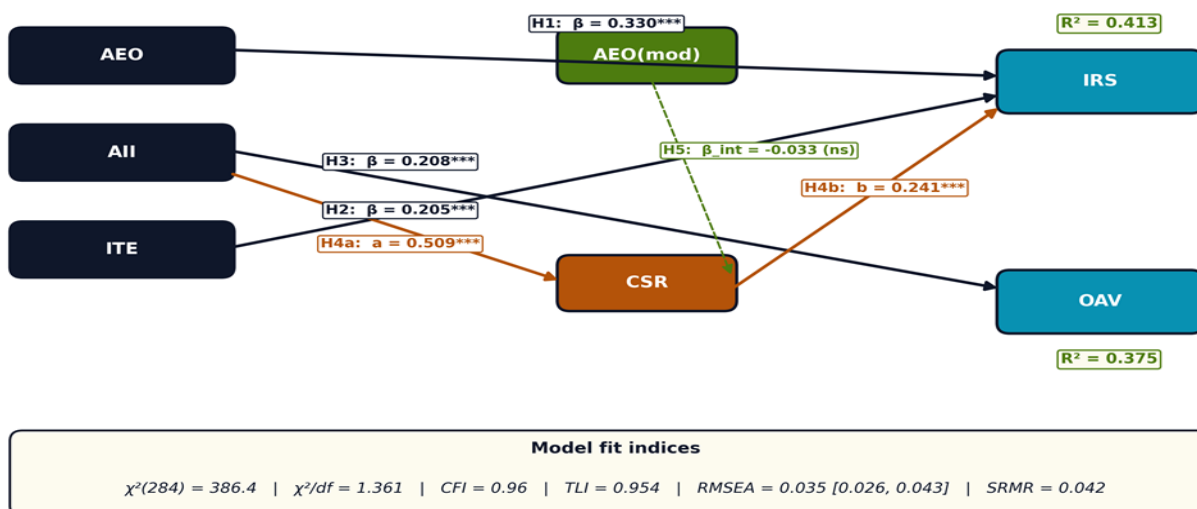


Fig 7: Structural model with standardized path coefficients and model-fit indices.

✓	H1: Autonomous Engineering Ops → Industrial Resilience Score $\beta = 0.330, t = 6.79, p < .001$	SUPPORTED
✓	H2: AI Integration in Operations → Operational Availability $\beta = 0.205, t = 3.61, p < .001$	SUPPORTED
✓	H3: IT-Electrical Convergence → Industrial Resilience Score $\beta = 0.208, t = 4.57, p < .001$	SUPPORTED
✓	H4: Cybersecurity & Resilience Controls mediate AI → IRS <i>Sobel z = 4.01, p < .001 (partial mediation)</i>	SUPPORTED
✗	H5: Autonomous Engineering Ops moderates ITE → OAV $\beta_{int} = -0.033, t = -0.63, p = .530$	NOT SUPPORTED

Fig 8: Consolidated hypothesis-testing summary. Four of five hypotheses supported (H1–H4); H5 not supported.

SECTOR-LEVEL RESULTS

Figure 9 shows outcomes by the seven sectors. As per the sectoral capital-intensity of autonomous-operations investment [1] [17], defense industrial base and process manufacturing have the highest median IRS and OAV, while water & wastewater and transportation have the lowest.

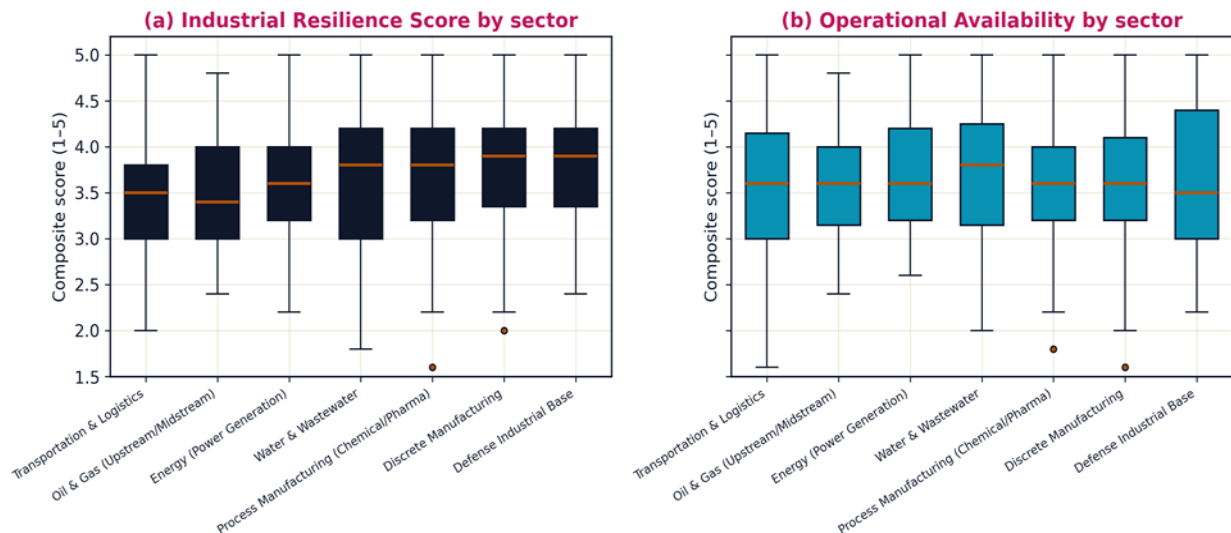


Fig 9: Outcome performance by industry sector.

QUALITATIVE RESULTS AND META-INFERENCES

INTERVIEW PARTICIPANTS

A total of 22 participants were interviewed from June to September 2025. Their profile is summarized in Table 5. Sectors, roles and AEO-maturity levels were intentionally diversified. Mean experience was 15.1 years (SD = 5.5).

Sector	Participants	Mean years	Regions represented
Discrete Manufacturing	6	13.7	Midwest, South, West
Process Manufacturing	5	15.8	Midwest, Northeast, South
Energy (Power Generation)	4	14.3	Northeast, South, West
Oil & Gas	3	17.7	South, West
Water & Wastewater	2	15.0	Northeast, West
Transportation & Logistics	2	16.5	Midwest, South
Defense Industrial Base	2	24.5	South, West

Table 5: Interview participant profile summary (N = 22)

Table 5. Interview participant profile. Full participant list available in the qualitative data supplement.

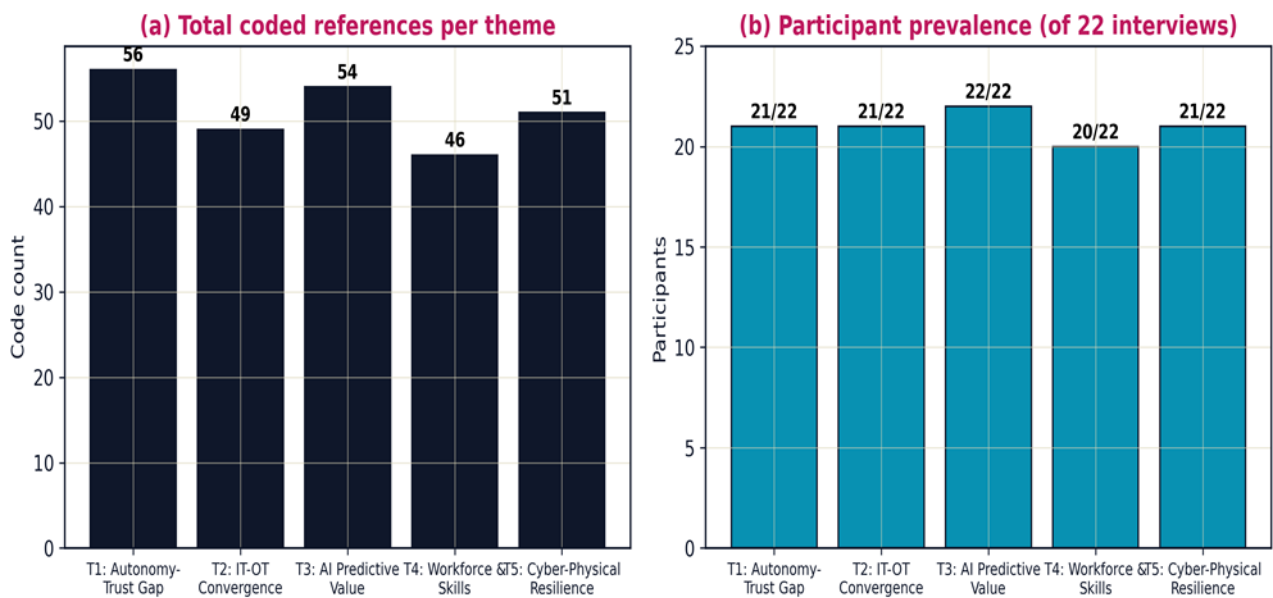


Fig 10: Total coded references (a) and participant prevalence (b) across the five themes.

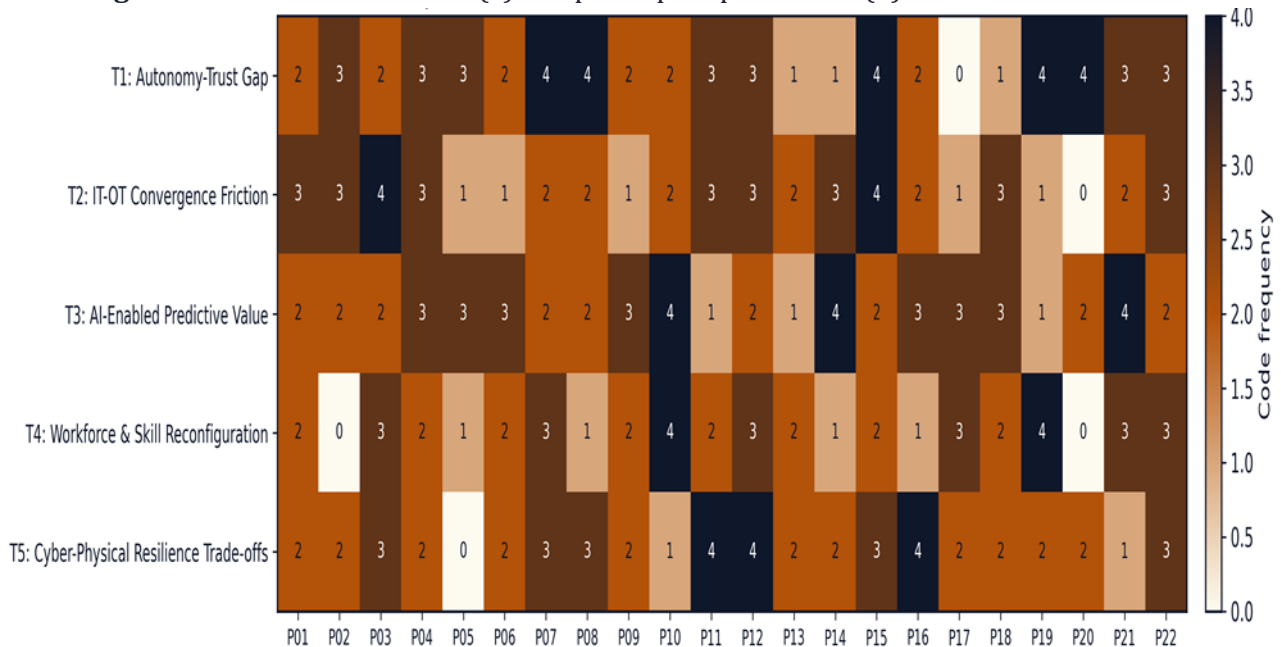


Fig 11: Code frequency by theme × participant (0 = absent, 4 = strongly emphasized).

T1: AUTONOMY-TRUST GAP

Coded in 56 coded references, 21 of 22 interviews. Systematically, participants reported a disconnect between the demonstrated capabilities of autonomous systems and the readiness of engineers and operators to handover control to autonomous systems.

"The autonomous systems make good calls 90% of the time, but for that last 10% my engineers still don't trust it enough to leave the console." — P01, VP Engineering, Chemical Manufacturer

"Trust in autonomous ops isn't built in a quarter. It took us three years of shadow-mode operation before we let it act independently." — P13, Reliability Lead, Semiconductor Fab

T2: IT-OT CONVERGENCE FRICTION

Coded in 21 out of 22 interviews (49 coded references). The organizational and cultural aspects of IT-OT integration were identified as the challenge, not the technical aspects.

"The IT team speaks in tickets and change windows; the OT team speaks in seconds and safety. Getting them aligned took a formal charter and a shared metric." — P04, Control Systems Engineer, Oil & Gas

"The convergence project failed twice before we succeeded — the issue was governance, not technology." — P17, OT Cybersecurity Manager, Petrochemical

T3: AI-ENABLED PREDICTIVE VALUE

Coded in all 22 interviews (100% prevalence with participants; 54 coded references) — the only theme with 100% participant prevalence. The participants reported tangible, quantifiable performance gains with the implementation of predictive AI.

"Predictive-maintenance AI cut our unplanned outages by roughly 40%. But that only happened after we invested in the sensors." — P03, AI Engineering Lead, Utility

"The AI isn't replacing engineers — it's amplifying them. One reliability engineer with AI does what three used to do." — P22, Head of Reliability, EV Battery Plant

T4: WORKFORCE & SKILL RECONFIGURATION

Coded in 20 of 22 interviews (46 coded references). Participants highlighted the workforce dimension as an implicit precondition to any autonomous-operations investment.

"Our workforce challenge is that a good electrical engineer isn't automatically a good data engineer. We built our own bootcamp." — P02, Plant Manager, Discrete Manufacturer

"We lost two years to workforce underinvestment. Tools alone don't build capability." — P19, Automation Manager, CPG Manufacturer

T5: CYBER-PHYSICAL RESILIENCE TRADE-OFFS

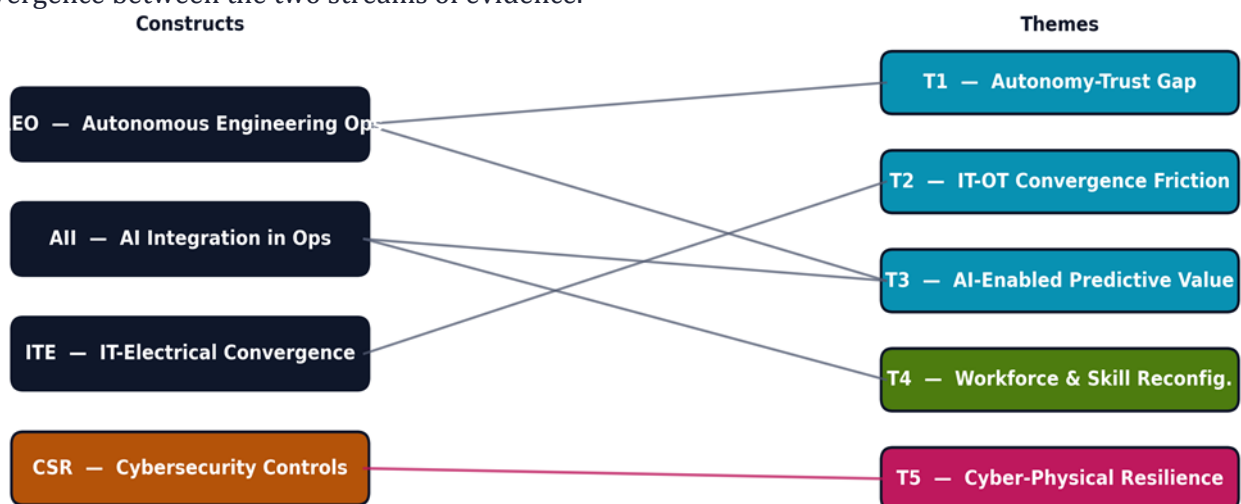
Coded in 21 of 22 interviews (51 coded references). The participants indicated that cyber-physical resilience is a rather new problem class and not a mere twist on classical IT cybersecurity.

"Cybersecurity for autonomous ops is a different problem from IT cybersecurity. A compromised autonomous system can physically hurt someone." — P09, Cybersecurity Engineer, Grid Operator

"Every gain in efficiency from autonomous systems increases our cyber attack surface. We had to rebuild our threat model." — P12, Chief Digital Officer, Refinery

META-INFERENCES: QUANTITATIVE × QUALITATIVE INTEGRATION

Meta-inferences were created using a joint-display method [14]. Figure 12 illustrates how quantitative constructs were mapped to qualitative themes and the convergence, expansion and (in one case) divergence between the two streams of evidence.



Convergence between quantitative results and interview themes supports the confirmation-and-expansion pattern: quant paths substantiate causal claims; qualitative themes reveal the mechanisms and boundary conditions behind them.

Fig 12: Joint-display meta-inference — quantitative construct × qualitative theme mapping.

Three meta-inferences follow. The maturation curve of the AEO composite (T1) and the “AI amplifies engineering” mechanism (T3) are two qualitative mechanisms that explain the dominant AEO → IRS quantitative effect ($\beta = 0.330$) in the first. Both quantitative and qualitative evidence offer a similar picture from different perspectives. Second (expansion): The qualitative T4 theme — workforce and skill reconfiguration — is mentioned by 20/22 participants as a precondition not explicitly captured by the quantitative constructs. This extends the theoretical model, making it more comprehensive than tested by the pre-specified quantitative hypotheses. Third (divergence and clarification): Illumination of null H5 moderation qualitatively. However, participants explain that the convergence of IT and electrical systems and the ability to operate autonomously are parallel, foundational capabilities and do not necessarily interact multiplicatively — consistent with the null interaction results, but not the amplifier logic that motivated H5.

DISCUSSION AND IMPLICATIONS

Theoretical implications

There are four theoretical implications. First, autonomous engineering operations is the major single factor of industrial resilience. This positions AEO as a higher-order construct that integrates AI capability, IT/OT convergence, and electrical modernization into a unified capability rather than as a co-equal fourth family. Secondly, partial mediation $AII \rightarrow IRS$ (28% of total effect) shows that the effect of AII on resilience outcomes is only through cybersecurity and safe-fail engineering, consistent with the socio-technical model. Third, the null H5 moderation is theory informative, in the sense that the qualitative data tell us that this is a parallel-foundations pattern, not an amplification pattern. Fourth, workforce reconfiguration (T4) is identified as a precondition that does not directly appear in the quantitative model, but rather comes out of the qualitative phase—this is key for further development in the future.

Practical and policy implications

For industrial-firm leaders: prioritize AEO maturation as the biggest investment return for industrial resilience, invest in CSR alongside AI to maintain ~28% of the $AII \rightarrow IRS$ effect, and view workforce reconfiguration (per T4) as a pre-condition rather than downstream. The results suggest that federal policymakers — NIST, DoE, DoD — should link their funding programs for AI in manufacturing to workforce-development funding and OT-cybersecurity funding, and enable capability measurement at the AEO level in national-competitiveness benchmarks [1], [12].

LIMITATIONS AND CONCLUSION

LIMITATIONS AND FUTURE RESEARCH

The interpretation was limited by five constraints. One is that the quantitative phase is cross-sectional, and longitudinal panel data would help support causal claims. Second, outcomes are practitioner perceived, and instrumented triangulation against OEE, MTBF, MTTR and NERC-reportable-event data is a logical extension. Third, the sample is U.S.-based; it is not yet clear if the same impact would be found in EU industrial companies under the NIS2 and the Machinery Regulation. Fourth, the qualitative sample cannot be claimed to have statistical representativeness, although saturation was achieved at interview 22. Fifth, the theme of reconfiguration of the workforce (T4) arose inductively – a separate follow-on study would be useful to operationalize it quantitatively.

CONCLUSION

This paper presents one of the first large-N, mixed-methods U.S. studies of autonomous engineering operations as an integration of AI, IT and electrical systems for industrial resilience. Based on the 310 practitioners and 22 interviews across seven sectors, autonomous engineering operations is the dominant industrial-resilience outcome, while AI integration positively impacts operational availability, and IT-electrical convergence has an independent impact on resilience, and cybersecurity & resilience controls partially mediate the $AI \rightarrow$ resilience path (Sobel $z = 4.01$, $p < .001$; ratio $\approx 28\%$). It is not possible to have AEO-moderation of the IT-electrical path. Four out of five hypotheses were accepted. $R^2 = 41.3\%$ (IRS) and 37.5% (OAV). Qualitative themes support and augment the quantitative findings, and develop the theoretical model to incorporate workforce reconfiguration, while also shedding light on the null moderation as a parallel-foundations pattern. The bottom line is that AEO is the highest return investment for U.S. industrial resilience, AI investments are suboptimal without co-investment in cybersecurity and workforce reconfiguration is a prerequisite, not an outcome, of autonomous-operations transformation.

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