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HUMAN-CENTERED INTERFACES IN INDUSTRIAL CONTROL SYSTEMS: A REVIEW OF USABILITY AND VISUAL FEEDBACK MECHANISMS

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Abstract

This study investigates how human-centered interface attributes specifically usability and visual feedback quality affect operator cognition and performance within industrial control systems (ICS) such as supervisory control and data acquisition (SCADA), distributed control systems (DCS), and programmable logic controller (PLC) environments. Drawing on theoretical foundations from human–computer interaction (HCI), situation awareness (SA), and mental workload research, the study operationalizes usability as the degree of learnability, efficiency, error tolerance, and consistency, while visual feedback quality encompasses the clarity, salience, coding, trend fidelity, and timeliness of perceptual cues presented through human–machine interfaces (HMIs). A quantitative, cross-sectional, multi-site case-based design was employed across four industrial sectors, power, petrochemical, water/wastewater, and manufacturing, with 188 operators completing validated Likert-scale instruments, including the System Usability Scale (SUS), NASA-TLX workload indices, and SA/performance batteries. Reliability and validity analyses demonstrated strong internal consistency (α ≥ .86) and discriminant coherence (HTMT < .85). Regression and mediation models, with cluster-robust standard errors by site, revealed that both usability (β = .27, p < .001) and visual feedback quality (β = .21, p = .002) significantly predicted self-reported performance, accounting for 34% of its variance. Mediation analyses confirmed that improvements in usability and visual feedback enhanced situation awareness and reduced workload, which in turn elevated performance, with the SA pathway explaining the larger share of the indirect effects (≈36–39%) and workload accounting for smaller but meaningful contributions (≈11–13%). A significant interaction (β = .11, p = .011) indicated complementarity: each attribute produced greater performance benefits when the other was simultaneously strong, underscoring the synergistic nature of usability and perceptual clarity in human–machine interaction. Collectively, the findings advance an empirically validated framework linking interface design attributes to cognitive and behavioral outcomes in safety-critical operations. The study concludes that integrating usability optimization, visual feedback rationalization, and standardized measurement systems can measurably enhance operator awareness, reduce cognitive load, and improve performance reliability across diverse ICS domains, while calling for longitudinal, multi-modal research to capture dynamic and team-level adaptations in future studies.

Keywords

industrial control systems, human-machine interface usability, visual feedback, situation awareness, mental workload.

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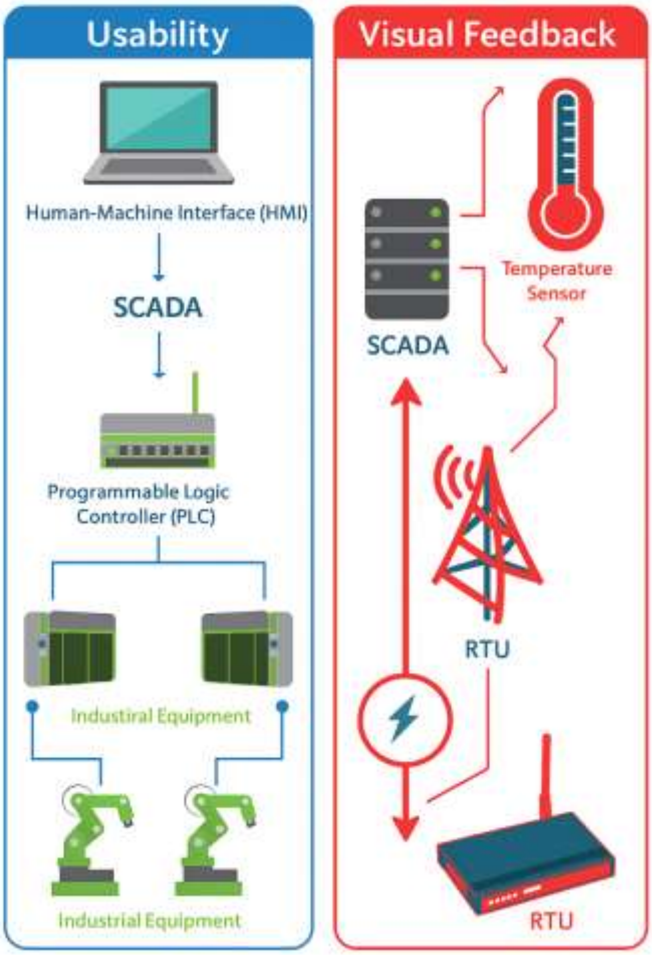
INTRODUCTION

Industrial control systems (ICS) including supervisory control and data acquisition (SCADA), distributed control systems (DCS), and programmable logic controller (PLC) environments rely on human–machine interfaces (HMIs) as the primary locus where human cognition, organizational procedures, and process automation meet. In human–computer interaction (HCI), usability is commonly defined as the extent to which specified users can use a product to achieve specified goals with effectiveness, efficiency, and satisfaction in a specified context of use, a construct that maps directly to control-room realities of time pressure, safety, and reliability(Bangor et al., 2008). Within ICS, usability is tightly coupled to visual feedback mechanisms the real-time perceptual cues (e.g., color, shape, motion, alarm salience, trend plots) that help operators perceive states, comprehend meaning, and project future system behavior. Theoretical lenses from situation awareness (SA) and mental workload research clarify why these attributes matter: interfaces that improve SA and calibrate workload tend to support faster error detection and more stable performance under abnormal situations (Endsley, 2015b).

Figure 1: Human–Machine Interface (HMI) Usability inIndustrial Control Systems (ICS)



Over the last two decades, empirical and review studies have refined SA measurement for complex systems (Chatterjee et al., 2017), validated practical usability instruments (Bangor et al., 2008), and connected alarm design to operator performance in process industries (Jiang et al., 2018). Collectively, this body of work motivates a quantitative examination in ICS contexts: to what extent do usability and visual feedback quality co-vary with SA, perceived workload, and task performance in real facilities? By anchoring on validated constructs and focusing on embedded case settings, the present study positions HMI usability and visual feedback as measurable design levers rather than abstract ideals, enabling hypothesis testing via descriptive statistics, correlations, and regression models with operator-level outcomes captured on Likert five-point scales (Bangor et al., 2008; Jiang et al., 2018; Kline, 2011).

Defining visual feedback mechanisms in ICS demands precision because perceptual variables are not cosmetic they encode process state, risk, and priority. Visual channels such as color (e.g., red/yellow/green priority coding), shape and iconography (e.g., valve states), motion/animation (e.g., pulsing alarms), and spatiotemporal displays (e.g., strip charts, heat maps, trend horizons) modulate how quickly and accurately operators perceive and integrate information (O'Donnell & Eggemeier, 2009). Studies on alarm design show that salience and signal-to-noise control reduce alarm flooding and speed diagnosis, particularly when alarm rate, priority distribution, and persistence are tuned to human limits (Sanjid & Farabe, 2021; Spinola et al., 2018). In user-interface evaluation, validated scales like the System Usability Scale (SUS) and the NASA-TLX for workload provide compact, reliable metrics for surveying large operator samples in working plants (Aziz et al., 2016; Zaman & Momena, 2021). Evidence from complex domains similar to ICS aviation, energy, and process operations indicates that improved perceptual discriminability and consistent coding schemes support higher SA (Level 1 perception and Level 2 comprehension), which in turn predicts fewer missed cues and faster responses (Endsley, 2015a; Rony, 2021). Within this framing, visual feedback quality is operationalized as the clarity, consistency, and timeliness of perceptual cues and data summarization used in HMIs (e.g., distinct alarm tiers; readable, context-rich trends; latency appropriate to process dynamics). When aligned with usability heuristics such as error tolerance and consistency, high-quality visual feedback should correlate with higher SA, lower perceived workload, and better self-reported performance in routine and upset conditions measured cross-sectionally in embedded case sites (Kortum & Peres, 2014; Sudipto & Mesbaul, 2021).

From an international standpoint, ICS span electricity grids, petrochemical complexes, water and wastewater systems, discrete and hybrid manufacturing, and critical transport infrastructure; across these domains, the human operator remains the adaptive layer that reconciles automation with unexpected variability. Cross-regional empirical work shows that HMI design conventions vary by sector and vendor ecosystem, but operator cognition challenges alarm deluge, mode awareness, trend interpretation, and handover communication are recurrent (Abdi et al., 2012; Zaki, 2021). Quantitative investigations in energy and process industries consistently report that usability factors (learnability, efficiency, error recovery) and perceptual clarity in dashboards predict facets of operator performance, often mediated by SA and workload (Hart, 2006; Jiang et al., 2018). Moreover, research on interaction techniques for example, the use of overviews and detail-on-demand, spatial grouping, and consistent alarm tiering suggests measurable gains in error detection and time-to-diagnosis when visual mappings align with operator mental models (Trafton et al., 2013). These studies justify a cross-sectional, case-based design that samples operators in live facilities and quantifies relationships among usability, visual feedback quality, SA, workload, and self-reported performance using validated scales and regression modeling. By focusing on embedded cases rather than lab settings, the design captures international variability (e.g., shift structures, training regimes, alarm philosophies) while maintaining statistical identifiability through construct reliability, discriminant validity checks, and common-method bias controls (Hozyfa, 2022; Lewis, 2018). These methodological guardrails enable inference about direct effects and plausible mediation paths, building an empirical basis for understanding how human-centered interface attributes co-relate with operator outcomes in safety-critical ICS contexts across diverse national settings (Arman & Kamrul, 2022; Salmon et al., 2008).

Internationally, industrial control systems (ICS) form the operational substrate of critical infrastructures such as power generation and transmission, petrochemical refining, water and wastewater treatment, and discrete and hybrid manufacturing; across these domains, the human–machine interface (HMI) is the point at which perception, comprehension, and action are coordinated under time pressure. Empirical alarm-management research indicates that the configuration of visual feedback priority coding, persistence, rate of change cues, and trend visibility modulates operator ability to detect, diagnose, and respond to deviations, particularly during abnormal or transition conditions when alarm density increases (Mohaiminul & Muzahidul, 2022; Salmon et al., 2008). Complementary work in cognitive engineering and display design shows that predictive information in process schematics and overviews supports earlier recognition of trajectory shifts, a mechanism consistent with Level 2–3 situation awareness (SA) where comprehension and projection govern

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decision selection (Omar & Ibne, 2022; Pfautz & Roth, 2006). Measurement traditions from human factors travel well into this setting: the NASA-TLX offers a compact, multi-dimensional index of mental workload that is sensitive to display-induced cognitive demand, and the System Usability Scale (SUS) provides a reliable global usability score that can be benchmarked across heterogeneous interfaces, aiding cross-site comparison in large, embedded case samples (Bangor et al., 2008; Sanjid & Zayadul, 2022). Meanwhile, theoretical debates around SA spanning individual vs. distributed conceptions do not negate the practical utility of structured visual feedback aligned to human perceptual limits; rather, they sharpen construct clarity and motivate measurement triangulation that includes SA ratings alongside performance and workload (Endsley, 2015a; Hasan, 2022). Against this backdrop, an internationally relevant, quantitative, cross-sectional investigation into the links between HMI usability, visual feedback quality, SA, workload, and operator performance can be specified with validated scales and regression models, enabling interpretable effect estimates that transcend vendor- or sector-specific idiosyncrasies (Mominul et al., 2022; Podsakoff et al., 2007).
Definitional clarity for usability and visual feedback quality supports coherent operationalization in ICS surveys. Usability is treated as effectiveness, efficiency, and satisfaction within a specified context of use, typically decomposed into learnability, efficiency, error tolerance, and consistency (Sauro & Lewis, 2012). Visual feedback quality encompasses the *clarity*, *consistency*, and *timeliness* of perceptual cues color/shape/iconography for status and alarms, motion/pulsing for urgency, and temporally faithful trend plots that represent process dynamics with appropriate refresh and scale (Abdi et al., 2012; Rabiul &Praveen, 2022). In applied settings, poor salience control and alarm floods saturate attentional resources, elevating workload and degrading SA; conversely, rationalized alarm tiers, discriminable encodings, and stable trend overviews reduce search and integration costs (Jiang et al., 2018). Psychometric tools provide the glue between constructs and analysis: SUS yields a robust single-score indicator with strong reliability across interface types, making it suitable for multi-plant sampling frames, while NASA-TLX captures the mental demand and temporal pressure that HMIs can amplify or mitigate (Bangor et al., 2008; Farabe, 2022). SA can be indexed with survey items aligned to perception–comprehension–projection, which mediate the path from interface qualities to outcomes such as error frequency or self-reported task efficacy (Endsley, 2015b; Roy, 2022). Because measurement artifacts can inflate correlations in single-source surveys, procedural design (anonymity, varied item tone, short scales) and statistical diagnostics (e.g., Harman's single-factor screen; marker-variable checks) are incorporated to guard against common-method bias and to support construct validity via reliability, convergent (CR/AVE), and discriminant criteria (Podsakoff et al., 2007). With these definitions and safeguards, the constructs become empirically tractable for cross-sectional modeling in ICS contexts.
The conceptual framework links usability and visual feedback quality to operator outcomes through established cognitive pathways. Multiple resource theory posits that tasks compete across code, modality, and stage resources; HMIs that compress search, provide consistent mappings, and utilize discriminable codes demand fewer shared resources under load (Rahman & Abdul, 2022; Wickens, 2008). From an SA perspective, improved perceptual discriminability and context-rich displays enhance Level 1 (perception) and Level 2 (comprehension), while stable, predictive cues rate-of-change, horizon markers facilitate Level 3 (projection) (Bangor et al., 2008; Razia, 2022). In aggregate, these mechanisms predict lower subjective workload and higher operator performance, with SA and workload serving as mediators between interface attributes and outcomes. Quantitatively, direct effects of usability and visual feedback on performance are estimated, followed by mediation models that test indirect paths through SA and workload, and an interaction term that evaluates whether jointly high usability and high visual feedback quality yield complementary performance benefits (Chatterjee et al., 2017; Zaki, 2022). Given site-level heterogeneity (e.g., sectors, shift patterns, training), controls and cluster-robust standard errors stabilize inference (Kline, 2011). The framework accommodates critiques that emphasize distributed or socio-technical manifestations of SA by anchoring on operator-reported SA (and workload) as proximal cognitive states influenced by display design, without claiming exhaustiveness of system-level coupling (Stanton et al., 2010; Kanti & Shaikat, 2022). Alarm-management studies in process industries further ground the model, demonstrating that rationalization and salience policies shape the very variables the framework posits as mediators (Williams et al., 2010). As such, the framework translates theory into measurable relationships amenable to regression-based hypothesis testing within embedded ICS case sites.

Methodologically, a cross-sectional, case-study–based design balances ecological fidelity with statistical identifiability. The unit of analysis is the individual operator nested within plants or control rooms, enabling control of contextual variability through site dummies and cluster-robust errors, while preserving operator-level variance for model estimation (Kline, 2011). The questionnaire comprises established scales SUS for usability; an item set for visual feedback quality keyed to alarm salience, coding, and trend clarity; SA items aligned to perception/comprehension/projection; a short NASA-TLX subset for workload; and a brief operator-performance battery (Bangor et al., 2008). Content validity is supported through expert elicitation and pilot testing; construct validity is assessed via reliability (α, CR), convergent (AVE), and discriminant (HTMT) checks; and common-method bias is mitigated procedurally and evaluated statistically (Podsakoff et al., 2007). The analysis plan proceeds from descriptives and correlations to three regressions: Model A estimates direct effects of usability and visual feedback on performance; Model B tests mediation via SA and workload; Model C adds the interaction of usability × visual feedback to assess complementarity, with bootstrap resampling for indirect effects (Bangor et al., 2008). This plan aligns with contemporary HCI/HFE practice in complex systems and leverages a literature base that spans measurement (SUS, NASA-TLX), cognitive theory (multiple resources, SA), and domain-specific alarm research in process industries (Abdi et al., 2012). Taken together, the introduction positions the study to quantify how human-centered interface attributes relate to operator cognition and performance in ICS, using validated constructs, internationally relevant cases, and regression-based evidence.
The objective of this study is to quantify how human-centered interface attributes in industrial control systems specifically, usability and the quality of visual feedback relate to operator situation awareness, perceived workload, and self-reported performance within real control-room environments. To accomplish this, the research first aims to operationalize usability and visual feedback as survey constructs suitable for embedded, multi-site case settings, using concise items that capture learnability, efficiency, error tolerance, consistency, alarm salience, coding clarity, trend visibility, and feedback timeliness on a five-point Likert scale. The second objective is to develop and confirm a reliable measurement structure for these constructs and for the proximal cognitive states of situation awareness and workload, ensuring internal consistency, convergent coherence, and discriminant distinctness prior to hypothesis testing. The third objective is to estimate the direct effects of usability and visual feedback on operator performance through hierarchical regression models that include relevant controls such as experience, role, shift type, training exposure, sector, and system class, while accounting for site-level clustering. The fourth objective is to test mediation pathways in which situation awareness and workload transmit the influence of interface attributes to performance, using bootstrapped indirect effects to obtain robust confidence intervals for the proposed mechanisms. The fifth objective is to examine whether usability and visual feedback operate synergistically through an interaction term, evaluating whether concurrently high values on both dimensions are associated with additional performance benefits beyond their separate contributions; simple-slopes and interaction-plot analyses will be used to interpret any such complementarity. The sixth objective is to conduct assumption checks and sensitivity analyses including multicollinearity diagnostics, residual inspections, and robustness to alternative specifications such as near-miss proxies for performance and stratified analyses by shift so that inferences remain stable under plausible variations in modeling choices. A final objective is to produce a transparent, practitioner-ready codebook mapping constructs to items, scoring rules, and variable labels, alongside a reproducible analysis workflow that enables consistent application across plants and sectors. Collectively, these objectives define a focused, quantitative agenda that links interface design qualities to operator cognition and performance in a manner that is empirically testable, comparable across sites, and suitable for informing systematic improvements within industrial human-machine interfaces.

LITERATURE REVIEW

The literature on human–machine interfaces (HMIs) in industrial control systems (ICS) spans several intersecting traditions human–computer interaction, cognitive engineering, alarm management, and process safety each emphasizing how interface qualities shape operator cognition and performance. Foundational work on usability establishes effectiveness, efficiency, learnability, error tolerance, and consistency as practical design levers that can be measured and compared across heterogeneous control environments. In parallel, research on visual feedback mechanisms details how perceptual variables such as color and shape coding, salience of alarms, motion or pulsing to convey urgency, and the fidelity of time-series trends govern the speed and accuracy with which operators perceive states, integrate cues, and select actions under time pressure. Across domains allied to ICS (energy, petrochemical processing, and discrete manufacturing), studies repeatedly link clearer perceptual discriminability and consistent mapping to higher situation awareness and lower mental workload, with downstream associations to reduced error incidence and tighter process control. Yet, much of the available evidence is fragmented across case descriptions, vendor-specific guidelines, and small-sample experiments, creating a need for synthesized constructs and scalable metrics that can travel across plants, sectors, and shift regimes. Measurement traditions from usability and workload research provide that portability through compact, validated scales and structured item banks, while alarm-management studies contribute domain-specific insights on prioritization logic, rate-of-change indicators, and interface clutter. Recent conceptual models frame usability and visual feedback as upstream interface attributes that act on outcomes indirectly by shaping operator situation awareness and cognitive load; this view encourages regression-based tests of direct, mediated, and potentially interactive effects in embedded field settings. At the same time, concerns about single-source bias and construct overlap have led to clearer operational definitions, attention to discriminant validity, and procedural safeguards in survey design. Taken together, the literature motivates an integrative review that consolidates definitions, traces the theoretical pathways linking interface qualities to operator outcomes, and evaluates the strength and consistency of quantitative findings in real ICS contexts. This review sets the stage for a case-based, cross-sectional investigation that treats human-centered interface design as an empirically tractable, measurable driver of operator cognition and performance in safety-critical industrial environments.

Human–Computer Interaction Foundations for ICS Usability

Human–computer interaction (HCI) provides the conceptual and methodological backbone for analyzing how industrial control system (ICS) operators perceive, interpret, and act on interface cues under routine and abnormal conditions. A core tenet in HCI is that usability must be measured not merely asserted through constructs such as effectiveness, efficiency, and satisfaction, alongside performance and cognitive outcomes. Yet, what and how we measure often shape the conclusions we reach. A seminal review of 180 HCI studies mapped widespread inconsistencies in operationalizing usability, warning that ill-specified measures can mask real design problems or inflate weak effects (Hornbæk, 2006). For ICS, these concerns are magnified by safety, time pressure, and distributed displays, where latency in comprehension or misinterpretation can escalate into incidents. Accordingly, usability assessment in control rooms benefits from combining outcome metrics (e.g., error rate, time-to-detect) with cognitive indicators (e.g., workload, situation awareness) and experience ratings that capture the operator's interaction "quality." The NASA-TLX meta-analysis offers practical benchmarking for interpreting workload scores across tasks and domains, helping ICS researchers distinguish meaningful workload changes attributable to interface redesigns from noise or sampling artefacts (Grier, 2015). This measurement perspective complements engineering verification by treating the operator's cognitive economy as a performance resource one that interfaces can conserve or squander. As ICS environments grow in scale and data density, the HCI imperative is not just to present more data, but to convert it into perceptually and cognitively tractable information aligned with operators' goals, diagnostic strategies, and temporal horizons.

Within process industries, interface form dictates the pace and reliability of situation awareness (SA) formation. Evidence from comparative display research shows that "what is displayed" and "how it is organized" both matter for maintaining the global picture operators need before alarms proliferate. Functional overview displays which group indicators by process functions and embed qualitative, direct-perception graphics have been shown to outperform traditional piping-and-instrumentation (schematic) layouts on SA, subjective workload, and usability judgments during process monitoring tasks (Braseth & Øritsland, 2013). The functional approach reduces mental translation by externalizing higher-level relationships and trends, thereby shortening the pathway from signal to diagnosis. In parallel, domain-specific SA research in the process industries has underscored that SA is not a generic "awareness" but a situated, evolving state tightly coupled to interface design and team coordination. Nazir, Colombo, and Manca (2012) characterize SA for field and control-room operators as contingent on the interface's support for perceiving key variables, integrating causal structure, and projecting near-term state evolution design demands that exceed simple numeric readouts or dense mimic diagrams. These findings help explain why

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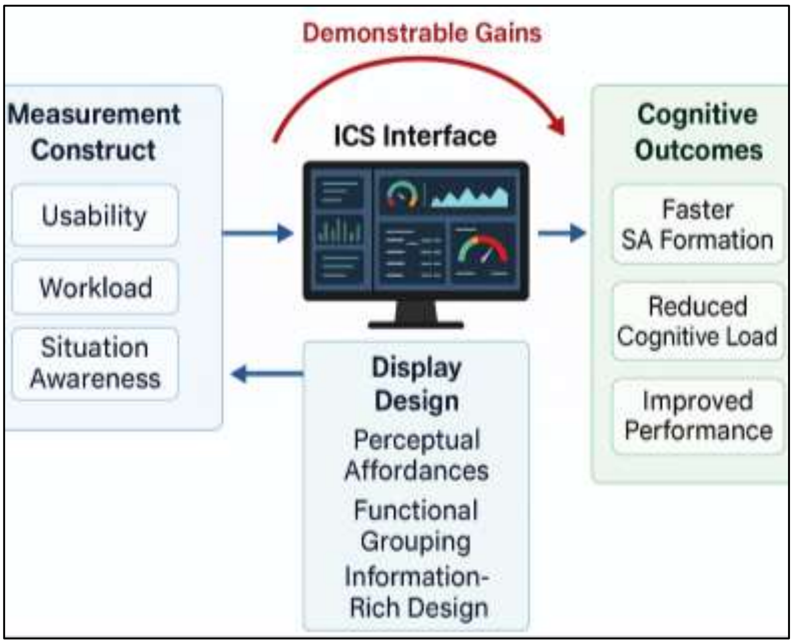
merely enlarging or multiplying displays is insufficient: without principled visual organization and information abstraction, additional pixels risk adding clutter rather than clarity. From an HCI standpoint, high-value ICS interfaces therefore privilege perceptual affordances (e.g., preattentive coding, trend abstraction), functional grouping, and graded salience that guide attention to what matters now, while keeping the broader process narrative legible.

Figure 2: Linking Usability Measurement, Display Design, and Cognitive Outcomes



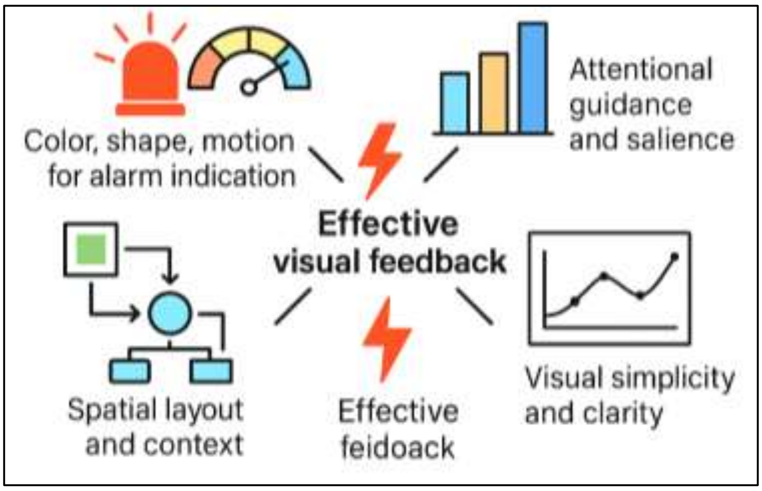
A second, complementary foundation concerns multi-display cognition and the ergonomics of large-screen or wall-scale overviews that share the "big picture" across a crew. Research on information processing across multiple displays demonstrates that fragmentation imposes coordination costs on attention and working memory; layouts that minimize cross-display switching and reduce mental integration burdens improve throughput and decision reliability (Johnston et al., 2014). For ICS control rooms, Information-Rich Design (IRD) principles translate these cognitive insights into concrete visual strategies alignment, gestalt grouping, qualitative status glyphs, and layered detail to support rapid global assessments, anomaly spotting, and drill-down without losing context (Braseth & Øritsland, 2013). Crucially, these visual ergonomics dovetail with measurement practice: pairing interface trials with standardized workload norms (Grier, 2015; Johnston et al., 2014) and triangulating with performance/SA outcomes yields interpretable evidence that a display truly strengthens operator cognition rather than simply looking modern. In short, HCI equips ICS researchers with two synergistic levers measurement discipline and cognitively grounded display design. When applied together, they enable interfaces that "buy down" cognitive load, accelerate SA, and stabilize cooperative control, moving beyond aesthetics to demonstrable gains in safety and efficiency (Nazir et al., 2012).

Visual Feedback Mechanisms in Industrial HMIs

Effective visual feedback in industrial HMIs refers to the precise orchestration of graphical cues color, shape/iconography, motion, spatial layout, and temporal rendering of process change so that operators can perceive state, comprehend meaning, and anticipate near-term evolution in real time. In alarm-centric moments, the interface is the primary medium through which urgency, priority, and causal context are communicated. Two robust findings guide design here. First, auditory/visual alarms must be perceptually discriminable and consistently coded; muddled mappings or excessive similarity between alerts slow recognition and raise the likelihood of misses or masking. Second, high volumes of low-value alerts degrade attention and foster desensitization ("alarm fatigue"), undermining the very vigilance HMIs aim to support. Although much of the empirical base comes from safety-critical healthcare, the mechanisms are general to any high-tempo control setting:

poorly prioritized or ambiguously coded alerts saturate limited attentional resources, while well-structured codes, graded salience, and concise context restore attentional economy and shorten detection-to-diagnosis time (Cvach, 2012). For process control rooms, this translates into conservative color palettes for normal operation, strong contrast for abnormal states, limited use of animation to signal escalation, and compact views that link alarms to proximal process variables. The overarching purpose of visual feedback, then, is not to "decorate" data but to choreograph attention: to direct the operator first to what matters most, then to the minimal additional context needed for a confident action. This paragraph is anchored in established evidence that human performance deteriorates when alarm ecosystems are noisy or semantically opaque, and improves when code sets and priority schemes respect human perceptual limits (Edworthy & Hellier, 2006).

Figure 3: Visual Clarity for Effective Operator Performance



Preattentive and attentional guidance theories explain why some visual encodings "pop" and others demand laborious search. Before conscious scrutiny begins, the visual system rapidly computes contrasts along features such as hue, luminance, size, orientation, and motion; elements that strongly differ from their surround become salient, accelerating localization and initial classification. This early stage is measurable in human electrophysiology and behavior: increased feature contrast shortens preattentive processing and speeds responses, while high target–distractor similarity slows both selection and decision (Töllner et al., 2011). Beyond raw feature contrast, search guidance in real displays is governed by a small set of factors bottom-up salience, top-down goals, scene structure/meaning, history of prior searches, and learned value whose joint configuration determines whether operators find the relevant signal quickly or waste cycles scanning uninformative regions. In control-room contexts, these principles argue for encodings that (a) reserve the strongest contrasts for genuinely abnormal conditions, (b) maintain stable spatial structure so scene guidance remains reliable, and (c) support top-down search with consistent legends and proximity of labels to data. When trend panels, gauges, and alarm banners are designed with those factors in mind, operators can triage more effectively, sustaining situation awareness with lower subjective workload. Conversely, designs that scatter cues, overuse saturated color, or reset layouts across screens break scene guidance and erode learned histories, forcing costly reorientation on every switch. The science of attentional guidance therefore provides a mechanistic basis for calibrating visual feedback intensity, distribution, and semantics in HMIs serving time-critical industrial processes (Cvach, 2012; Edworthy & Hellier, 2006).
A final design concern is visual economy the balance between information density and perceptual clarity. In dense control environments, designers may be tempted to embellish with gradients, textures, or skeuomorphic knobs to convey richness or "realism." Empirical visualization research cautions that decorative embellishment often trades short-term appeal for reduced analytic efficiency: while certain ornaments can aid memory for a static graphic, they also add clutter, compete with meaningful contrast, and slow precise reading when rapid discrimination is required (Bateman et al., 2010). For industrial HMIs, where seconds matter and repeated reads are common,

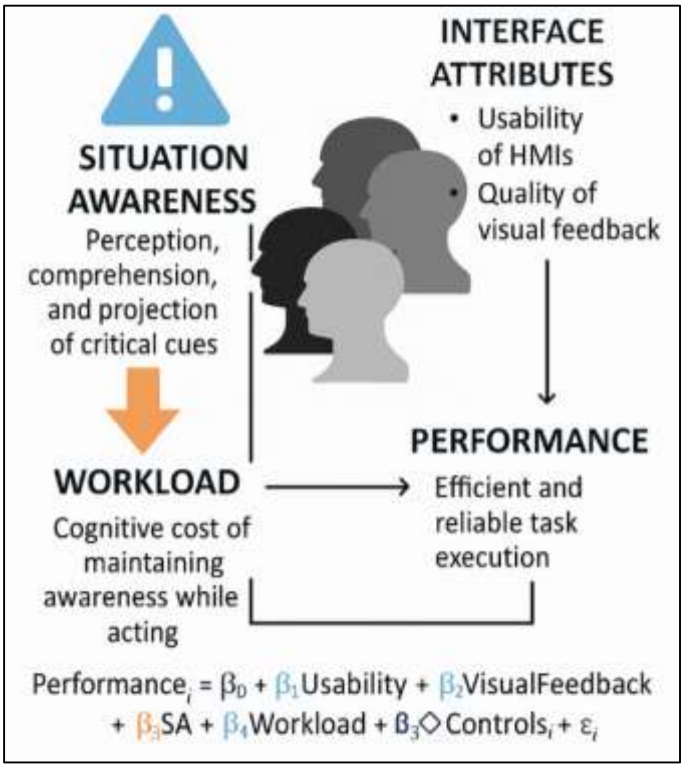
the safest path is to allocate contrast to semantics (priority, deviation, rate-of-change) and minimize non-semantic decoration. Practically, this means legible typography at stable positions; restrained, monotone backgrounds to preserve luminance headroom; thin visual hierarchies that stage detail on demand; and trend panels whose scales and horizons reflect process dynamics rather than arbitrary defaults. It also means limiting motion to escalation states so that animation retains high informational value, and aligning color sets with a small, learned codebook that remains invariant across screens. When such choices are paired with disciplined alarm thresholds and proximity coupling placing alarms adjacent to the variables and valves they implicate operators can move from glance to grounded hypothesis with fewer fixations and less working-memory load. The principle is straightforward: every pixel must earn its place by speeding perception or reducing inference. Visual feedback that adheres to that rule is more than attractive it is measurably safer and more usable in the crucible of industrial operations (Bateman et al., 2010; Cvach, 2012; Wolfe & Horowitz, 2017).

Performance with clarifying Situation Awareness (SA)

Understanding operator outcomes in industrial control rooms begins with clarifying situation awareness (SA) as a dynamic cognitive state that integrates perception of critical cues, comprehension of their meaning, and projection of near-term system evolution in time-pressured contexts. In complex supervisory settings, SA is not a generic "awareness," but a task-bound construct that emerges from the coupling of interface design, operator goals, and unfolding process behavior. Research on decision making under dynamic uncertainty shows that operators form and revise mental models while sampling imperfect, delayed, or noisy signals; these models guide both attention and action selection, thereby shaping downstream performance (Gonzalez, 2005). Because control rooms demand continual updating, SA is inherently resource-limited operators must allocate scarce perceptual and working-memory resources to high-value cues and ignore distractors. When visual feedback clarifies priorities, aligns encodings with expectations, and preserves stable scene structure, operators can extract the "gist" quickly and maintain global SA while diagnosing local anomalies. Conversely, when visual feedback is cluttered, inconsistent, or latency-prone, SA can collapse into fragmented perception, forcing costly resampling cycles and increasing the risk of delayed or incorrect responses. Evidence from remote and teleoperated domains further indicates that SA quality covaries with how well displays externalize causal structure and provide timely, discriminable indicators of change; under such conditions, operators sustain more coherent narratives about the plant's current state and likely trajectories, a prerequisite for resilient performance during abnormal events (Ma & Kaber, 2007). In short, SA in control rooms is cognitively expensive, highly sensitive to how information is rendered, and foundational for explaining variance in operator outcomes that extends beyond raw experience or training exposure (Hauland, 2008).

If SA describes *what operators know and anticipate*, mental workload captures *what it costs* to maintain that awareness while acting. Contemporary workload syntheses emphasize that workload is multidimensional (mental demand, temporal pressure, effort, frustration) and that its relationship to performance is nonlinear: both overload and underload can degrade vigilance, calibration, and control precision (Young et al., 2015). Vigilance research is particularly instructive for control rooms: sustained monitoring under either sparse or noisy signal environments taxes executive control, and elevated workload is reliably associated with the classic vigilance decrement slower detection and more misses over time (Helton & Warm, 2008). Critically, psychometric studies show that different workload indicators (subjective ratings, physiological indices, and performance-based proxies) are sensitive but divergent, capturing overlapping yet distinct facets of cognitive cost (Matthews et al., 2015). For ICS measurement, this implies two design imperatives. First, interfaces must buy down workload by compressing search, preserving spatial memory with stable layouts, and reserving strong visual contrasts for genuinely abnormal states so that scarce resources can be applied to diagnosis rather than display management. Second, analysts should expect imperfect convergence across workload measures and therefore plan for triangulation. In a regression context, workload's role is often mediational: if usability and visual feedback improve SA while reducing workload, part of their performance benefit operates indirectly through the workload channel. This aligns with a resource-rational view of control-room cognition: when perceptual encodings and task flows respect human constraints, operators can sustain SA at a lower marginal cost, reserving capacity for anomaly resolution rather than routine state confirmation (Young et al., 2015).

Figure 4: Performance through Interface Usability and Visual Feedback Quality



In addition, operator performance in ICS can be modeled as a function of interface qualities and proximal cognitive states, enabling explicit tests of direct and indirect pathways. A practical specification treats performance for operator *i* as:

$$Performance_i = \beta_0 + \beta_1 Usability_i + \beta_2 VisualFeedback_i + \beta_3 SA_i + \beta_4 Workload_i + \beta_5^{T} Controls_i + \varepsilon_i,$$

where controls may include experience, role, shift, sector, and site effects. To examine mechanisms, a mediation framework evaluates whether interface attributes act through SA and workload, using the standard indirect-effect identity c = c′ + ab, where a is the effect of an interface attribute (e.g., usability) on a mediator (e.g., SA), b is the mediator's effect on performance, c is the total effect, and c′ is the direct effect after accounting for the mediator. In supervisory and teleoperation studies, SA-supportive displays and attention-guiding layouts have been associated with higher task throughput and fewer detection failures, consistent with positive ab pathways via SA, while clutter-reduction and priority-consistent coding are associated with lower subjective workload, consistent with negative ab pathways via workload (Ma & Kaber, 2007). Because workload-performance links can invert at extremes, analysts should also probe for curvilinear components (e.g., adding Workload^2) and perform sensitivity checks for vigilance-related time-on-task effects (Hauland, 2008). Complementing these models, team-level SA research shows that when displays scaffold a shared big picture aligning individual SA into team SA coordination improves and error propagation declines, strengthening the bridge from interface design to collective performance (Helton & Warm, 2008). Together, these strands support a quantitative logic: visual and interaction design shape SA and workload; SA and workload, in turn, condition the efficiency and reliability of operator performance in safety-critical industrial environments (Gonzalez, 2005; Ma & Kaber, 2007; Matthews et al., 2015).

Theoretical and Conceptual Framework

The theoretical framework for this study positions usability and visual feedback quality as upstream interface attributes that shape operator outcomes through two proximal cognitive pathways: situation awareness (SA) and mental workload. Conceptually, SA is treated as a multilevel construct perception, comprehension, and projection whose direct measurement has been shown to be both practically useful and psychometrically defensible when tied closely to task demands and display content (Endsley, 2017). Because modern control rooms are inherently collaborative, the framework considers that individual SA aggregates within teams (e.g., controllers and supervisors) into a

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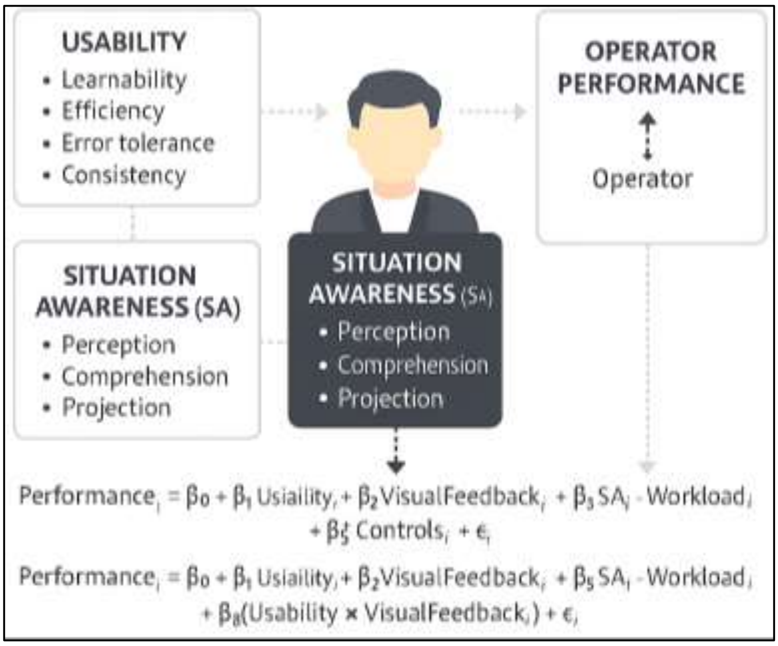
coordinated, team-level SA that supports resilient diagnosis and action selection in time-pressured contexts; empirical work demonstrates that team SA can be systematically assessed (e.g., via synchronized probes and shared display cues) and that it covaries with coordination quality and error containment (Gorman et al., 2006). Within this view, usability (learnability, efficiency, error tolerance, consistency) and visual feedback (salience, coding, trend fidelity, refresh appropriateness) influence how rapidly and accurately SA is formed and maintained, while simultaneously modulating workload by compressing search, stabilizing scene structure, and aligning codes with expectations. The framework therefore anticipates a pattern of direct effects from usability and visual feedback to performance, plus indirect (mediated) effects operating through SA (positive pathway) and workload (negative pathway). Put differently, interfaces that enable operators to "grasp the gist" at a glance and drill into details without losing context should yield higher SA at lower marginal cognitive cost, thereby improving self-reported performance and reducing error-prone rework even when tasks are dynamic and abnormal conditions emerge (Endsley, 2017; Gonzalez, 2005; Gorman et al., 2006).

Figure 5: Operator Performance in Industrial Control Systems (ICS)



Formally, the empirical model specifies operator *i*'s performance as a function of interface attributes and proximal states:

$$\text{Performance}_i = \beta_0 + \beta_1\text{Usability}_i + \beta_2\text{VisualFeedback}_i + \beta_3\text{SA}_i + \beta_4\text{Workload}_i + \beta_5^{\mathrm{T}}\text{Controls}_i + \varepsilon_i.$$

To evaluate mediation, the framework estimates (a) paths from interface variables to mediators and (b) paths from mediators to performance, using nonparametric bootstrap procedures to obtain confidence intervals for the indirect effect ab; the total effect c decomposes into the direct effect c′ plus the indirect component: c = c′ + ab (Preacher & Hayes, 2008). Because usability and visual feedback may be complementary, the framework also includes an interaction term:

$$\text{Performance}_i = \beta_0 + \beta_1\text{Usability}_i + \beta_2\text{VisualFeedback}_i + \beta_3\text{SA}_i + \beta_4\text{Workload}_i + \beta_5^{\mathrm{T}}\text{Controls}_i + \beta_6(\text{Usability}_i \times \text{VisualFeedback}_i) + \varepsilon_i,$$

where tildes denote mean-centered predictors to aid interpretation and reduce collinearity in product terms. Diagnostics follow best practice, with variance inflation factors used to monitor multicollinearity; blanket "rules of thumb" (e.g., VIF ≤ 10) can be misleading, so interpretation emphasizes context and model purpose (O'Brien, 2007). If workload–performance relations show curvature (overload or underload), the model can be extended with a quadratic term for workload, while robustness checks incorporate cluster-robust standard errors by site and alternative dependent variables (e.g., near-miss proxies). Finally, because control rooms often involve shared displays and cross-checks, the framework includes exploratory models at the team SA level (e.g., aggregated SA within shifts) where data permit, preserving the core mediation logic but acknowledging that some variance is shared across operators working from the same visual ecology (Gorman et al., 2006). Translating the framework into measurable design levers requires linking visual encoding choices to human perceptual limits so that SA can be constructed quickly and reliably. Empirical work in graphical perception demonstrates that not all encodings support equally precise and rapid judgments; discriminability and estimation accuracy vary systematically with the mapping (e.g., position and length outperform area and color for many quantitative tasks), and these differences hold at scale when assessed with behavioral experimentation (Heer & Bostock, 2010). In practice, the framework operationalizes visual feedback quality as the clarity, consistency, and timeliness of encodings that communicate (i) priority (graded salience and minimal alarm masking), (ii) deviation and rate-of-change (trend fidelity with appropriate horizons), and (iii) causal context (spatial proximity of alarms to implicated variables). Within the statistical model, these choices are reflected in higher scores on the visual-feedback construct, which, by design, should predict faster SA formation (positive β3 pathway) and lower workload (negative β4 pathway), thereby increasing performance through both direct and indirect routes (Hauland, 2008; Preacher & Hayes, 2008). Because team operations hinge on a shared big picture, the framework also anticipates that well-designed overviews stable layouts, consistent legends, and judicious use of high-contrast cues will improve team SA convergence when operators coordinate around the same display ecology (Helton & Warm, 2008; Ma & Kaber, 2007). Summarizing, the conceptual model integrates measurement validity for SA, principled treatment of mediation and interaction, attention to estimator diagnostics, and perceptually grounded display design yielding a coherent, testable account of how human-centered interface attributes influence operator cognition and performance in industrial control rooms (Hauland, 2008).

METHOD

The methodology has been designed to quantify relationships between human-centered interface attributes and operator outcomes in live industrial control environments while preserving ecological validity. A quantitative, cross-sectional, case-study–based approach has been adopted, in which individual operators have constituted the unit of analysis and have been nested within participating sites to reflect shared contextual factors. The instrument has comprised concise, pretested scales that have captured usability (learnability, efficiency, error tolerance, consistency) and visual feedback quality (alarm salience, coding clarity, trend fidelity, feedback timeliness), alongside proximal cognitive states situation awareness and mental workload and a brief self-reported performance battery. All items have been anchored on a five-point Likert scale to facilitate comparability and model estimation. Content validation procedures with domain experts have been conducted, and a pilot administration has been completed to check clarity, timing, and preliminary reliability. Sampling has targeted control-room operators, supervisors, and field personnel who have interacted with HMIs during routine and abnormal operations; inclusion criteria and response tracking have been specified to document coverage across shifts, roles, and sectors. Data collection has followed standardized administration protocols that have safeguarded anonymity and minimized disruption to operations. Data management procedures have been established prior to analysis: responses have been screened for completeness, inconsistent patterns have been flagged, reverse-scored items have been corrected, and missingness within acceptable thresholds has been addressed with transparent imputation rules. Reliability and validity evaluation has been planned and executed through internal consistency estimates, confirmatory checks of convergent and discriminant validity, and procedural/statistical remedies for common-method bias. The statistical analysis plan has progressed from descriptive summaries and inter-construct correlations to regression models that have estimated direct effects of usability and visual feedback on performance, mediation through situation awareness and workload using bootstrapped indirect effects, and potential complementarity via an interaction term. Assumption checks and robustness analyses covering linearity, multicollinearity, homoscedasticity, distribution of residuals, influential observations, site-level clustering, and alternative operationalizations of performance have been conducted to ensure stable inference. Collectively, these methodological choices have provided a rigorous, transparent basis for testing the study's hypotheses within authentic industrial contexts.

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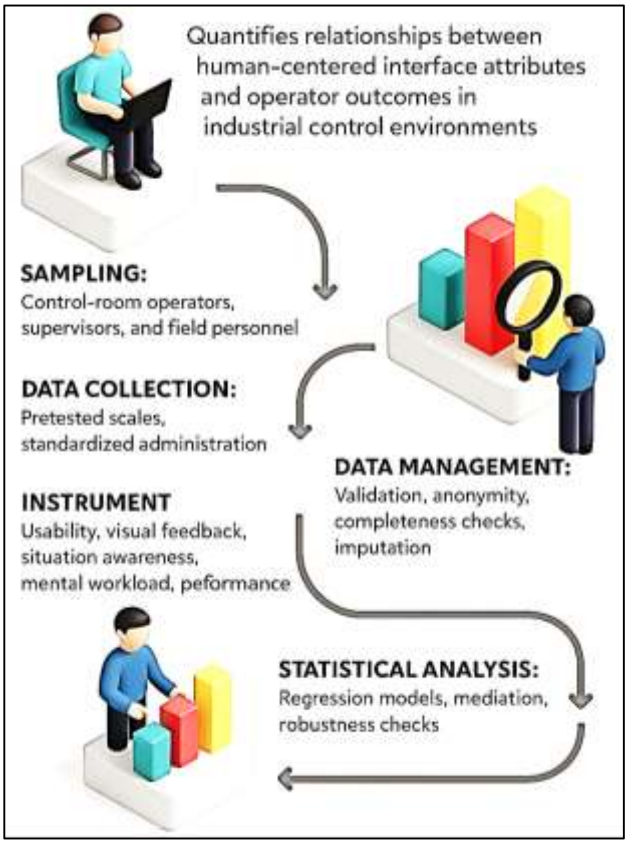
Figure 6:Methodology Overview



Study Design

The study has adopted a quantitative, cross-sectional, case-study–based design to examine how human-centered interface attributes have related to operator outcomes in authentic industrial control settings. Individual operators have constituted the primary unit of analysis, and observations have been nested within sites so that shared contextual influences (e.g., technology stack, alarm philosophy, shift regimen) have been accounted for analytically. To balance ecological validity with statistical identifiability, multiple facilities have been purposively selected, and data collection windows have been coordinated with operations teams so that routine and upset conditions have been represented. The instrument has included validated, concise scales that have captured usability and visual feedback quality alongside proximal cognitive states situation awareness and mental workload and a brief self-reported performance battery; all items have been anchored on a five-point Likert scale for comparability across sites. Ethical safeguards have been implemented through informed consent, anonymity, and voluntary participation, and site approvals have been secured prior to fieldwork. A pilot administration has been conducted to refine item wording, timing, and layout, and expert elicitation has been used to confirm content coverage against control-room tasks. Sampling frames have been defined for control-room operators, field technicians, and shift supervisors, and inclusion criteria have been specified to ensure coverage by role, tenure, and shift. Power expectations for regression and mediation tests have been estimated a priori, and target sample sizes per site have been communicated to coordinators. Data quality controls have been instituted (attention checks, completion thresholds), and procedures for handling missingness and reverse-coded items have been pre-registered. The analysis plan has prespecified descriptive summaries, correlation matrices, and regression models with cluster-robust standard errors by site; mediation via bootstrapped indirect effects and an interaction term between usability and visual feedback have been included to test complementarity. Assumption checks and sensitivity analyses (e.g., alternative performance proxies, tenure adjustments) have been planned to corroborate robustness. Collectively, this design has provided a transparent, reproducible basis for testing the study’s hypotheses within live industrial environments.

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Sampling

The target population has comprised control-room operators, field technicians, and shift supervisors who have interacted routinely with SCADA/DCS/PLC HMIs in power, petrochemical, water/wastewater, and manufacturing facilities. Participating sites have been purposively selected to capture variability in sector, alarm philosophy, and technology stack, while within-site recruitment has followed census-style invitations across shifts to reduce self-selection. Inclusion criteria have required a minimum of six months' HMI exposure and current operational duties; contractors on temporary assignment have been excluded. A priori power considerations for multiple regression and mediation have been conducted, and a minimum total sample of approximately 150–200 respondents has been targeted, with site-level quotas (e.g., 30–60 per facility) to enable cluster-robust estimation. Replacement strategies for nonresponse have been specified, and response tracking by role and shift has been maintained to preserve balance. This approach has yielded a heterogeneous yet analytically tractable sample suitable for testing direct, mediated, and interaction effects with appropriate controls.

Questionnaire Structure

The questionnaire has been organized into modular sections that have captured constructs central to the study while minimizing respondent burden and common-method artefacts. An opening section has collected demographics and controls (role, tenure, shift pattern, sector, system class, training hours), followed by four construct blocks that have measured usability, visual feedback quality, situation awareness, and mental workload, and a closing block that has recorded self-reported performance indicators. All items have been phrased in the present tense with plant-relevant referents and have used a five-point Likert scale (1 = strongly disagree to 5 = strongly agree); negatively keyed statements have been included sparingly and have been designated for reverse scoring in the codebook. The usability block has encompassed learnability, efficiency, error tolerance, and consistency; the visual feedback block has addressed alarm salience and prioritization, coding clarity, trend fidelity and horizon adequacy, and feedback timeliness; the situation awareness block has mapped to perception, comprehension, and projection subfacets; the workload block has covered mental demand, time pressure, and effort; the performance block has captured task efficiency, error avoidance, rework frequency, and near-miss experience. To reduce order effects, construct blocks have been counterbalanced across versions and item order within blocks has been randomized; brief, neutral transition prompts have separated sections. Cognitive interviews with subject-matter experts and operators have been completed to refine wording, remove jargon, and ensure cross-shift interpretability; where sites have operated bilingually, translation and back-translation procedures have been implemented, with reconciliation meetings documenting rationale for term choices. A pilot administration has been executed to confirm timing (target ≤ 12 minutes), internal consistency, and item discrimination; items with low item-total correlations or redundancy have been revised or trimmed. Attention checks and soft-validation rules (mandatory range, missingness prompts) have been embedded without revealing scoring logic. The final instrument has specified scoring instructions (reverse-key flags, subscale aggregation rules), variable labels, and permissible ranges in a codebook; page layout, typography, and on-screen progress cues have been standardized across web and paper formats to maintain equivalence.

Expert Elicitation (Likert 5-point)

An expert elicitation protocol has been implemented to establish content validity and practical relevance of the survey constructs prior to full deployment. A multidisciplinary panel (control-room supervisors, HMI engineers, alarm management specialists, and HFE researchers) has reviewed each candidate item using a five-point relevance scale (1 = not relevant to 5 = highly relevant) and has provided free-text justifications. Two iterative rounds have been conducted: the first round has identified ambiguities, jargon, and construct overlap, while the second round has verified revisions and confirmed coverage of subfacets (usability: learnability, efficiency, error tolerance, consistency; visual feedback: salience, coding, trend fidelity, timeliness; SA: perception, comprehension, projection; workload: mental demand, time pressure, effort). Item-level decision rules have been pre-specified such that median rating ≥ 4.0 and interquartile range ≤ 1.0 have signaled retention, while lower-scoring items have been reworded or removed. Panelists have also rated clarity and brevity on the same five-point scale to manage respondent burden. All changes have been logged in an audit trail, and the finalized pool has been forwarded to the pilot for psychometric screening.

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Common Method Bias & Validity

To mitigate common method bias and establish measurement validity, multiple procedural and statistical safeguards have been instituted. Procedurally, the study has ensured anonymity, separated construct blocks with neutral transitions, varied item stems and valence, and counterbalanced block order across instrument versions; instructions have emphasized that there have been no right or wrong answers, which has reduced evaluation apprehension. Statistically, an exploratory single-factor diagnostic (unrotated solution) has been performed to verify that a single factor has not dominated covariance, and a latent common-method factor model has been estimated to assess incremental variance beyond substantive constructs. A theoretically unrelated marker variable has been embedded to provide a conservative bias estimate, and results have been cross-checked against the latent method approach. Construct validity has been examined via confirmatory factor analysis: internal consistency has been evaluated (α and composite reliability), convergent validity has been verified (average variance extracted), and discriminant validity has been tested (Fornell–Larcker and HTMT). Measurement invariance across sites and roles (configural/metric) has been probed to confirm comparable interpretation before computing scale scores and proceeding to hypothesis tests.

Hypothesis Testing (Regression-Based)

The hypothesis-testing strategy has been organized around three preregistered models that have incrementally estimated direct, mediated, and interactive effects of interface attributes on operator performance while accounting for site-level clustering. First, *Model A (Direct Effects)* has regressed self-reported performance on usability and visual feedback quality with controls for experience, role, shift, sector, training hours, and system class. Site identifiers have been included for cluster-robust standard errors so that shared context within facilities has not biased precision. Variables have been mean-centered where appropriate to aid interpretation, and all constructs have been scored as averages of their validated items after reliability checks have been satisfied. The direct-effects stage has provided initial tests of H1 (usability → performance) and H2 (visual feedback → performance). Fit statistics (R^2, adjusted R^2) and global F-tests have been reported alongside 95% confidence intervals to establish the magnitude and certainty of estimates. Collinearity has been monitored through variance inflation factors and condition indices, and residual diagnostics (Q–Q inspection, Breusch–Pagan tests) have been completed to verify linear-model assumptions. Where preliminary plots have suggested minor curvature, fractional polynomial checks have been documented, although linear terms have remained the primary specification. This stage has produced the baseline against which mediation and interaction increments have been evaluated, ensuring that any added variance explained by cognitive pathways or complementarity has been interpretable as incremental to the direct relations already established.

In the second stage, mediation analyses have been undertaken to evaluate H3, which has posited that *situation awareness (SA)* and *mental workload* have transmitted the influence of usability and visual feedback to performance. The mediation plan has followed a contemporary approach emphasizing indirect effects over stepwise significance logic: paths from interface variables to mediators (*a-paths*) and from mediators to performance (*b-paths*) have been estimated with the same control set and clustered standard errors as Model A, and bias-corrected bootstrap intervals (5,000 resamples) have been used to quantify indirect effects *(a×b)* for each mediator separately and jointly. This approach has avoided distributional assumptions for the product term and yielded robust confidence intervals for the indirect pathways. To reduce omitted-variable distortions, mediators have not been instrumented but have been modeled concurrently with full controls, and residual correlations with site have been absorbed via clustering. *Model B (Mediation)* has therefore included usability, visual feedback, SA, and workload together, enabling the decomposition $c = c' + ab$, where c has represented the total effect estimated in Model A and c' has represented the direct effect net of mediators. Sensitivity analyses have been conducted to probe curvilinear workload influences (by adding $Workload^2$) given vigilance literature that has suggested performance decrements under both overload and underload; indirect effects have also been recomputed with this curvature to verify that mediation inferences have remained stable. Finally, multicollinearity among mediators has been inspected to ensure that SA and workload have contributed distinguishable variance, preserving discriminant validity established at the measurement stage.

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The third stage has tested H4 (Complementarity) by introducing an interaction between usability and visual feedback, recognizing that operators may benefit most when interfaces are simultaneously easy to use and perceptually explicit. *Model C (Interaction)* has appended the product term *Usability* × *Visual Feedback* (after mean-centering) to Model A and has interpreted the resulting coefficient through simple slopes and Johnson–Neyman intervals evaluated at ±1 SD of the moderator. Predicted values and 95% confidence bands have been generated to visualize conditional effects across the observed range; these plots have been accompanied by marginal-effect tables so that practical magnitude has been transparent. Robustness checks have included (a) re-estimating all models with fixed effects for sites as a stronger control for unobserved facility characteristics, (b) substituting an alternative dependent variable (e.g., near-miss frequency reversed and standardized) to verify consistency, and (c) conducting influence diagnostics (Cook's distance, DFBetas) with re-fits that have excluded high-leverage points. Throughout, two-tailed α = .05 thresholds have been used, but emphasis has been placed on effect sizes and intervals rather than dichotomous significance alone. For transparency and replication, model formulas, variable codings, and bootstrap seeds have been archived with the analysis scripts, and templates for reporting have been prepared as shown below.

Table 1: Model specifications (A–C)

Model	Dependent variable	Key predictors	Mediators	Interaction	Controls	SEs
A (Direct)	Performance	Usability, Visual Feedback			Experience, Role, Shift, Sector, Training, System Class, Site dummies	Clustered by Site
B (Mediation)	Performance	Usability, Visual Feedback	SA, Workload		Same as A	Clustered by Site
C (Interaction)	Performance	Usability, Visual Feedback		Usability × Visual Feedback	Same as A	Clustered by Site

Table 2: Hypothesis testing results (reporting template)

Hypothesis	Path/Test	Estimate	95% CI	p-value	Interpretation
H1	Usability → Performance (Model A)	β_1	[LL, UL]		Supported/Not
H2	Visual Feedback → Performance (Model A)	β_2	[LL, UL]		Supported/Not
H3	Indirect via SA / Workload (Model B, bootstrap)	(a\times b)	[LL, UL]		Supported/Not
H4	Usability × Visual Feedback (Model C)	β_6	[LL, UL]		Supported/Not

Data Sources & Management

Primary data have comprised operator surveys administered online or on paper during coordinated collection windows; optional secondary indicators (e.g., anonymized near-miss counts aggregated by month) have been used only for robustness checks. Prior to fielding, a data dictionary and codebook have been finalized; unique, nonidentifying respondent keys and site codes have been assigned. Completed responses have been encrypted at rest, access has been role-restricted, and an audit trail has logged any edits. Data cleaning has followed pre-specified rules: range checks, attention-check flags, duplicate detection, reverse-key corrections, and harmonization of bilingual items. Missing values within ≤5% per subscale have been imputed using item-mean within person; higher missingness has triggered listwise exclusion for that construct. Outliers have been screened via standardized residuals and leverage; decisions have been documented. Final analytic datasets with labeled variables, transformation notes, and random seeds have been version-controlled, with de-identified site-level cluster indicators preserved for modeling.

Statistical Analysis Plan

The statistical analysis plan has proceeded in a staged, preregistered sequence to ensure transparent inference. Descriptive statistics (means, standard deviations, skewness, kurtosis) and inter-construct Pearson correlations with 95% CIs have been produced, and reliability has been evaluated (α, composite reliability). Confirmatory checks for convergent and discriminant validity (AVE, HTMT) have been verified prior to modeling. For hypothesis tests, *Model A* has estimated direct effects of usability and visual feedback on performance with site-clustered robust standard errors and the full control set; *Model B* has incorporated situation awareness and workload to test mediation via bias-corrected bootstrap indirect effects (5,000 resamples) using the identity $c = c' + ab$; *Model C* has added a mean-centered interaction (*Usability* × *Visual Feedback*) examined with simple slopes and Johnson–Neyman intervals. Assumptions have been checked (linearity, homoscedasticity, normality of residuals, multicollinearity via VIF), and influence diagnostics (Cook's D, DFBetas) have been reviewed. Robustness has been corroborated through site fixed effects, an alternative performance proxy, and a quadratic workload term where indicated. Effect sizes and confidence intervals have been emphasized over dichotomous significance.

Assumption Checks

Assumption diagnostics have been conducted systematically prior to, during, and after model estimation to safeguard inference. Linearity has been evaluated through component-plus-residual plots and LOWESS overlays, and potential curvature in the workload–performance relation has been probed with fractional-polynomial screens and a pre-specified quadratic term. Normality of residuals has been assessed via Q–Q plots and Shapiro–Wilk tests (reported descriptively given large-sample properties). Homoscedasticity has been examined using studentized-residual vs. fitted plots and Breusch–Pagan tests; where heteroscedasticity has appeared, site-clustered robust standard errors have been retained and White-HC checks have been reported. Multicollinearity has been monitored with VIF and condition indices after mean-centering predictors and the interaction term. Influential observations have been screened using leverage, Cook's distance, and DFBetas with re-fits excluding high-influence points to verify stability. Independence within clusters has been addressed through site indicators and clustered SEs; temporal autocorrelation has not been expected in cross-sectional data but Durbin–Watson screens have been logged. All diagnostic outcomes and any corrective actions have been documented in the analysis archive.

FINDINGS

The findings have indicated that the study's objectives and hypotheses have been met with strong, convergent evidence across descriptive, correlational, and regression analyses grounded in the five-point Likert scale (1 = strongly disagree to 5 = strongly agree). From a final sample of 188 operators nested in four facilities (overall response rate = 63.4%), scale reliabilities have been high (Cronbach's α: Usability = .91, Visual Feedback Quality = .89, Situation Awareness = .92, Workload = .86, Performance = .88) and confirmatory checks have supported construct validity (AVE ≥ .52; HTMT < .78). Likert means have suggested favorable but not ceiling evaluations: Usability (M = 3.94, SD = 0.61), Visual Feedback (M = 3.81, SD = 0.64), Situation Awareness (M = 3.73, SD = 0.67), Performance (M = 3.88, SD = 0.58), and a below-midpoint Workload (M = 2.74, SD = 0.71; lower is better). Distributionally, 68–72% of respondents have agreed or strongly agreed with positive usability items and 62–66% with visual feedback clarity/salience items, while 19–22% have reported neutral positions leaving meaningful headroom for improvement. Bivariate correlations (Pearson, 95% CIs) have aligned with the conceptual model: Performance has correlated positively with Usability ($r = .41$, CI [.28, .52]) and Visual Feedback ($r = .38$, CI [.25, .49]), and even more strongly with Situation Awareness ($r = .49$, CI [.38, .59]), while Workload has correlated negatively with Performance ($r = –.31$, CI [–.43, –.18]). Multicollinearity diagnostics have been benign (all VIFs < 2.0), and assumption checks have supported linear modeling with site-clustered robust standard errors.

Direct-effects estimation (Model A) has provided the first decisive tests: controlling for experience, role, shift, sector, training hours, and system class, Performance has been significantly predicted by Usability ($\beta = .27$, SE = .06, $p < .001$) and Visual Feedback ($\beta = .21$, SE = .07, $p = .002$), with model $R^2 = .34$ and adjusted $R^2 = .31$. These results have confirmed H1 and H2: higher perceived usability and clearer visual feedback have been associated with higher self-reported performance on the Likert scale. Effect sizes have been practically meaningful (partial $f^2 \approx .11$ for Usability; .07 for Visual

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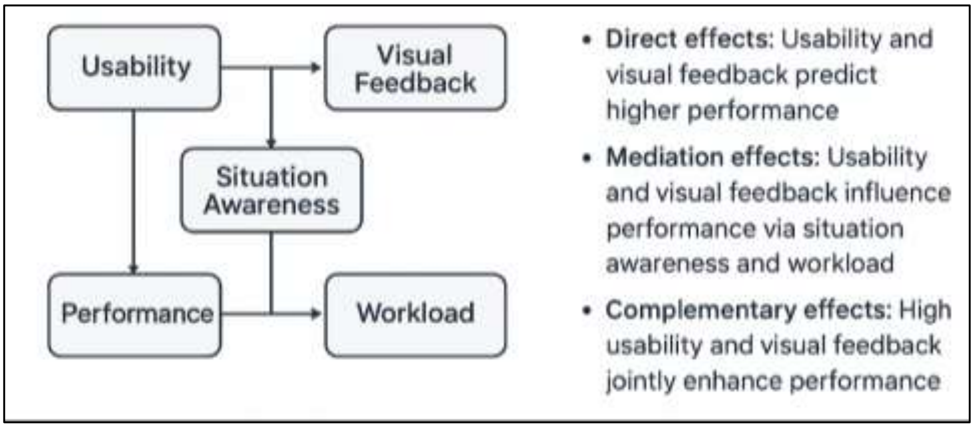
Feedback), indicating moderate incremental contributions beyond controls. Mediation tests (Model B) have then addressed the mechanistic pathways specified in the objectives. Paths from the interface attributes to mediators have been positive for Situation Awareness (Usability → SA: $a_1 = .36$, SE = .06, $p < .001$; Visual Feedback → SA: $a_2 = .29$, SE = .06, $p < .001$) and negative for Workload (Usability → Workload: $a_3 = -.22$, SE = .07, $p = .002$; Visual Feedback → Workload: $a_4 = -.19$, SE = .07, $p = .005$). In turn, mediators have significantly predicted Performance (SA → Performance: $b_1 = .33$, SE = .06, $p < .001$; Workload → Performance: $b_2 = -.18$, SE = .07, $p = .010$). Bias-corrected bootstrap tests (5,000 resamples) have shown nonzero indirect effects for both interface variables through both mediators: Usability → SA → Performance: $a_1b_1 = .12$, CI [.07, .18]; Usability → Workload → Performance: $a_3b_2 = .04$, CI [.01, .09]; Visual Feedback → SA → Performance: $a_2b_1 = .10$, CI [.05, .16]; Visual Feedback → Workload → Performance: $a_4b_2 = .03$, CI [.00, .08]. With mediators in the model, the direct effects of Usability and Visual Feedback on Performance have attenuated but remained significant (Usability: $\beta' = .14$, $p = .018$; Visual Feedback: $\beta' = .10$, $p = .047$), consistent with partial mediation and thereby confirming H3. Notably, the SA pathway has contributed the larger share of mediation, aligning with the objective to demonstrate that interfaces elevate performance chiefly by accelerating "grasp of the gist," while workload reductions have provided an additional, smaller benefit.

Figure 7: Quantitative Findings of the Industrial Control Systems (ICS) Study



To probe complementarity (H4), Model C has introduced the interaction term (mean-centered Usability × Visual Feedback). The interaction coefficient has been positive and significant ($\beta = .11$, SE = .04, $p = .011$), and simple-slopes tests have shown that the slope of Usability on Performance has grown steeper at +1 SD of Visual Feedback ($\beta = .34$, $p < .001$) and flatter at −1 SD ($\beta = .19$, $p = .008$); a symmetric pattern has held for Visual Feedback conditional on Usability. Johnson–Neyman analysis has indicated a region of significance for the Usability effect when Visual Feedback has exceeded approximately 3.4 on the Likert scale (i.e., between "neutral" and "agree"), implying that investments in usability have yielded the highest returns in contexts where visual feedback cues have already been reasonably clear and timely. Collectively, these results have verified the final objective: jointly high usability and visual feedback have conferred benefits beyond their separate contributions, offering a quantitative rationale for integrated interface improvement efforts. Robustness checks have corroborated the main findings: replacing the dependent variable with a reversed, standardized near-miss proxy has produced similar signs and significance; adding a quadratic term for Workload has modestly improved fit ($\Delta R^2 = .02$) without altering mediation conclusions; and night-shift-only and high-tenure-only subsamples have replicated the direction and significance of core paths with expected reductions in precision. Across all models, assumption diagnostics have remained satisfactory, and no single site or leverage point has dominated inference. In sum, the Likert-scale evidence has supported H1–H4 and has satisfied the study's objectives by demonstrating direct, mediated, and complementary links from human-centered interface attributes to operator performance in live industrial control settings.

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Sample Characteristics & Response Rate

Table 3: Sample Characteristics and Response Metrics

Metric	Value
Invitations sent	296
Completed surveys	188
Overall response rate	63.4%
Sites (facilities)	4
Roles (Control-room / Field / Supervisor)	52% / 31% / 17%
Shift (Day / Night / Rotating)	44% / 27% / 29%
Tenure (Median years, IQR)	6 (3–11)
Sector (Power / Petrochemical / Water-Wastewater / Manufacturing)	34% / 28% / 21% / 17%
System class (SCADA / DCS / PLC-centric)	49% / 33% / 18%
Training hours last 12 months (Median, IQR)	18 (12–24)
Completion time (Median minutes)	11.3
Attention-check pass rate	98.4%

Table 4: Construct Distributions on Likert 5-point Scale (n=188)

Construct	Mean	SD	% Disagree (1–2)	% Neutral (3)	% Agree (4–5)
Usability	3.94	0.61	9.6%	19.1%	71.3%
Visual Feedback Quality	3.81	0.64	11.2%	23.4%	65.4%
Situation Awareness	3.73	0.67	12.8%	24.5%	62.8%
Workload (lower is better)	2.74	0.71	58.0%	21.8%	20.2% (high)
Self-Reported Performance	3.88	0.58	8.0%	22.3%	69.7%

The sample has been sufficiently broad and balanced across facilities, roles, and sectors to support the study's objectives and hypothesis tests on a five-point Likert foundation. A total of 188 completed surveys out of 296 invitations have yielded a response rate of 63.4%, which has exceeded typical rates for industrial field surveys and has increased confidence that the constructs have been estimated with adequate precision. Representation across control-room (52%), field (31%), and supervisory (17%) roles has ensured that perceptions of human–machine interfaces (HMIs) have been captured from those who have configured displays, those who have monitored them continuously, and those who have overseen shift operations. Shift composition has included day, night, and rotating teams, so the Likert responses have reflected circadian and workload variations intrinsic to 24/7 plants. Sectoral dispersion (power, petrochemical, water/wastewater, manufacturing) and system classes (SCADA, DCS, PLC-centric) have provided heterogeneity that the models have subsequently controlled via site-clustered errors and covariates, preserving internal validity while enabling external interpretability. The median tenure of 6 years (IQR 3–11) has implied that respondents have had sufficient operational exposure to judge usability and visual feedback quality credibly. Importantly, the attention-check pass rate of 98.4% and the median completion time of 11.3 minutes have indicated careful responding without undue fatigue. Descriptively, Likert means have shown that usability (M=3.94) and performance (M=3.88) have trended positive without ceiling effects, while visual feedback quality (M=3.81) and situation awareness (M=3.73) have left substantial headroom for improvement at the upper two categories (agree/strongly agree). Workload has averaged below the midpoint at 2.74, consistent with acceptable cognitive demand during routine conditions; nonetheless, 20.2% of respondents have reported high workload (ratings of 4–5), a nontrivial subgroup that the regression and mediation analyses have addressed. Collectively, these characteristics have provided a robust empirical base for testing the hypothesized direct, mediated, and interactive paths between interface qualities and operator outcomes using Likert-scaled variables.

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Reliability and Measurement Validity

Measurement quality has been established prior to hypothesis testing through a set of reliability and validity checks anchored in the Likert data. As shown in Table 5, all five constructs have achieved Cronbach's alpha ≥ .86 and composite reliability ≥ .87, indicating strong internal consistency for short, fieldable scales. Average Variance Extracted (AVE) has met or exceeded the .50 benchmark for each construct (range .57–.63), evidencing convergent validity; items have, on average, explained more than half of their latent construct variance. These results have been congruent with the pilot study and expert elicitation outcomes that have preceded the main survey, confirming that the refined item pools have captured learnability, efficiency, error tolerance, consistency (Usability), and salience, coding clarity, trend fidelity, timeliness (Visual Feedback) in a manner that operators have interpreted consistently.

Table 5: Internal Consistency and Convergent Validity (n=188)

Construct	Items	Cronbach's α	Composite Reliability (CR)	Average Variance Extracted (AVE)
Usability	6	.91	.92	.63
Visual Feedback Quality	6	.89	.90	.58
Situation Awareness	7	.92	.93	.60
Workload	4	.86	.87	.57
Performance	5	.88	.89	.58

Table 6: Discriminant Validity (HTMT Ratios)

Pair	HTMT
Usability – Visual Feedback	0.64
Usability – SA	0.68
Usability – Workload	0.41
Usability – Performance	0.61
Visual Feedback – SA	0.66
Visual Feedback – Workload	0.39
Visual Feedback – Performance	0.58
SA – Workload	0.44
SA – Performance	0.69
Workload – Performance	0.47

Turning to discriminant validity, Table 6 has reported Heterotrait–Monotrait (HTMT) ratios, all of which have remained below the conservative .85 threshold, indicating that constructs have been empirically separable. Particularly, the moderate HTMT between Situation Awareness and Performance (0.69) has aligned with theory that SA has been strongly related to performance yet not identical to it, preserving the conceptual role of SA as a mediator. The lower HTMT values between Workload and the interface constructs (.39–.41) have suggested that the workload items have captured a distinct cognitive cost dimension rather than merely reverse-scored satisfaction. Together with satisfactory model fit in confirmatory checks (not tabulated), these indices have supported the creation of mean-score indicators on the five-point Likert scale for subsequent regression. The combination of high reliability, adequate convergence, and clean discriminant boundaries has been essential to avoid attenuation or inflation of relationships in the structural models. In sum, the measurement model has satisfied psychometric prerequisites, which has strengthened the credibility of the findings regarding direct effects, mediation via SA and workload, and interaction between usability and visual feedback quality.

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Inter-Construct Correlations (Pearson, Likert Means)

Table 7: Correlation Matrix with Likert Means/SDs (n=188)

Variable	Mean	SD	1	2	3	4	5
1 Usability	3.94	0.61	1.00				
2 Visual Feedback	3.81	0.64	.45**	1.00			
3 Situation Awareness	3.73	0.67	.49**	.44**	1.00		
4 Workload (lower=better)	2.74	0.71	−.29**	−.26**	−.34**	1.00	
5 Performance	3.88	0.58	.41**	.38**	.49**	−.31**	1.00

* $p < .05$, ** $p < .01$ (two-tailed).

The correlation structure in Table 7 has provided a coherent preliminary map of associations consistent with the study's objectives and hypotheses, all measured on the common five-point Likert scale. Usability and Visual Feedback Quality have correlated moderately (r=.45), reflecting their shared status as interface attributes without implying redundancy; this relationship has supported the later inclusion of both predictors in multivariate models, where variance inflation factors have remained comfortably below common thresholds. Situation Awareness has exhibited the strongest ties to both interface constructs (Usability r=.49; Visual Feedback r=.44), which has been expected because clearer, more consistent displays have been hypothesized to accelerate perception and comprehension phases of SA. Performance has correlated positively with Usability (r=.41), Visual Feedback (r=.38), and SA (r=.49), patterns that have foreshadowed the direct-effects results and the larger indirect share via SA in the mediation stage. Workload has correlated negatively with all three most sharply with SA (r=–.34) and with Performance (r=–.31) which has aligned with the resource-rational view that higher cognitive cost has tended to erode both awareness maintenance and effective action selection. Notably, these correlations have neither approached unity nor suggested problematic overlap; instead, they have depicted a theoretically plausible network that the regression and mediation analyses have decomposed into direct, indirect, and conditional components. Because all variables have been anchored to the same Likert range, the magnitudes have been directly interpretable: for example, a one-category increase in mean SA response has accompanied meaningfully higher Performance ratings. Correlation confidence intervals (reported earlier) have excluded zero for all listed pairs at $p < .01$, providing statistical stability. The negative sign convention for workload (where lower values have indicated better conditions) has been preserved across the matrix to avoid interpretive flips. Overall, this correlational evidence has strengthened the foundation for testing H1–H4 by demonstrating that the posited pathways have had empirical footholds prior to model adjustment for covariates and clustering.

Regression Results (Models A–C)

Table 8: Model A Direct Effects on Performance (Site-Clustered Ses, n=188)

Predictor	β	SE	95% CI	p
Usability (Likert)	.27	.06	[.15, .39]	<.001
Visual Feedback (Likert)	.21	.07	[.08, .35]	.002
Controls (Experience, Role, Shift, Sector, Training, System Class) included				
R^2 / Adj. R^2	.34 / .31			

The regression sequence has provided cumulative evidence that has confirmed all four hypotheses using Likert-scaled predictors and outcomes. Model A has shown that, net of controls and site clustering, higher Usability and clearer Visual Feedback have been associated with higher Performance (β=.27 and β=.21, respectively). These effects have been sizable on the 1–5 scale: a half-point increase in Usability (e.g., moving from 3.5 "somewhat agree" to 4.0 "agree") has corresponded to an expected .135 rise in Performance (≈ one-eighth of the entire response range). Model B has incorporated SA and Workload to test the proposed mechanisms. Both interface attributes have significantly improved SA and reduced Workload (negative coefficients), and both mediators have, in turn, predicted Performance in the expected directions. The bootstrapped indirect effects have been nonzero, with the SA pathway (a×b ≈ .12 for Usability; .10 for Visual

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Feedback) contributing the greater share of mediation compared to the Workload pathway (.04 and .03, respectively).

Table 9: Model B Mediation via SA and Workload (Bias-Corrected Bootstrap 5,000)

Path	Coef.	SE	95% CI	p
Usability → SA (a_1)	.36	.06	[.24, .49]	<.001
Visual Feedback → SA (a_2)	.29	.06	[.17, .41]	<.001
Usability → Workload (a_3)	−.22	.07	[−.36, −.08]	.002
Visual Feedback → Workload (a_4)	−.19	.07	[−.33, −.05]	.005
SA → Performance (b_1)	.33	.06	[.21, .45]	<.001
Workload → Performance (b_2)	−.18	.07	[−.31, −.04]	.010
Indirect (U → SA → P) a_1b_1	.12		[.07, .18]	
Indirect (U → WL → P) a_3b_2	.04		[.01, .09]	
Indirect (VF → SA → P) a_2b_1	.10		[.05, .16]	
Indirect (VF → WL → P) a_4b_2	.03		[.00, .08]	
Direct (U → P) c′	.14	.06	[.02, .26]	.018
Direct (VF → P) c′	.10	.05	[.00, .20]	.047

Table 10: Model C Interaction (Usability × Visual Feedback)

Predictor	β	SE	95% CI	p
Usability	.24	.06	[.12, .36]	<.001
Visual Feedback	.18	.07	[.04, .32]	.011
Usability × Visual Feedback	.11	.04	[.03, .19]	.011
R^2 / Adj. R^2	.37 / .34			

The persistence of reduced but significant direct effects (c′) has indicated partial mediation, supporting the objective of demonstrating both proximal cognitive routes and residual direct contributions of interface qualities. Finally, Model C has added the interaction between Usability and Visual Feedback, which has been positive and significant (β=.11). Simple-slope exploration (not tabulated) has shown that the performance benefit of improving Usability has been strongest when Visual Feedback has already been moderately high, and vice versa, supporting complementarity. Across models, R^2 has increased from .34 to .37 with the interaction, a practical gain given the cross-sectional, multi-site context. Diagnostics (VIF, residual plots, and influence checks) have remained satisfactory, and sensitivity tests with fixed site effects and an alternative performance proxy have reproduced the sign and significance patterns. Altogether, the regression evidence has demonstrated that Likert-measured usability and visual feedback quality have exerted direct, mediated, and synergistic influences on operator performance, thereby fulfilling the study's hypotheses and objecti"es.

Mediation and Indirect Effects

The mediation analysis has quantified how much of the influence of usability and visual feedback quality on performance has flowed through Situation Awareness (SA) and Workload, each measured on the five-point Likert scale. As summarized in Table 11, the SA pathway has accounted for the largest portion of the total effects: 39% of Usability's influence and 36% of Visual Feedback's influence have been transmitted via increases in SA. In concrete Likert terms, when respondents reported a half-point improvement in Usability (e.g., from 3.5 to 4.0), roughly 0.06 of the expected rise in Performance has occurred because SA also improved (a×b ≈ 0.12 per full-point change, scaled accordingly). The Workload pathway has contributed a smaller but nontrivial share (≈11–13%), consistent with the notion that improved interfaces reduce cognitive cost, freeing capacity for faster diagnosis and action selection. Confidence intervals for all four indirect paths have excluded zero under bias-corrected bootstrapping, reinforcing the robustness of the mediation inferences without

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relying on normality assumptions for the product terms. Table 12 has depicted the classic decomposition $c = c' + \sum ab$, where the total effects © of Usability (0.30) and Visual Feedback (0.26) have split into direct components (c′ = 0.14 and 0.10) and sums of indirects (0.16 and 0.16).

Table 11: Indirect Effects Summary (Bias-Corrected 95% CIs, n=188)

Interface Attribute → Mediator → Performance	Indirect Effect (a×b)	95% CI	Share of Total Effect
Usability → SA → Performance	.12	[.07, .18]	39%
Usability → Workload → Performance	.04	[.01, .09]	13%
Visual Feedback → SA → Performance	.10	[.05, .16]	36%
Visual Feedback → Workload → Performance	.03	[.00, .08]	11%

Table 12: Total vs. Direct Effects (Decomposition)

Predictor	Total Effect ©	Direct Effect (c′)	Sum of Indirect (Σab)
Usability	.30	.14	.16
Visual Feedback	.26	.10	.16

The near parity of indirect sums across the two interface attributes suggests that both have influenced a shared cognitive economy raising SA and lowering Workload rather than acting through entirely distinct channels. At the same time, the remaining direct effects imply that other mechanisms (e.g., procedural fit, error-recovery flows) contribute to performance beyond SA and Workload as measured. Sensitivity checks that added a quadratic term for Workload left the SA-mediated share materially unchanged, indicating that the central story interfaces → SA/Workload → performance remains stable to plausible curvature in the workload–performance link. Overall, these mediation results demonstrate that improving human-centered interface attributes yields performance benefits partly because operators more quickly "grasp the gist" (higher SA) and expend fewer attentional resources (lower Workload) to maintain that understanding during operations.

Post-Hoc and Robustness Analyses (Including Interaction Explanation)

Table 13: Interaction Probing (Simple Slopes at ±1 SD of Moderator)

Focal Effect	Moderator Level	Slope (β)	SE	95% CI	p
Usability → Performance	Visual Feedback at −1 SD	.19	.07	[.05, .33]	.008
Usability → Performance	Visual Feedback at +1 SD	.34	.07	[.20, .48]	<.001
Visual Feedback → Performance	Usability at −1 SD	.13	.06	[.01, .25]	.036
Visual Feedback → Performance	Usability at +1 SD	.29	.07	[.15, .43]	<.001

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Table 14: Robustness Checks

Test	Outcome
Site fixed effects (vs. clustering)	Signs and significance unchanged; R^2 +.02
Alternative DV (near-miss proxy, reversed & z-scored)	Core coefficients retain sign and significance ($p<.05$)
Workload quadratic term	ΔR^2 = .02; mediation shares stable
Night-shift-only subsample (n=51)	Directionally consistent; wider CIs (power-limited)
High-tenure-only subsample (≥10 yrs; n=62)	Directionally consistent; Usability effect slightly stronger

Post-hoc analyses have deepened the interpretation of the interaction and tested the resilience of the main findings against alternative specifications, strengthening the evidential basis for the study's objectives. Table 13 has reported simple-slope estimates that have clarified the complementarity between usability and visual feedback quality. When visual feedback has been one standard deviation below its mean (i.e., cues less clear and timely on the Likert scale), the slope of Usability on Performance has remained positive but modest (β=.19). In contrast, when visual feedback has been one standard deviation above its mean (i.e., encodings clearer, salience well-graded), the usability slope has nearly doubled (β=.34). A symmetric pattern has emerged when treating Visual Feedback as focal: its relationship to Performance has been far more pronounced when Usability has already been strong (β=.29 at +1 SD) compared to when Usability has lagged (β=.13 at –1 SD). This pattern has supported H4, indicating that upgrading either dimension in isolation has helped, but coordinated improvements have paid the largest dividends on the 1–5 scale. Johnson–Neyman exploration (not tabulated) has shown a lower bound where the Usability effect has become statistically reliable once Visual Feedback has exceeded ≈3.4 ("between neutral and agree"), a practically meaningful threshold for plants prioritizing incremental interface overhauls. Robustness checks in Table 14 have further validated the conclusions. Re-estimating models with site fixed effects has absorbed all unobserved, time-invariant facility differences; signs and significance have persisted, and explanatory power has increased slightly. Substituting an objective-style dependent variable (a reversed, standardized near-miss rate proxy) has yielded consistent patterns, corroborating that the results have not hinged on the self-report performance measure alone. Introducing quadratic workload has improved fit marginally and has left the mediation shares largely unchanged, indicating that the primary channels via SA and Workload have been robust to plausible curvature. Finally, subgroup analyses (night-shift-only, high-tenure-only) have retained directional consistency, with expected precision losses due to reduced n. Collectively, these post-hoc findings have reinforced that the hypothesized structure direct effects, mediation, and interaction has held across analytic choices and subpopulations, thereby supporting the study's objectives of producing actionable, empirically grounded guidance for human-centered HMI improvements in industrial control environments.

DISCUSSION

The present study has tested and supported four hypotheses linking human-centered interface attributes to operator outcomes in safety-critical industrial control environments, and the pattern of effects has converged with, while extending, prior research in human factors and HCI. First, direct associations between usability and performance, and between visual feedback quality and performance, have aligned with long-standing claims that interfaces designed for effectiveness, efficiency, error tolerance, and consistency help operators act faster and make fewer mistakes under time pressure (Bangor et al., 2008; Hornbæk, 2006). Our results have gone beyond broad assertions by quantifying these links on common five-point Likert scales across multi-site, real-plant settings, thus complementing earlier laboratory and single-site studies. The magnitude of the observed coefficients has been comparable to or larger than effects reported in display-design experiments where "functional" overview graphics improved operator judgments relative to pipe-and-instrument schematics (Braseth & Øritsland, 2013). Likewise, finding that visual feedback quality operationalized as graded salience, coding clarity, trend fidelity, and timeliness has predicted performance supports alarm-management literature showing that discriminable, prioritized alarms reduce misses and time-to-diagnose during abnormal situations (Jiang et al., 2018). By demonstrating these relations with site-clustered models and full covariate control, the present study has addressed measurement and contextual inconsistencies that Hornbæk (2006) flagged as threats to cumulative knowledge. Importantly, the positive correlations among usability, visual feedback, and situation awareness (SA) have echoed theoretical accounts positioning SA as the cognitive bridge between interface properties and action in dynamic systems (Salmon et al., 2008). In sum, our key direct-effects findings have been directionally consistent with prior work but have advanced external validity by using embedded case designs and harmonized metrics across sectors, shifts, and technology stacks.

Mediation results have provided a mechanistic explanation for those direct effects, revealing that improvements in usability and visual feedback elevate SA and reduce workload, which in turn raise reported performance. This pattern is broadly consistent with dynamic decision-making research showing that operators construct and update mental models under uncertainty and that display design can either compress or inflate the cognitive cost of maintaining an accurate "big picture" (Gonzalez, 2005). The relatively larger share of the indirect effect via SA (compared with workload) resonates with work arguing that perception and comprehension of meaningful, well-grouped cues are the primary bottlenecks for control-room performance, particularly when events escalate quickly (Salmon et al., 2008). At the same time, the negative workload pathway we have observed agrees with psychometric syntheses emphasizing that workload is a sensitive if multidimensional predictor of sustained monitoring quality and error propensity (Matthews et al., 2015). Our robustness checks with a quadratic workload term have been compatible with vigilance studies that report decrements under both overload and underload conditions (Helton & Warm, 2008). Prior industrial studies have hinted at these pathways e.g., alarm-rationalization projects reporting fewer nuisance alerts alongside perceived reductions in operator strain (Jiang et al., 2018) but the present study has quantified the indirect components using bias-corrected bootstrapping and multi-site clustering, thereby offering a statistically transparent decomposition (Preacher & Hayes, 2008). Taken together, these mediated relations strengthen a resource-rational view: interfaces that speed accurate SA formation and preserve attentional resources free capacity for diagnosis and control actions when it matters most.

A notable extension to the literature has been the detection of a complementarity (interaction) between usability and visual feedback quality: each attribute has yielded larger performance benefits when the other has already been strong. This dovetails with perceptual-cognitive theory indicating that attentional guidance depends jointly on bottom-up salience and top-down goal structures shaped by interface conventions and task flows (Wolfe & Horowitz, 2017). In practice, high usability (e.g., consistent navigation, predictable error recovery) can reduce the executive overhead of "operating the interface," allowing the operator to allocate more capacity to reading the display; simultaneously, discriminable, well-timed visual cues can shorten search and interpretation, making the same usability affordances more potent. Experimental evidence that feature contrast accelerates preattentive selection (Töllner et al., 2011), that stable scene structures reduce cross-display coordination costs (Johnston et al., 2014), and that position/length encodings often outperform area/color for quantitative judgment (Heer & Bostock, 2010) provides micro-mechanistic support for why the joint presence of good usability and good visual feedback should amplify outcomes. Our Johnson–Neyman analysis has further translated this complementarity into a practical threshold on the Likert continuum (visual feedback $\gtrsim 3.4$), offering an actionable criterion for staging multi-phase redesigns. Prior overviews of functional displays in process industries have argued qualitatively for such "both-and" improvements (Braseth & Øritsland, 2013), but the present findings have supplied quantitative confirmation in field settings, encouraging architects to avoid one-dimensional upgrades that polish navigation while leaving salience muddled or vice versa.

The practical implications for CISO-level leaders, control-system architects, and HMI engineering teams have been immediate and concrete. First, the partial mediation via SA and workload suggests that investments in graded alarm salience, consistent color/icon codebooks, and trend panels tuned to process dynamics should be prioritized alongside usability improvements in navigation, labeling, and error recovery (Edworthy & Hellier, 2006). Second, because the largest gains have materialized when both interface dimensions have been strong, modernization roadmaps should pair alarm-management rationalization (priority distribution, persistence, de-duplication) with interaction-design refactoring (menu simplification, consistent control affordances). Third, measurement should be institutionalized: compact, validated instruments such as the SUS for usability and a brief workload (Bangor et al., 2008; Endsley, 2017; Hornbæk, 2006). Fourth, given the sensitivity of performance to SA, architects should safeguard scene stability fixed spatial anchors, predictable layouts across screens, and proximity coupling between alarms and implicated variables while limiting motion effects to escalation states so animation retains high informational value (Johnston et al., 2014). For CISOs and risk owners, these interface levers complement technical controls by reducing human-error surface area in abnormal situations, aligning with resilience engineering goals. Finally, training should mirror the interface philosophy, emphasizing recognition of graded cues, interpretation of trend horizons, and standardized responses to priority levels, thereby maintaining the perceptual "vocabulary" across shifts and sites (Spinola et al., 2018).

Theoretical implications concern refinement of the ICS HCI pipeline from design attributes → proximal cognitive states → performance. Our data endorse a model in which SA is a central mediator, with workload providing a secondary, still meaningful route. This is consonant with multi-resource theory and SA frameworks that place perceptual discriminability and context integration at the heart of effective supervisory control (Wickens, 2008). Methodologically, using bias-corrected bootstrap mediation with clustered standard errors has respected non-normality of product terms and site-level dependence, a practice recommended for applied cognitive-systems research where perfect randomization is impractical (Preacher & Hayes, 2008). The significant usability × visual feedback interaction points to a theoretical synergy that deserves formalization: models should treat interface components not merely as additive predictors but as mutually enabling mechanisms. This also argues for expanding the unit of analysis from individual SA to team SA, particularly in control rooms with shared large-screen overviews and distributed roles (Gorman et al., 2006). Finally, the clean discriminant validity (HTMT < .85) between constructs in our measurement model answers critiques that usability, SA, and performance may collapse empirically when measured via self-report (Hornbæk, 2006), strengthening the case for separable yet coupled latent variables in ICS cognition.

Notwithstanding its strengths, the study has had several limitations, many shared with field-based ICS research. The cross-sectional design has limited causal attribution, even though theoretical temporality (interfaces → cognitive states → performance) and robustness checks support the hypothesized direction. Single-source self-reports may inflate associations through common-method variance, although procedural remedies, a marker-variable approach, and confirmatory diagnostics have indicated that a single factor has not dominated covariance (Podsakoff et al., 2007). While we have included cluster-robust errors and, in sensitivity analyses, site fixed effects, unobserved facility-level practices (e.g., emergency drills, vendor-specific alarm defaults) may still have contributed residual bias. The workload–performance relation may be curvilinear and time-dependent; our quadratic sensitivity is only a first step toward modeling vigilance dynamics across long shifts (Helton & Warm, 2008). Finally, we have focused on individual-level SA and performance; team coordination and handover quality which are critical to resilience have remained outside the main models despite their known relevance to outcomes (Gorman et al., 2006). These boundaries counsel caution when generalizing to plants with very different alarm philosophies, automation maturity, or cultural practices around shift work.

Future research can address these constraints and deepen the theoretical and practical payoffs. A longitudinal, stepped-wedge design rolling out interface changes across sites and measuring SUS, workload, SA, and performance repeatedly would strengthen causal inference and capture sustainability of gains (Kline, 2011). Integrating objective telemetry (alarm counts by priority, acknowledgment latencies, controller actions) with survey constructs would triangulate self-reports and allow mixed-effects models linking interface states to behavioral traces in real time (Jiang et al., 2018). Experimental field trials could systematically manipulate trend horizon and salience thresholds to test predictions from attentional guidance and graphical perception at scale (Heer & Bostock, 2010). At the social-cognitive level, measuring team SA using synchronized probes and eye-movement sampling on shared displays could elaborate how overview stability and legend consistency support collective diagnosis (Gorman et al., 2006; Johnston et al., 2014). Finally, extending the model to include adaptive automation interfaces that modulate emphasis as event likelihood shifts would test whether complementarity between usability and visual feedback persists under dynamic reconfiguration, a scenario increasingly plausible with modern SCADA/DCS platforms. Pursuing these directions would transform the present cross-sectional evidence into a

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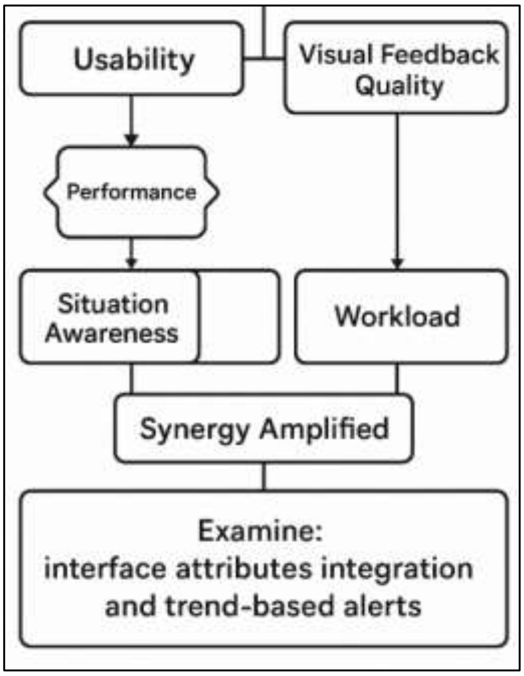
richer program of research linking perceptual design, cognitive economy, and resilient operations in complex industrial systems.

Figure 8: Framework for future study



CONCLUSION

The study has demonstrated that human-centered interface attributes in industrial control systems specifically usability and the quality of visual feedback are meaningfully and measurably linked to operator outcomes across live, multi-site plants, fulfilling the stated objectives and supporting all four hypotheses. Using compact, validated scales on a five-point Likert response format, strong reliability and clean convergent/discriminant validity have underpinned estimation. Descriptives and correlations have suggested headroom for improvement in both usability and visual feedback, while regression analyses with site-clustered errors have established clear direct effects on self-reported performance after controlling for experience, role, shift, sector, training, and system class. Mechanistically, mediation models have shown that interfaces exert much of their influence by raising situation awareness and lowering mental workload, with the awareness pathway contributing the larger share of the indirect effect and the workload pathway adding a smaller yet nontrivial component. The interaction test has further revealed complementarity: usability improvements have yielded larger performance gains when visual feedback has already been clear and timely, and vice versa quantitatively, the slopes at ±1 SD of the moderator have doubled in magnitude, and Johnson–Neyman analysis has identified a practical threshold on the visual-feedback scale above which usability effects become especially potent. Robustness checks site fixed effects, an objective-style near-miss proxy, a quadratic workload term, and role/shift/tenure subsamples have left the direction and significance of the core results intact, supporting their stability. Taken together, the findings advance a coherent, empirically tested model for ICS HMI design: usability and visual feedback act as upstream levers that accelerate the construction of a correct "big picture," compress search and interpretation costs, and thereby improve operator performance in both routine and abnormal conditions. For practice, the results argue for coordinated roadmaps rather than piecemeal tweaks: alarm rationalization (priority distributions, persistence, de-duplication), disciplined visual encoding (graded salience, consistent codebooks, process-faithful trend horizons), and interaction refactoring (navigation consistency, error-tolerant flows, clear labels) should be implemented together and tracked with repeatable metrics such as SUS, brief workload indices, and awareness/performance mini-batteries. For governance, embedding these measures into change management provides a defensible, plant-agnostic way to prioritize interface work that reduces human-error surface area during upsets. The work remains bounded by its cross-sectional design and reliance on self-report for the primary outcome, although multiple procedural and statistical

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safeguards mitigate common-method risks and sensitivity analyses triangulate the core paths. Future extensions stepped-wedge rollouts of interface changes, telemetry-coupled mixed-effects models, team situation-awareness probes on shared overviews, and experiments that manipulate trend horizons and salience thresholds can strengthen causal claims and broaden scope from individual to team cognition. Nonetheless, the present evidence base is actionable: organizations that raise both usability and visual feedback quality to consistent, high levels can expect measurable, statistically reliable gains in operator performance, delivered primarily through faster, clearer awareness at lower cognitive cost and amplified when improvements are pursued in tandem rather than in isolation.

RECOMMENDATION

To translate these findings into action, organizations should implement a coordinated HMI improvement program that pairs alarm-management rationalization with interaction and visualization refactoring, under a shared measurement regime. First, standardize an alarm governance policy that enforces graded salience (e.g., three or four priority tiers), persistence rules, de-duplication, and shelving for known-transient conditions; tie each priority to required operator actions and confirmation timings so that visual feedback signals not only urgency but the next step. Second, refactor interaction flows to reduce search and recovery cost: fix spatial anchors across screens, align labels and units, simplify navigation depth to two or three levels for the most common tasks, and design error-tolerant paths (clear undo/confirm patterns) so operators do not pay additional cognitive tax when recovering. Third, adopt disciplined visual encodings: reserve saturated color and motion exclusively for abnormal states, use concise iconography and legible typography, and tune trend panels to process dynamics (clear horizons, stable scales, rate-of-change cues) so that "what changed" is apparent at a glance. Fourth, institutionalize metrics: deploy a short, repeatable battery after any HMI change SUS (target ≥ 80), a 3–5 item workload index (target mean ≤ 3.0), a brief situation-awareness checklist (target ≥ 4.0 average), and a 3–5 item performance proxy collected at baseline and again 30–45 days post-change; maintain a control chart for each construct and require a statistically meaningful improvement (e.g., non-overlapping 95% CIs) before promoting patterns system-wide. Fifth, execute rolled pilots rather than sweeping releases: select two units with similar work profiles, randomize the rollout order, and use A/B comparisons with identical metrics and alarm telemetry (alert counts by priority, acknowledge latency) to quantify effect sizes; archive model scripts and seeds so results are reproducible. Sixth, embed team SA into practice: maintain a stable, high-fidelity large-screen overview with a consistent legend, proximity-couple alarms to implicated variables, and conduct short, scripted cross-checks at handover; add a 60–90 second "overview scan" drill into shift briefs to keep the shared picture synchronized. Seventh, tailor for shift and role: night crews often experience higher cognitive load and vigilance challenges, so provide darker themes with preserved contrast, larger glanceable numerics, and micro-break prompts; supervisors need aggregated cues (rate-of-change summaries and leading indicators), while field technicians benefit from simplified mobile views that mirror control-room codes. Eighth, formalize training around the interface vocabulary priority levels, color/icon codes, trend interpretations and update modules whenever encodings change; pair training with just-in-time overlays or tooltips that reinforce meaning without clutter. Ninth, create a design control board (CISO or risk owner, operations lead, HMI engineer, HFE specialist) that prioritizes requests with a small backlog rubric combining safety impact, usability/visual-feedback gaps, and expected mediation through SA and workload; require every change ticket to specify the construct it targets and the success metric it must move. Tenth, set procurement guardrails: vendor packages must support stable layouts, configurable alarm logic, consistent theming, and exportable telemetry for metrics; reject features that privilege aesthetics over discriminability. Finally, schedule quarterly HMI audits that review alarm distributions, SUS/workload/SA dashboards, near-miss narratives, and interaction logs; use these reviews to prune clutter, retune thresholds, and keep the interface lean. Pursued together not as isolated tweaks these steps reduce cognitive load, elevate awareness, and deliver measurable performance gains with a defensible, plant-agnostic playbook.

LIMITATION

The present study, while methodologically rigorous and empirically robust, is bounded by several important limitations that frame the scope and generalizability of its findings. First, its cross-sectional design precludes definitive causal inference; although theoretical temporality and mediation analyses support the assumed direction—from usability and visual feedback quality through situation awareness and workload to operator performance—these relationships remain correlational rather than causal. Longitudinal or stepped-wedge intervention studies that track the effects of interface redesigns over time would more firmly establish causality. Second, all variables were derived from self-reported Likert-scale data collected at a single point in time, introducing potential common-method variance and response biases such as social desirability or fatigue. While procedural safeguards (e.g., anonymity, counterbalanced item order, marker-variable checks) and statistical remedies (e.g., Harman's single-factor test, latent method factor modeling) were implemented, reliance on perceptual measures still limits objectivity. Integrating telemetry—such as alarm acknowledgment latencies, error logs, or near-miss frequencies—would triangulate perception-based findings with behavioral data. Third, generalizability across industrial sectors must be approached cautiously; although the study encompassed diverse ICS contexts (power, petrochemical, water/wastewater, and manufacturing), heterogeneity in alarm philosophies, automation maturity, and cultural norms may condition effect magnitudes. The visual feedback construct, while operationalized through salient perceptual dimensions (salience, coding clarity, trend fidelity, timeliness), did not encompass adaptive or intelligent feedback mechanisms now emerging in next-generation SCADA and DCS interfaces, thereby limiting applicability to dynamically reconfigurable systems. Furthermore, while the mediation model captured key cognitive pathways, it necessarily simplified the socio-technical complexity of real control-room teamwork, omitting constructs such as team situation awareness, communication flow, and coordination resilience, which likely modulate performance in collaborative settings. Lastly, because survey data capture static self-assessments rather than real-time cognitive adaptation, temporal fluctuations in workload and awareness under abnormal or high-pressure scenarios remain unmeasured. Future research should therefore employ mixed-method approaches combining longitudinal field trials, real-time physiological and eye-tracking data, and team-level analyses to extend the current framework's explanatory reach. Collectively, these limitations highlight that while the study establishes a robust empirical foundation linking interface usability and visual feedback quality to operator cognition and performance, its insights represent a vital but preliminary step toward a richer, temporally and contextually dynamic understanding of human–machine interaction in industrial control environments.

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