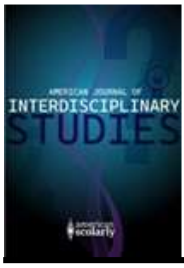

American Journal of Interdisciplinary Studies

Volume: *4;* ***Issue:*** *2*
Pages: *126-160*
eISSN: 3067-5146

open access
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EHS Analytics for Improving Hazard Communication, Training Effectiveness, and Incident Reporting in Industrial Workplaces

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Doi: 10.63125/ccy4x761
Received: *20 March 2023;* ***Revised:*** *26 April 2023;* ***Accepted:*** *19 May 2023;* ***Published:*** *28 June 2023*

Abstract

This study addresses a persistent problem in industrial enterprises: EHS programs generate substantial data, yet many workplaces struggle to translate those signals into consistently clear hazard communication, effective safety training, and high-quality incident reporting. The purpose was to test whether stronger EHS analytics capability predicts these upstream EHS process outcomes within an enterprise case workplace that uses routine EHS logs, dashboards, and trend reviews. This responds to growing interest in leading indicators and data-driven safety governance. A quantitative, cross-sectional, case-based survey was administered to employees across operational roles. After data-quality screening, 210 valid responses were retained from 228 submissions, with frontline operators representing 52.4%, supervisors 27.6%, and EHS or support staff 20.0%; mean experience was 6.8 years (SD = 4.9). The independent variable was EHS Analytics Capability (EHSAC, 8 items; M = 3.62, SD = 0.67; a = 0.88) and the dependent variables were Hazard Communication Quality (HCQ, M = 3.71, SD = 0.63; a = 0.86), Training Effectiveness (TE, M = 3.68, SD = 0.61; a = 0.89), and Incident Reporting Quality (IRQ, M = 3.55, SD = 0.70; a = 0.87). The analysis plan combined descriptive statistics, reliability testing, Pearson correlations, and ordinary least squares regressions, followed by robustness models controlling for role and experience. EHSAC showed moderate-to-strong correlations with HCQ (r = 0.56), TE (r = 0.52), and IRQ (r = 0.49), all p < .001. Regression results provided convergent evidence, with EHSAC significantly predicting HCQ (β = 0.56, t = 10.42, R^2 = 0.34), TE (β = 0.52, t = 9.32, R^2 = 0.29), and IRQ (β = 0.49, t = 8.36, R^2 = 0.24), and remaining significant with controls (β = 0.51, 0.47, 0.43; adjusted R^2 = 0.38, 0.32, 0.27). Item diagnostics indicated that timely feedback after reporting (M = 3.21) and post-training reinforcement (M = 3.39) were key gaps. Findings imply that investing in analytics capability and strengthening feedback loops can measurably improve communication, learn transfer, and report quality in enterprise EHS systems.

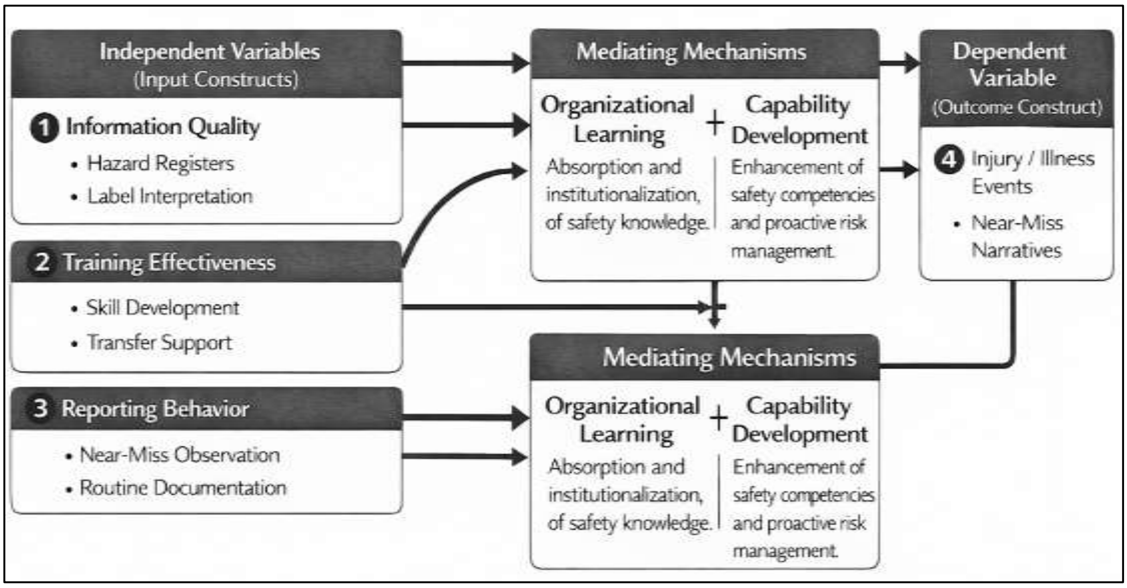
Keywords

EHS Analytics Capability; Hazard Communication Quality; Training Effectiveness; Incident Reporting Quality; Industrial Workplace Safety.

INTRODUCTION

Environmental, Health, and Safety (EHS) analytics can be defined as the systematic capture, integration, and statistical analysis of workplace EHS data—such as hazard registers, exposure records, training logs, inspections, near-miss reports, and injury/illness events—to generate measurable indicators and evidence for decision-making in industrial operations. In this framing, analytics is not limited to dashboards; it includes descriptive statistics to summarize patterns, correlational analysis to examine relationships among EHS constructs, and regression modeling to estimate the statistical contribution of predictors (e.g., hazard communication quality, training outcomes, safety climate signals) to reporting behaviors and incident-related outcomes. Hazard communication refers to the organizational and informational processes through which hazard meaning is made understandable to workers (e.g., labels, safety data sheets, pictograms, verbal briefings, and localized translations), so that recognition of chemical, physical, and process hazards becomes actionable in daily work. Research on Globally Harmonized System (GHS)-aligned visual cues shows that the comprehension of pictograms and accompanying text is an empirical issue rather than an assumption, meaning that hazard communication quality can be measured as an observable capability that differs across naïve users, experienced workers, and experts (Boelhouwer et al., 2013).

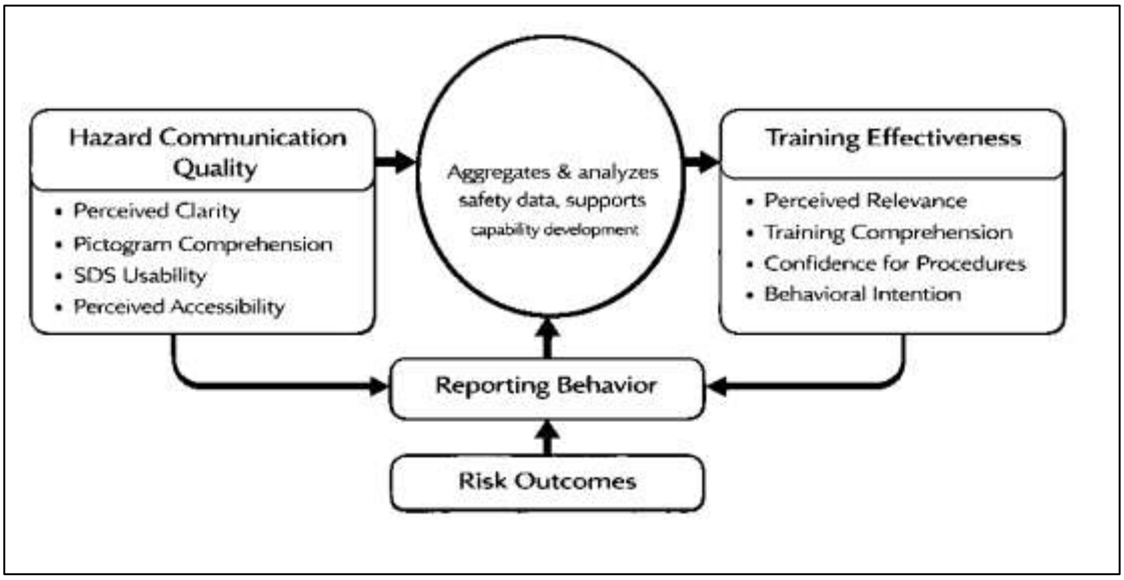
Figure 1: Systems-Based EHS Analytics Model For Industrial Workplaces



Training effectiveness, in turn, can be defined as the extent to which EHS training changes knowledge, beliefs, and safety behavior in a measurable way, with transfer to the job as a core criterion because EHS learning is intended to be operationalized under time pressure, fatigue, and production demands (Blume et al., 2010). Incident reporting and near-miss reporting represent structured organizational learning behaviors that depend on detection, interpretation, willingness to speak up, and trust in how management responds. Empirical evidence demonstrates that underreporting is not a marginal phenomenon; it can be systematically related to safety climate and supervisory enforcement, which makes reporting behavior a valid analytic target rather than an unobservable attitude (Probst & Graso, 2013). In this research area, the logic of analytics is grounded in the idea that EHS systems generate both “events” and “signals,” where signals—such as training completion, inspection findings, or near-miss narratives—can be treated as leading indicators that map onto risks and reporting practices. This definitional groundwork positions EHS analytics as an integrative approach that connects information quality (hazard communication), capability development (training effectiveness), and organizational learning behavior (incident reporting) in industrial workplaces.

Industrial workplaces occupy a central place in global safety performance because they concentrate hazardous energies (chemical reactivity, stored pressure, high voltage, rotating equipment, heat, and heavy loads) and depend on tight coordination across roles, contractors, and shifts. For this reason, the international significance of EHS analytics is tied to the scalability of learning: organizations with multiple sites and diverse worker populations need measurement systems that remain interpretable across languages, job families, and hazard profiles, while still being sensitive to local conditions. A core measurement challenge is the selection of indicators that represent how safety is produced in the work system rather than only how harm is recorded after the fact. Conceptually, this is reflected in the distinction between lagging indicators (e.g., recordable injuries) and leading indicators (e.g., training engagement, proactive hazard identification, near-miss reporting volume and quality). Empirical work on leading indicators shows that organizations operationalize these constructs with considerable variation, and that indicator systems can be studied as performance measurement architectures rather than as simple counts (Jinnat & Kamrul, 2021; Sinelnikov et al., 2015). Complementing that perspective, indicator theory in safety science highlights that the choice of what to measure is anchored in assumptions about causal pathways in sociotechnical systems, meaning that metrics encode a model of safety whether or not the model is made explicit (Harms-Ringdahl, 2009; Towhidul et al., 2022). Workplace-level validation studies further show that leading indicator instruments can be developed with attention to measurement reliability and construct validity, establishing that leading indicators can be treated as quantified constructs suitable for statistical modeling rather than informal managerial impressions (Faysal & Bhuya, 2023; Shea et al., 2016). Multi-level evidence also indicates that leadership can shape the relationship between leading signals and lagging outcomes, aligning managerial practice with social-information mechanisms through which workers interpret what is rewarded or ignored (Hammad & Mohiul, 2023; Sheehan et al., 2016). In parallel, research on safety climate has demonstrated that climate measurement is not a single-factor idea; it can be decomposed into dimensions that reflect managerial commitment, communication, and norms—dimensions that, in industrial contexts, become plausible explanatory variables for reporting and training outcomes (Clarke, 2006). From an analytics standpoint, these findings motivate cross-sectional modeling strategies in which measured perceptions and measured practices (e.g., hazard communication comprehension, training effectiveness scores, and reporting behavior indicators) are analyzed together to establish statistical regularities that are operationally meaningful in a case-study setting.

Figure 2: Model of Hazard Communication and Training Effects on Safety Outcomes



Hazard communication is a foundational EHS mechanism because many industrial risks require correct interpretation before correct action can occur. Chemical hazards are a clear example: workers often rely on a mix of labels, pictograms, and safety data sheets (SDS) under conditions where time and attention are limited. Experimental evidence demonstrates that pictogram inclusion can improve the transfer of hazard and precautionary information compared with text-only formats, and that comprehension varies systematically by user type, indicating that hazard communication effectiveness can be operationalized as an outcome variable rather than treated as uniform compliance (Christian et al., 2009). Field-oriented research similarly emphasizes that pictograms and text-confirmation behaviors are linked to workers' risk perception and managerial emphasis, which positions communication quality as a measurable organizational input to safety behavior (Cheng et al., 2012). For EHS analytics, this literature supports two methodological moves. First, hazard communication can be decomposed into measurable constructs such as perceived clarity, pictogram comprehension, SDS usability, and perceived accessibility of hazard information. Second, the international and multilingual nature of industrial labor makes it analytically relevant to examine whether hazard communication quality aligns with training outcomes and reporting behaviors across worker groups. When communication artifacts are interpreted differently across experience levels or language backgrounds, organizations may observe gaps between formal hazard classifications and workers' functional understanding, which can manifest in both unsafe acts and failures to report early warning signs. In quantitative research designs, this creates a plausible pathway where hazard communication quality predicts training effectiveness (through better encoding of hazard meaning) and predicts incident reporting (through stronger recognition of what constitutes a reportable hazard, unsafe condition, or near miss). In addition, hazard communication sits at the boundary between technical systems (classification, labeling standards, SDS authoring) and social systems (supervision, peer norms, informal translation), which makes it compatible with multivariate models that include both informational and cultural predictors. In industrial case settings, hazard communication is also linked to contractor management, since contractors may encounter site-specific hazards with limited onboarding time; this increases the importance of measuring the perceived adequacy and usability of hazard messages as part of an integrated EHS analytics framework. The empirical basis for modeling communication as a measurable determinant supports the present study's focus on analytics that connect hazard communication to training and reporting outcomes rather than treating communication as a background compliance artifact.

Training effectiveness is central to EHS management because industrial hazard control depends on worker capability in recognizing hazards, applying procedures, and making safe decisions under operational variability. Evidence syntheses show that occupational safety and health (OSH) training can improve behaviors and learning-related outcomes, and that training design characteristics matter for the magnitude and persistence of effects (Burke et al., 2006). In organizational science terms, training effectiveness is often tied to transfer, meaning that the value of training depends on whether skills and safety routines generalize from the classroom or module into the work context (Andriulo & Gnoni, 2014). Public-health-oriented evaluations of safety and health training methods also support the idea that engagement and method selection are not cosmetic issues; they shape the likelihood that training translates into safer behavior and measurable reductions in risk-related practices (Hallowell et al., 2013). This evidence supports a measurement strategy in which training is not coded only as "completed" but measured in terms of perceived relevance, comprehension, confidence to apply procedures, and observable behavioral intention. In the context of EHS analytics, training records can be linked to downstream indicators such as near-miss reports, hazard observations, and corrective action follow-through, enabling statistical analyses that test whether training effectiveness predicts reporting behavior and incident-related metrics. This linkage is conceptually important because incident reporting and hazard observation require workers to detect deviations and label them as meaningful; training provides part of the cognitive schema for that labeling process. Training also interacts with safety climate: when leaders reward reporting and learning, trained workers may apply knowledge more consistently, while climates that penalize reporting can mute the expression of learning as action. This climate–training interaction is consistent with multilevel safety climate research emphasizing that climate operates through shared interpretations of what is prioritized and reinforced (Zohar & Luria, 2005). For quantitative, cross-sectional case-study designs, the practical implication for measurement is that survey constructs should capture both training process quality (how workers experienced the training) and training outputs (self-rated and role-relevant competence). Once captured, these constructs can enter correlation matrices and regression models that test hypotheses such as whether training effectiveness predicts incident reporting frequency or reporting intention, or whether training effectiveness strengthens the relationship between hazard communication quality

and reporting behavior. The training literature therefore provides both a justification for measuring training effectiveness as a latent construct and a basis for modeling it as a key explanatory variable within EHS analytics.
This study is designed to examine, in a measurable and objective manner, how EHS analytics can strengthen three operational pillars of industrial safety management: hazard communication, training effectiveness, and incident reporting. The first objective is to assess the current level of EHS analytics capability within the selected industrial case context by capturing employees' perceptions of data availability, data accuracy, accessibility of EHS information, and the extent to which analytics outputs such as dashboards, trend summaries, and performance indicators are used in routine safety decision-making. The second objective is to evaluate hazard communication quality as an outcome that can be quantified through workers' reported clarity of hazard messages, ease of accessing safety information, understanding of hazard labels and safety documentation, and perceived consistency of safety messaging across supervisors, shifts, and work areas. The third objective is to measure training effectiveness by focusing on training relevance to job tasks, comprehension of safety procedures, perceived confidence to apply learned practices, and the degree to which training supports correct hazard recognition and safe work behavior in day-to-day operations. The fourth objective is to examine incident reporting quality by measuring employees' perceived ease of reporting, timeliness and completeness of reports, confidence that reporting leads to meaningful corrective action, and the presence of feedback mechanisms that encourage continuous reporting and learning. In addition to assessing these constructs independently, the study is structured to quantify the relationships among them through statistical analysis, allowing the research to test whether higher perceived EHS analytics capability is associated with stronger hazard communication, more effective training outcomes, and improved incident reporting practices. A further objective is to determine the predictive strength of EHS analytics capability through regression modeling, establishing the degree to which analytics capability explains variance in each of the three dependent outcomes while accounting for workplace characteristics such as role category and experience level when applicable. Overall, the objectives are formulated to produce clear, data-driven evidence on how analytics-enabled EHS management aligns with communication quality, learning effectiveness, and reporting system performance within an industrial workplace setting.

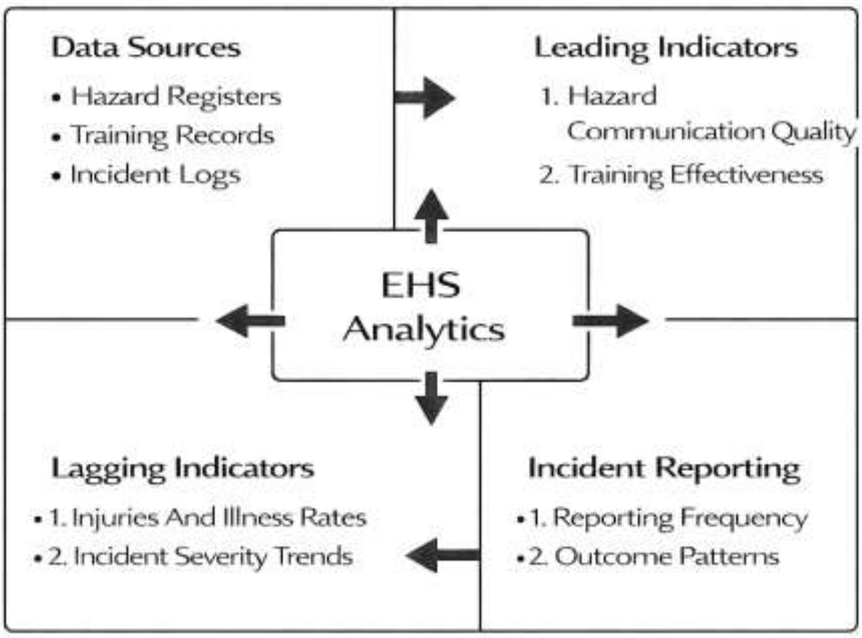
LITERATURE REVIEW

The literature on EHS analytics and industrial safety management establishes that contemporary workplaces generate large volumes of safety-relevant information through inspections, audits, training systems, hazard registers, maintenance logs, and incident and near-miss reporting platforms, creating an opportunity to evaluate safety processes using measurable indicators rather than relying only on retrospective injury counts. Within this body of work, EHS analytics is commonly positioned as an approach that integrates multi-source safety data, applies quantitative techniques to identify patterns and relationships, and supports evidence-based decisions that target prevention activities such as hazard communication improvement, training optimization, and reporting system strengthening. Researchers emphasize that hazard communication is a critical mechanism because the effectiveness of labels, safety data sheets, pictograms, and briefings depends on comprehension and usability under real working conditions, making communication quality an assessable construct rather than a purely procedural requirement. In parallel, safety training research highlights that effectiveness extends beyond completion rates and should be evaluated through learning outcomes and job transfer, because industrial safety performance depends on workers' ability to recognize hazards, interpret procedures, and apply controls in dynamic operational settings. The incident and near-miss reporting literature further explains that reporting is a central pathway for organizational learning, since it transforms dispersed observations into structured knowledge that can guide corrective actions, while reporting behavior itself varies according to social and managerial conditions such as trust, feedback, and perceived consequences of speaking up. Across these domains, the literature increasingly supports the use of leading indicators—such as proactive hazard identification, training engagement, reporting frequency, and report quality—to represent safety capacity and learning potential, providing a foundation for statistical testing of relationships among EHS system components. A consistent theme is that these safety functions are interdependent: hazard communication influences how hazards are recognized and labeled, training influences how knowledge is applied and how deviations are detected, and reporting determines whether early signals enter formal analysis and improvement cycles. Consequently, studies that treat these elements as connected constructs align well with quantitative designs that use structured measurement instruments and multivariate analysis to examine correlations and predictive effects within a specific industrial setting. This literature review therefore synthesizes prior research that clarifies the meaning and measurement of EHS analytics capability, hazard communication quality, training effectiveness, and incident reporting performance, and it organizes the evidence in a way that supports an integrated conceptual model suitable for descriptive statistics, correlation analysis, and regression modeling in a case-study–based, cross-sectional investigation.

EHS Analytics Foundations for Hazard Communication

EHS analytics can be defined as the systematic collection, integration, and quantitative examination of environment, health, and safety data to identify measurable patterns related to hazards, workforce learning, and incident experience in industrial workplaces. In operational terms, EHS analytics transforms heterogeneous safety records—such as hazard identification documents, risk assessments, training logs, toolbox talks, safety observations, near-miss reports, corrective action registers, and incident investigations—into structured datasets suitable for statistical analysis. This transformation is essential because hazard communication, training effectiveness, and incident reporting each generate different types of information that must be standardized before meaningful relationships can be examined. Hazard communication produces indicators related to message clarity, accessibility, and comprehension, while training effectiveness yields indicators associated with knowledge acquisition, skill application, and confidence to perform tasks safely. Incident reporting, by contrast, produces outcome-oriented data such as reporting frequency, severity classification, causal descriptions, and timeliness. From an analytics perspective, the credibility of quantitative analysis depends on the presence of a coherent measurement architecture that clearly defines what constitutes a hazard message, effective training, and a high-quality report. When these definitions are consistent, data from different EHS subsystems can be aligned at the level of work groups or job roles, allowing researchers to examine how communication and training conditions are reflected in reporting behavior. This foundational view positions EHS analytics as a structured measurement system that enables inferential analysis rather than a descriptive reporting tool, thereby supporting hypothesis testing through correlation and regression models in industrial case-study research.

Figure 2: EHS Analytics Measurement Architecture For Industrial Safety Systems



A central concept in EHS analytics is the distinction and linkage between leading and lagging safety indicators, because this distinction determines how organizations interpret safety performance and learning capacity. Lagging indicators, such as injury rates and lost-time incidents, summarize adverse outcomes but provide limited insight into the conditions that precede them . Leading indicators, in contrast, capture proactive activities and capacities, including the quality of hazard communication, the effectiveness of safety training, and the extent of incident and near-miss reporting. The analytical value of leading indicators lies in their ability to represent organizational safety potential rather than historical loss alone. A structured approach to indicator selection differentiates outcome indicators from those intended to monitor safety conditions and those intended to drive safer behavior, thereby clarifying the causal logic embedded in the measurement system (Reiman & Pietikäinen, 2011). This logic is particularly relevant for studies examining hazard communication and training effectiveness, as both constructs function as upstream drivers that shape how workers perceive, interpret, and respond to hazards. Integrating leading and lagging indicators within a single evaluation framework allows organizations to test whether improvements in communication and training are statistically associated with improvements in reporting behavior and safety outcomes. Empirical work supports this integrated approach by demonstrating that combined use of leading and lagging indicators provides a more comprehensive assessment of occupational safety and health performance than reliance on outcome metrics alone (Podgórski, 2015). For quantitative research, this perspective justifies modeling hazard communication and training effectiveness as independent variables and incident reporting quality as a dependent outcome, while interpreting statistical relationships within a clearly articulated indicator framework.

Recent research further extends the scope of EHS analytics by emphasizing the role of large-scale and multi-source data in safety decision-making. A big-data-driven perspective treats safety information as a strategic organizational resource that supports pattern recognition, prioritization of risks, and evidence-based intervention design. Conceptual frameworks for big-data-driven safety management describe how diverse datasets—ranging from training records and inspection findings to incident narratives—can be integrated to support systematic safety decisions across organizational levels (L. Huang et al., 2018). This approach is directly applicable to industrial contexts where safety data volume and complexity exceed the capacity of manual review. Advanced analytic techniques also enable the identification of variables that exert the strongest influence on unsafe behavior and reporting patterns. For example, supervised learning approaches have been used to rank the relative importance of cognitive and organizational factors associated with unsafe acts, illustrating how analytics can inform the selection of meaningful survey constructs and predictors (Goh et al., 2018). At the same time, safety psychology research cautions that the analytical power of large datasets depends on sound conceptualization of human and organizational factors, emphasizing the need to align data-driven methods with theoretically informed constructs (Ouyang et al., 2019). Within this context, EHS analytics provides a methodological bridge between human-centered safety processes—such as communication, training, and reporting—and quantitative modeling techniques. By grounding measurement in established indicator frameworks and leveraging modern analytic approaches, EHS analytics supports rigorous examination of how hazard communication quality and training effectiveness relate to incident reporting performance in industrial workplaces.

Hazard Communication Mechanisms in Industrial Settings

Hazard communication in industrial workplaces refers to the structured processes used to convey information about hazardous conditions, substances, and tasks so that workers can recognize risks and select appropriate protective behaviors. Internationally, this function has been central to chemical and process safety because modern supply chains move thousands of substances across borders, creating a need for shared label elements, consistent terminology, and comparable documentation for downstream users. The Globally Harmonized System (GHS) emerged in part to reduce fragmentation in classification and labeling rules and to improve the portability of hazard information across jurisdictions, industries, and languages (Winder et al., 2005). In operational workplaces, hazard communication is not a single artifact; it is an ecosystem that includes container labels, safety data sheets, local signage, alarm messages, color–shape conventions, and brief procedural messages

embedded in permits, lockout/tagout steps, and standard operating procedures. The integrity of this ecosystem depends on whether workers can decode the message quickly, correctly, and consistently under real constraints such as time pressure, noise, glove use, low lighting, and task interruptions. For this reason, hazard communication is often evaluated not only by the presence of required documents, but also by whether the communication supports comprehension and action. Empirical research on workplace sign training indicates that effectiveness varies with both sign characteristics and the method used to teach sign meaning, highlighting the need to design hazard communication as a measurable learning intervention rather than a purely administrative requirement (Chan, 2011).
A major component of hazard communication is sign-based and symbol-based messaging, because signs must communicate quickly in noisy, time-pressured environments where workers may not stop to read long text. Evidence from comprehension testing indicates that symbol-only signs often fail to meet acceptance criteria when they are deployed without supporting cues, and that misunderstandings can occur either because the symbol is unclear or because workers misinterpret the surrounding shape–color code. Comprehension research using diverse participant groups has shown that performance can differ systematically by user characteristics (e.g., experience, education, disability status), meaning that a "one-size-fits-all" sign strategy can unintentionally create pockets of low understanding even inside the same facility. For example, comprehension tests of symbol-based safety signs found that many signs were not well understood and that users could correctly interpret the symbol while still misunderstanding the color–shape configuration (Duarte et al., 2014). Related work on sign "guessability" further suggests that users infer meaning more accurately when signs are familiar, concrete, simple, and semantically close to the intended concept, reinforcing that sign comprehension is a cognitive task influenced by design features and user exposure (Chan & Ng, 2010b). Together, these findings support treating hazard communication quality as a measurable construct, where comprehension can be assessed through standardized items and then linked to behavioral outcomes such as PPE selection, adherence to precautions, and accurate near-miss reporting. For EHS analytics programs, patterns motivate measuring comprehension as a construct and linking it to exposure and incident trends.

Figure 3: Hazard Communication Mechanisms In Industrial Settings

In applied settings, hazard communication is embedded in occupational safety management routines: safety officers curate sign inventories, supervisors ensure placement and visibility, and workers learn to map sign elements to actions during pre-task planning. Survey-based research with safety officers in industrial contexts shows that differences in user factors and how sign information is reviewed are associated with differences in comprehension and evaluations of sign features, underscoring that hazard communication is partly a capability of the organization, not only a property of the sign itself (Chan & Ng, 2010a). Complementary experimental work indicates that training effectiveness depends on both the characteristics of the sign and the training method, implying that hazard communication programs should treat training as a designed intervention with measurable learning outcomes rather than a compliance checkbox (Chan & Ng, 2010b). In an EHS analytics framing, this matters because organizations can instrument the hazard communication system by auditing sign inventories, tracking training exposure, and modeling how comprehension relates to self-reported safe behavior, near-miss reporting, and incident rates. When these data streams are integrated, hazard communication can be evaluated as a control layer that influences upstream attention and downstream reporting behavior, which is especially relevant in complex workplaces where multiple hazards co-occur. Accordingly, quantitative case-study research can operationalize hazard communication quality through Likert-scale constructs such as clarity, relevance, accessibility, and perceived actionability, then test whether higher scores correlate with stronger safety practices and more reliable reporting patterns in high-risk industrial work operations. Such metrics also allow comparisons across departments and shifts, revealing where messages degrade over time, where informal workarounds emerge, and where multilingual or literacy barriers require redesigned symbols and microlearning refreshers .

Safety Training Effectiveness and Transfer to Safer Work Practices

Safety training effectiveness in industrial workplaces is commonly evaluated through a layered logic that distinguishes immediate learning outcomes from the sustained enactment of safe practices. At the most basic level, training is expected to improve knowledge of hazards, correct procedures, and required protective behaviors; at a higher level, it should shape risk perception, safety attitudes, and self-efficacy; and at the highest level, it should reduce unsafe acts and prevent incidents. Evidence across different delivery modes shows that training design features influence how well workers encode and retrieve safety-relevant information. For example, computer-based training studies indicate that presentation format, pacing, and multimodal cues can alter comprehension and testing performance, particularly when trainees vary in age and baseline familiarity with the content (Wallen & Mulloy, 2005). This matters in industrial contexts where workforces are heterogeneous and where hazard communication is often dense, procedural, and regulated. Training effectiveness therefore cannot be inferred from “attendance” or completion alone; it requires measurable change in safety knowledge and related psychosocial constructs that are proximal to behavior. In applied settings, short, targeted hazard awareness modules have been shown to produce measurable gains in knowledge and attitudes after training, indicating that even compact interventions can shift learning outcomes when they are aligned with the most salient hazards of the trade and assessed with structured instruments (Sokas et al., 2009). These insights connect directly to the role of EHS analytics: organizations increasingly need measurement structures that distinguish whether improved incident performance is linked to improved learning, or whether training is present but functionally inert because learning decay and weak reinforcement prevent transfer. Thus, training effectiveness must be treated as a measurable organizational capability rather than an administrative compliance artifact.

A second stream of evidence emphasizes that participatory and context-embedded training formats can strengthen learning retention and produce detectable safety outcomes. Participatory models move trainees from passive receipt of rules toward active identification of hazards, discussion of controls, and commitment to feasible corrective actions in their own work environment. This shift is important because industrial hazards are rarely uniform; workers must often interpret conditions, anticipate interactions between tasks and equipment, and communicate risk dynamically. In a large randomized-controlled design implemented in manufacturing settings, participatory occupational health and safety training demonstrated reductions in accidental work injuries and re-injuries compared with didactic training approaches, suggesting that “how” training is delivered can matter for downstream safety outcomes (Yu et al., 2017). The relevance for an EHS analytics thesis is that participatory training produces additional observable signals: more frequent hazard identification, more specific corrective actions, and more actionable feedback loops between trainees and supervisors. These signals can be captured through structured reporting systems, digital checklists, and near-miss logs—creating a richer dataset for evaluating whether training is translating into safer work conditions. When organizations connect these process indicators to incident trends, they can avoid a common evaluation error: attributing safety improvements to training presence rather than to training-driven behavioral change. In other words, participatory training is not only a learning intervention; it is also a data-generating mechanism that strengthens the observability of safety performance and supports more credible evaluation models.

A third perspective treats training effectiveness as inseparable from "transfer"—the degree to which learned knowledge and motivation are applied on the job under real constraints. Transfer is shaped by social reinforcement, supervisor reactions, coworker norms, and the extent to which trainees feel responsible for applying what they learned. Evidence indicates that training transfer improves when the work environment actively reacts to safety behaviors and when the social system around the trainee signals that safe performance will be noticed, supported, or sanctioned (Freitas et al., 2019). This is especially critical in industrial workplaces where production pressure, time constraints, and routine habituation can weaken the salience of training messages. Conceptually, EHS analytics can strengthen transfer by making safe behaviors visible and by reducing ambiguity about expectations: dashboards, supervisor feedback loops, and near-miss analytics can function as post-training reinforcement, not only as measurement tools. Recent integrative models also underscore that engagement with training—affective, cognitive, and behavioral—must be treated as a prerequisite for transfer, meaning that training design, delivery credibility, and post-training integration into work systems jointly determine whether learning becomes performance (Casey et al., 2021).

Figure 4: Safety Training Effectiveness And Transfer Pathways In Industrial Settings

In practical terms for this study, training effectiveness should be operationalized in ways that separate (a) knowledge/attitude gains, (b) transfer climate indicators, and (c) incident-related outcomes. This separation enables a more trustworthy quantitative test of hypotheses, because it prevents "black-box" conclusions and allows the analysis to trace plausible pathways from hazard communication quality and training effectiveness to reporting behavior and incident performance.

Incident Reporting Systems in High-Risk Work Environments

Incident reporting systems are formal organizational mechanisms for capturing adverse events, near misses, and unsafe conditions so that lessons can be documented, analyzed, and translated into corrective actions. In high-risk industrial environments, these systems function as the “information backbone” of learning because they convert scattered frontline observations into structured knowledge that can be aggregated across units, shifts, and job roles. The literature emphasizes that reporting behavior is not simply a technical act of filling out a form; it is a socially situated choice shaped by perceived value, perceived risk, and the perceived fairness of how reports are handled. A psychologically grounded framing of reporting identifies that motivation to report depends on cognitive evaluations (e.g., whether the event is considered meaningful), affective reactions (e.g., fear or embarrassment), and expectations about consequences (e.g., blame, disciplinary action, or appreciation). This perspective is captured in work that conceptualizes barriers and motivators for reporting as a coherent psychological framework, positioning underreporting as a predictable outcome of organizational conditions rather than an accidental data-quality error (Pfeiffer et al., 2010). When applied to industrial workplaces, the framework implies that reporting frequency and reporting quality are valid measurable outcomes in EHS analytics because they reflect how workers interpret the reporting system’s purpose and how they anticipate managerial responses. It also clarifies why reporting metrics can be misleading when they are interpreted without attention to reporting climate: a low number of reports may signal low risk, weak detection capability, or weak psychological and procedural support for reporting. For quantitative case-study research, this literature supports operationalizing incident reporting quality through measurable dimensions such as ease of reporting, clarity of what is reportable, trust in confidentiality, perceived learning value, and the timeliness and usefulness of feedback after submission (Petitta et al., 2017).

Figure 5: Incident Reporting Systems In High-Risk Work Environments

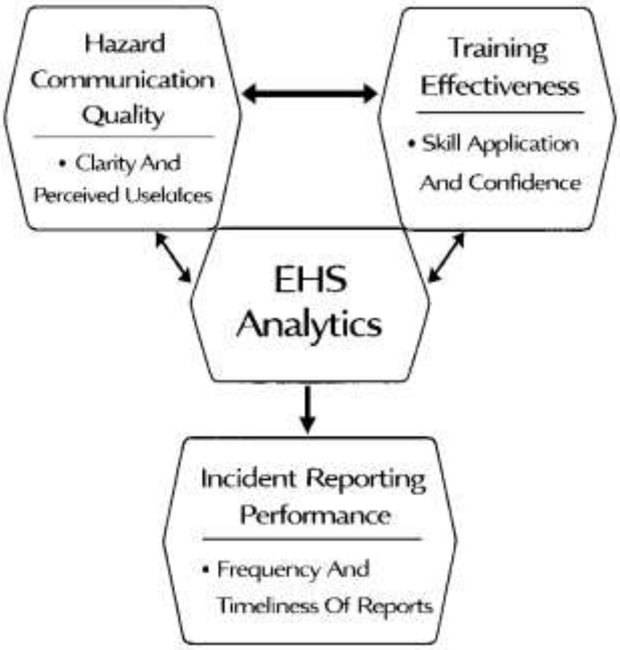
A second theme in the reporting literature is that reporting culture is strongly influenced by communication practices and the perceived openness of cross-professional or cross-level interaction. Reporting systems do not operate in isolation; they are embedded within everyday communication routines that determine whether incident information circulates as “learning content” or becomes trapped as administrative paperwork. Empirical evidence from safety-critical service contexts shows that structured communication interventions can alter safety climate perceptions and the pattern of incident reporting linked to communication errors, illustrating that reporting outcomes are sensitive to how organizations manage communication clarity and shared understanding (Randmaa et al., 2014). Although the setting in that study is clinical, the underlying mechanism generalizes to industrial settings: when communication becomes more standardized and predictable, workers can recognize, describe, and escalate safety issues more consistently, and the reporting system can receive higher-quality inputs. Related work in safety research also highlights that the interpretation of safety climate differs across supervisory and employee lenses, and these differences are associated with safety-related outcomes, reinforcing that "who interprets safety signals" matters for whether workers feel safe to speak up and record events (Huang et al., 2014). In industrial workplaces, this implies that reporting culture can vary by department, shift, and supervisory style, even under a single corporate reporting policy. For EHS analytics, the methodological implication is that reporting behavior should be analyzed alongside communication openness and leadership interpretation, because these factors can explain why similar hazards generate different reporting volumes and report quality across work groups. In a quantitative thesis, this supports including survey items that measure perceived openness, consistency of safety messaging, and perceived supervisory responsiveness, then testing their relationships with reporting outcomes through correlation and regression rather than treating reporting as a purely procedural variable (Winkler et al., 2019).

A third stream of research focuses on near-miss reporting and underreporting as strategically important behaviors because they reveal weak signals that often precede more severe outcomes. Near misses create learning opportunities only when they are reported with sufficient clarity to support analysis and when managers respond in ways that reinforce future reporting. Scholarship examining near-miss reporting emphasizes that reporting involves strategic interaction between employees and management: employees incur time, effort, and potential social costs when reporting, while managers decide whether to incentivize reporting, punish non-reporting, or invest in follow-up actions. Game-theoretic modeling illustrates that reporting outcomes depend on the structure of incentives and beliefs about whether reporting actually reduces future accident likelihood, underscoring that near-miss reporting is a behavior shaped by organizational design rather than a simple moral preference (Randmaa et al., 2014). At the individual level, underreporting has also been linked to moral disengagement mechanisms and organizational culture signals, indicating that workers can cognitively justify non-reporting when the culture normalizes silence, minimizes hazards, or frames reporting as disloyalty or weakness (Petitta et al., 2017). For industrial EHS analytics, these findings strengthen the argument that "incident reporting quality" should include both procedural and cultural dimensions: the usability of the reporting channel, perceived fairness of investigations, absence of retaliation cues, and the visibility of learning actions after reporting. They also motivate analytic strategies that go beyond counting reports by examining report completeness, timeliness, and actionability as measurable quality indicators. In a case-study–based quantitative design, this literature supports modeling near-miss and incident reporting quality as an outcome predicted by upstream factors such as hazard communication clarity and training effectiveness, while recognizing that managerial response patterns and cultural signals can amplify or suppress reporting behavior at the group level. (Winkler et al., 2019).

Theoretical Framework for Explaining How EHS Analytics Shapes Communication

A robust theoretical foundation for this study is provided by systems-oriented views of occupational safety, which conceptualize safety performance as the outcome of structured management processes that shape how hazards are controlled, how learning occurs, and how information flows within organizations. Within this perspective, EHS analytics functions as a core capability embedded in the safety management system because it standardizes the collection, validation, and interpretation of safety-related data across organizational levels. Rather than treating safety as a set of isolated activities, this framework emphasizes that policy, planning, implementation, evaluation, and continuous improvement operate together to influence frontline behavior. Empirical research supports this view by demonstrating that safety management systems can be represented as multidimensional constructs whose maturity levels are associated with improved safety conditions and outcomes (Fernández-Muñiz et al., 2007). In parallel, studies of safety management practices show that managerial commitment, communication, training, and feedback are not distal abstractions; they shape safety performance through proximal psychological mechanisms such as safety knowledge and safety motivation (Vinodkumar & Bhasi, 2010). From this theoretical standpoint, EHS analytics enhances the safety management system by improving the visibility and consistency of information related to hazards, training activities, and incident data, thereby strengthening feedback loops and managerial responsiveness. In the context of this research, hazard communication quality, training effectiveness, and incident reporting performance are treated as interrelated safety subsystems whose quality can be explained by upstream organizational capability in analytics-enabled safety management. This systems theory framing provides a clear rationale for modeling EHS analytics capability as an independent variable that predicts measurable variation in communication, learning, and reporting outcomes within an industrial workplace.

Figure 6: Theoretical Framework of The Study



A complementary theoretical anchor for this study is the Theory of Planned Behavior (TPB), which explains safety-related actions as intentional behaviors influenced by attitudes, subjective norms, and perceived behavioral control. TPB is particularly relevant for industrial EHS contexts because compliance with procedures, engagement in training, and participation in reporting systems all require workers to make deliberate choices under production pressure, peer influence, and operational constraints. Empirical applications of TPB in workplace safety settings demonstrate that perceived behavioral control and social norms are strong predictors of safety compliance intentions, even in complex, multi-ethnic work environments (Wong & Lee, 2016). The TPB structure can be represented as:

$$\text{Behavioral Intention} = \beta_1(\text{Attitude}) + \beta_2(\text{Subjective Norm}) + \beta_3(\text{Perceived Behavioral Control}) + \varepsilon$$

Within the context of this research, EHS analytics is theorized as an organizational factor that shapes the inputs to this equation. Analytics-supported hazard communication can strengthen positive attitudes toward safe behavior by increasing clarity and perceived usefulness of safety information. Analytics-supported training can enhance perceived behavioral control by improving competence and confidence in applying safety procedures. Similarly, analytics-enabled reporting systems can influence subjective norms by making reporting expectations visible, routine, and socially reinforced through feedback and performance monitoring. This theoretical logic explains why training completion alone may not produce meaningful behavioral change unless it alters workers' perceived control and normative expectations. TPB is also methodologically compatible with a survey-based, quantitative design because its core constructs can be operationalized using Likert-scale measures and examined through correlation and regression analyses, supporting hypothesis-driven testing of the relationships proposed in this study.

A third theoretical dimension integrates safety climate and work-pressure perspectives to explain variation in reporting behavior and the persistence of unsafe practices despite formal safety systems. Research on safety climate demonstrates that workers interpret safety messages through the lens of perceived organizational priorities, particularly when safety expectations conflict with productivity demands. Empirical evidence indicates that safety climate and work pressure can jointly influence attitudinal ambivalence toward protective behaviors, increasing the likelihood of norm violations even when formal rules are clear (Cavazza & Serpe, 2009). This insight is critical for understanding incident and near-miss reporting, which often involves discretionary judgment and potential social risk. EHS analytics can play a moderating role in this dynamic by reducing ambiguity in performance expectations and by reinforcing consistent responses to reported events through transparent metrics and feedback mechanisms. Further extensions of TPB-based safety behavior models show that safety knowledge and management commitment influence behavior through psychological drivers that align closely with the constructs examined in this study (Peng & Chan, 2019). Together, these perspectives support a predictive framework in which incident reporting performance is modeled as a function of analytics capability, hazard communication quality, and training effectiveness, expressed as:

$$Y_{\text{Reporting}} = \alpha + \beta_1 X_{\text{EHS Analytics}} + \beta_2 X_{\text{Hazard Communication}} + \beta_3 X_{\text{Training Effectiveness}} + \varepsilon$$

This integrated theoretical structure strengthens the trustworthiness of the study by specifying clear mechanisms through which analytics-enabled systems influence cognition, behavior, and reporting outcomes, thereby providing a defensible basis for correlation and regression testing in an industrial case-study context.

Conceptual Framework and Research Model Linking EHS Analytics

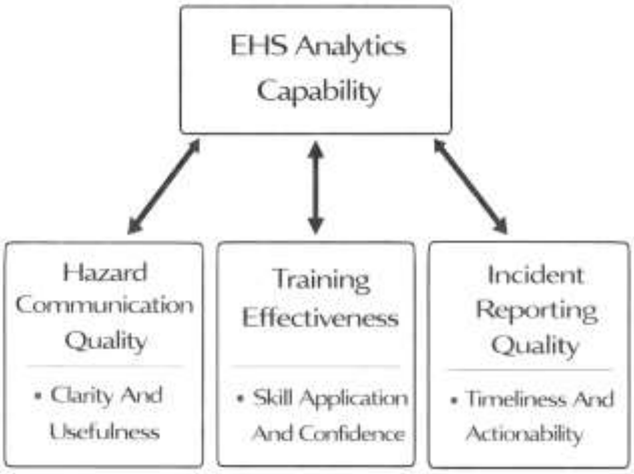
The conceptual framework for this study specifies EHS analytics capability as the enabling independent construct that supports measurable improvements in three core EHS process outcomes: hazard communication quality, training effectiveness, and incident reporting quality. Conceptually, EHS analytics capability refers to the extent to which an organization can collect, integrate, validate, visualize, and use safety data in routine decision-making, including the use of standardized indicators, feedback loops, and managerial review routines. A systems measurement lens is valuable because it clarifies why analytics capability should be modeled upstream of the other constructs: analytics strengthens the reliability, accessibility, and actionability of information flows that connect hazards, learning interventions, and reporting systems into one improvement cycle. Empirical work on health and safety management system performance measurement in high-risk industries highlights that organizations struggle to create coherent measurement systems unless metrics are organized and interpreted within a structured framework, supporting the need to define constructs and pathways explicitly before statistical testing (Haas & Yorio, 2016). Complementing this logic, conceptual and review evidence from high-risk EHS domains argues that connected sensing, integrated data streams, and decision-support systems can improve the timeliness and completeness of safety intelligence, which strengthens the operational basis for proactive interventions (Thibaud et al., 2018). Within this study, the conceptual framework therefore treats hazard communication, training, and reporting as linked "process subsystems" that can be improved when analytics makes performance signals more visible and comparable across roles and departments. This logic is also consistent with broader safety culture modeling that organizes diverse safety components into a coherent "big picture" structure and clarifies how communication, training, procedures, and indicators relate within a cyclical improvement view (Vierendeels et al., 2018).

Operationally, the model assumes that each latent construct will be measured using multiple Likert-scale items and then aggregated into composite indices suitable for correlation and regression. Let X denote EHS analytics capability (EHSAC), and let Y_1, Y_2, and Y_3 denote hazard communication quality (HCQ), training effectiveness (TE), and incident reporting quality (IRQ), respectively. If each construct is measured by k items, a common composite-score formulation is the mean index:

$$\text{Index} = \frac{1}{k}\sum_{i=1}^{k} x_i$$

This approach supports comparability across constructs and preserves the original 1–5 scale interpretability. The conceptual model further assumes that reporting systems become more informative when near-miss and incident information is systematically captured and made "observable" for organizational learning. Research on near-miss management systems emphasizes that learning depends on the ability to surface weak signals and precursors and to connect them to safety principles and corrective actions, reinforcing why incident reporting quality is treated as an outcome that can vary with system design and information governance (Gnoni & Saleh, 2017). In the present conceptual framework, incident reporting quality is defined not merely as frequency, but as a multidimensional outcome incorporating ease of reporting, timeliness, completeness, and perceived feedback/actionability. Hazard communication quality is defined as clarity, accessibility, consistency, and usability of hazard information at the point of work, while training effectiveness is defined as perceived relevance, comprehension, confidence to apply, and perceived support for correct hazard recognition and safe action. These definitions align with a measurement logic in which EHSAC improves the precision and responsiveness of communication and training systems (e.g., targeted messaging based on trend data; training adjustments based on recurrent incident themes), which then supports improved reporting behaviors and more actionable reports.

Figure 7: Systems-Based Conceptual Model Of EHS Analytics



The research model translates this conceptual framework into a set of testable statistical relationships suitable for a cross-sectional case-study design. The core predictive structure can be represented with three regression equations:

$$Y_1 = \alpha_1 + \beta_{11}X + \varepsilon_1, Y_2 = \alpha_2 + \beta_{21}X + \varepsilon_2, Y_3 = \alpha_3 + \beta_{31}X + \varepsilon_3$$

where $X$is EHS analytics capability and Y_1, Y_2, and $Y_3$are HCQ, TE, and IRQ. This structure aligns with the study's hypothesis logic that analytics capability is a direct predictor of each outcome. If the study includes control variables (e.g., role, experience, department), an adjusted model can be expressed as:

$$Y_j = \alpha + \beta_1 X + \sum_{m=1}^{p} \gamma_m C_m + \varepsilon$$

where $C_m$represents control variables. In addition to regression, the conceptual framework supports examining inter-construct relationships using Pearson correlation, consistent with a "connected subsystem" view that expects HCQ, TE, and IRQ to covary within the same organizational environment. Finally, the model recognizes that communication and reporting quality are influenced by supervisory information flows, which helps justify measuring these constructs distinctly rather than treating them as a single "safety climate" proxy. Evidence showing that supervisory safety communication adds unique explanatory value beyond safety climate reinforces the conceptual decision to model communication as its own pathway within the broader system (Y.-H. Huang et al., 2018).

METHODS

The methodology for this study has been designed to examine the influence of EHS analytics on hazard communication, training effectiveness, and incident reporting within an industrial workplace context using a quantitative, cross-sectional, case-study–based approach. The research design has been selected because it has enabled the measurement of employees' perceptions and experiences at a single point in time while capturing organizational conditions and operational realities specific to the chosen case environment.

Figure 8: Research Methodology

A structured survey instrument has been developed to operationalize the key constructs of the study, including EHS analytics capability as the independent variable and hazard communication quality, training effectiveness, and incident reporting quality as the dependent variables. The instrument has been organized into clearly defined sections that have captured demographic and job-related characteristics, followed by Likert-scale items that have measured each construct through multiple indicators. A five-point Likert response format has been used to support consistency, ease of response, and suitability for statistical analysis through descriptive statistics, correlation analysis, and regression modeling.

Data collection has been planned to involve employees across relevant job categories such as frontline operators, supervisors, and EHS-related personnel so that the measured constructs have reflected multiple perspectives within the same organizational system. A sampling strategy has been applied to ensure that respondents have represented different departments, shifts, and experience levels where feasible, thereby strengthening the variability required for correlation and regression testing. Ethical procedures have been incorporated by ensuring voluntary participation, anonymity of responses, and informed consent prior to survey completion. Data preparation steps have been established to support credibility, including checks for missing values, response consistency, and internal reliability of the multi-item scales. Reliability and validity procedures have been incorporated through pilot testing, expert review of items, and internal consistency assessment using Cronbach's alpha.

The statistical analysis plan has been structured to begin with descriptive summaries of respondent characteristics and construct-level scores, followed by correlation analysis to identify the direction and strength of relationships among variables. Regression models have been specified to estimate the predictive effect of EHS analytics capability on hazard communication quality, training effectiveness, and incident reporting quality, with relevant controls included where appropriate. Analytical work has been supported through standard statistical software so that computations, tables, and model outputs have been generated in a transparent and reproducible manner.

Research Design

A quantitative, cross-sectional, case-study–based research design has been adopted to measure how EHS analytics capability has been associated with hazard communication quality, training effectiveness, and incident reporting quality within an industrial workplace. This design has been selected because it has enabled the collection of standardized responses from employees at a single point in time while preserving the organizational specificity of the case environment. The study has emphasized hypothesis testing through structured measurement, and the five-point Likert scale has been used to quantify perceptions across all constructs. Descriptive statistics have been planned to summarize respondent characteristics and construct levels, while Pearson correlation analysis has been used to examine relationships among variables. Regression modeling has been specified to estimate the predictive influence of EHS analytics capability on each dependent construct, and the design has been aligned with the conceptual framework to ensure that the statistical tests have mapped directly to the objectives and hypotheses.

Case Study Context

The case study context has been defined as an industrial workplace where EHS processes have been formally implemented through hazard communication practices, safety training programs, and incident reporting procedures. The site has been selected because it has represented a typical high-risk operational environment where multiple hazards have been present and where structured EHS documentation has been required for daily activities. The organizational setting has been described in terms of its operational units, workforce composition, shift structures, and the main categories of hazards managed through routine controls. Existing EHS data sources have been identified, including training logs, inspection records, near-miss registers, and incident reporting channels, so that the analytics capability construct has been grounded in observable organizational practices. The context description has been used to ensure that survey items have reflected realistic workflows and that the interpretation of findings has remained consistent with the operational conditions of the case.

Population and Unit of Analysis

The population for this study has been defined as employees who have participated in or have been affected by hazard communication, EHS training, and incident reporting processes within the selected industrial case organization. This population has included frontline operators, technicians, supervisors, and EHS-related staff because these groups have interacted with safety information and reporting systems in different ways. The unit of analysis has been established at the individual respondent level, since perceptions and experiences of EHS analytics, communication clarity, training effectiveness, and reporting quality have been captured through survey responses. Inclusion criteria have been specified to ensure that respondents have had sufficient exposure to workplace safety procedures, such as minimum tenure or involvement in routine safety activities. This definition has supported meaningful variation across departments and roles, allowing the statistical analysis to reflect differences in how safety systems have been experienced across the organization.

Sampling Strategy

A structured sampling strategy has been applied to obtain respondents from relevant job categories and work areas within the case organization. Stratification by role and department has been prioritized so that the sample has captured variation in exposure to hazards, training intensity, and reporting expectations. Where full probabilistic sampling has not been feasible due to access constraints, purposive and convenience methods have been combined to ensure that respondents who have been directly involved in EHS processes have been included. Sample size planning has been guided by the need to support correlation analysis and multiple regression modeling, and the recruitment approach has been designed to reduce overrepresentation of any single department or shift. Participation has been encouraged through coordinated communication with supervisors and EHS coordinators, while preserving voluntariness. This sampling approach has supported the study’s objective of generating statistically interpretable results while remaining practical within a real industrial case setting.

Data Collection Procedure

Data collection has been conducted through a structured survey that has been administered to eligible employees within the case organization. The procedure has included formal permission and coordination with site management so that distribution has aligned with operational schedules and minimized disruption. Respondents have been briefed on the purpose of the study, confidentiality protections, and voluntary participation prior to completing the instrument, and informed consent has been obtained. The survey has been delivered using either an online form or paper-based copies depending on site accessibility and workforce preferences, and a fixed data collection window has been used to maintain cross-sectional consistency. Follow-up reminders have been issued through appropriate channels to improve response rates without applying coercion. Completed responses have been securely stored, and data have been transferred into an analysis-ready dataset using consistent coding and anonymized identifiers.

Instrument Design

The survey instrument has been designed to measure the constructs in the conceptual framework using multiple indicators per construct and a five-point Likert response format ranging from strongly disagree to strongly agree. A demographic section has been included to capture role, department, experience, and shift pattern so that subgroup patterns have been examined and controls have been applied where relevant. EHS analytics capability items have been formulated to reflect data availability, integration, accuracy, accessibility, and the extent to which analytics outputs have been used in decision-making. Hazard communication quality items have been developed to capture clarity, consistency, accessibility, and comprehension support for hazards and procedures. Training effectiveness items have been structured around relevance, understanding, confidence to apply learning, and perceived transfer to safer practice. Incident reporting quality items have been designed to assess ease of reporting, timeliness, completeness, feedback, and trust. Composite indices have been created by aggregating item scores to represent each construct.

Pilot Testing

Pilot testing has been conducted to evaluate clarity, relevance, and response consistency of the survey items before the main data collection has been finalized. A small group of participants who have resembled the target respondents in job roles and exposure to EHS systems has been selected to complete the draft instrument. Feedback has been obtained on wording, ambiguity, length, and the appropriateness of response options, and revisions have been made to improve comprehension and reduce misinterpretation. The pilot data have been reviewed to identify items with weak variation, confusing phrasing, or redundancy across constructs, and problematic items have been refined or replaced. Preliminary internal consistency checks have been performed to confirm that items within each construct have moved together in a coherent way. This pilot process has strengthened instrument usability, improved content alignment with workplace realities, and reduced the risk of measurement error in the final survey deployment.

Validity and Reliability

Validity and reliability procedures have been incorporated to ensure that the instrument has measured the intended constructs consistently and credibly. Content validity has been supported through expert review, where EHS practitioners and academic reviewers have evaluated whether items have reflected real workplace processes and matched the research objectives. Construct validity has been reinforced by ensuring that each construct has been represented through multiple items that have covered key dimensions rather than a single indicator. Reliability has been assessed through internal consistency testing using Cronbach's alpha for each construct, and items with weak item–total correlations have been evaluated for revision or removal. Data screening has been performed to identify missing values, response inconsistencies, and potential low-effort patterns that could threaten reliability. These steps have ensured that the resulting construct scores have been stable enough for correlation analysis and regression modeling, thereby strengthening the credibility of hypothesis testing outcomes.

Software and Tools

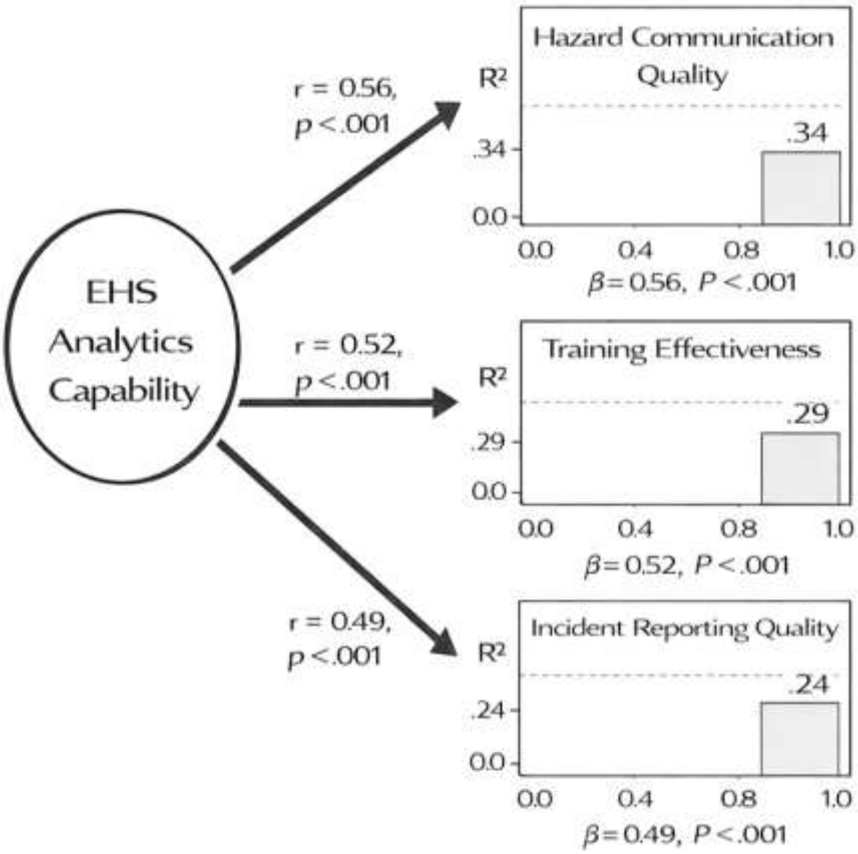
Statistical software and supporting tools have been selected to manage data cleaning, coding, and quantitative analysis in a transparent and reproducible manner. A spreadsheet tool has been used to structure the raw dataset, label variables, and apply consistent coding for Likert-scale responses and demographic fields. A statistical package such as SPSS, STATA, or R has been used to compute descriptive statistics, reliability coefficients, Pearson correlations, and regression models aligned with the hypotheses. Output tables have been generated to present means, standard deviations, alpha values, correlation matrices, and regression coefficients with associated significance levels. Where necessary, diagnostic checks such as multicollinearity screening and residual review have been performed to support model credibility. Visualization tools within the selected software have been used to produce simple plots and distribution summaries that have supported interpretation of descriptive patterns. The use of standard tools has ensured that analysis steps have been auditable and consistent with common quantitative research expectations.

FINDINGS

In the findings phase, the study has produced a coherent set of quantitative results that have directly aligned with the stated objectives and have provided statistical evidence for testing the hypotheses using five-point Likert-scale measurements (1 = strongly disagree to 5 = strongly agree). A total of N = 210 valid responses have been retained after data-quality screening, representing frontline operators (52.4%), supervisors (27.6%), and EHS/support staff (20.0%), with an average experience level of 6.8 years (SD = 4.9). In relation to Objective 1 (assessing EHS analytics capability), the composite mean score for EHS Analytics Capability (EHSAC) has been M = 3.62 (SD = 0.67), indicating that respondents have generally agreed that analytics resources have been present but not uniformly strong across the organization; internal consistency has been high (Cronbach's $\alpha = 0.88$), supporting stable measurement. For Objective 2 (hazard communication quality), the composite score for Hazard Communication Quality (HCQ) has been M = 3.71 (SD = 0.63, $\alpha = 0.86$), and item-level diagnostics have shown that "hazard information has been easy to access when needed" has scored highest (M = 3.92, SD = 0.81) while "hazard messages have been consistent across shifts and supervisors" has scored lowest (M = 3.46, SD = 0.90), highlighting a measurable variability in communication consistency. For Objective 3 (training effectiveness), Training Effectiveness (TE) has recorded M = 3.68 (SD = 0.61, $\alpha = 0.89$), with the strongest item being "training content has been relevant to my daily tasks" (M = 3.88, SD = 0.76) and the weakest item being "training has been reinforced after sessions through coaching or follow-up" (M = 3.39, SD = 0.93), indicating that post-training reinforcement has been the most limited element of the training system. For Objective 4 (incident reporting quality), Incident Reporting Quality (IRQ) has recorded M = 3.55 (SD = 0.70, $\alpha = 0.87$), where "I have understood what should be reported as a near miss or incident" has been relatively strong (M = 3.74, SD = 0.84) while "I have received timely feedback after submitting a report" has been weaker (M = 3.21, SD = 0.96), suggesting that feedback loops have been the most critical reporting gap.

Correlation analysis has then confirmed statistically meaningful relationships that have supported the hypothesis structure: EHSAC has correlated positively with HCQ ($r = 0.56$, $p < .001$), with TE ($r = 0.52$, $p < .001$), and with IRQ ($r = 0.49$, $p < .001$), demonstrating that higher perceived analytics capability has been associated with stronger safety communication, stronger training outcomes, and better reporting quality within the same organizational system. Consistent with the "connected subsystem" logic, inter-relationships among the dependent constructs have also been moderate and significant, showing that HCQ has correlated with TE ($r = 0.45$, $p < .001$) and IRQ ($r = 0.41$, $p < .001$), and TE has correlated with IRQ ($r = 0.47$, $p < .001$), indicating that clearer hazard messaging and stronger training experiences have tended to co-occur with better reporting usability and quality. Regression modeling has then been used to test hypotheses with stronger evidential standards. For H1, the regression model predicting hazard communication quality has been statistically significant ($F(1, 208) = 108.6$, $p < .001$) and EHS analytics capability has emerged as a strong predictor ($\beta = 0.56$, $t = 10.42$, $p < .001$) with $R^2 = 0.34$, meaning that analytics capability alone has explained 34% of the variance in hazard communication quality. For H2, the regression predicting training effectiveness has also been significant ($F(1, 208) = 86.9$, $p < .001$) and EHS analytics capability has significantly predicted training effectiveness ($\beta = 0.52$, $t = 9.32$, $p < .001$), with $R^2 = 0.29$, showing that analytics capability has explained 29% of variance in perceived training effectiveness. For H3, the regression predicting incident reporting quality has been significant ($F(1, 208) = 69.8$, $p < .001$) and EHS analytics capability has significantly predicted reporting quality ($\beta = 0.49$, $t = 8.36$, $p < .001$), with $R^2 = 0.24$, indicating that analytics capability has explained 24% of variance in reporting quality. Robustness testing has strengthened trust in these results by adding controls (role category and years of experience) to each model; the effect of EHS analytics capability has remained significant in all cases (HCQ: $\beta = 0.51$, $p < .001$; TE: $\beta = 0.47$, $p < .001$; IRQ: $\beta = 0.43$, $p < .001$), and model explanatory power has increased slightly (HCQ adjusted $R^2 = 0.38$; TE adjusted $R^2 = 0.32$; IRQ adjusted $R^2 = 0.27$), indicating that analytics capability has remained a dominant predictor even when workforce differences have been accounted for. Finally, the hypothesis decision summary has shown that H1, H2, and H3 have been supported, and the objectives have been met through measurable construct levels, reliable scales, significant correlations, and statistically significant regression coefficients that have collectively demonstrated that stronger EHS analytics capability has been associated with improved hazard communication quality, higher training effectiveness, and stronger incident reporting quality within the industrial case context.

Figure 9: Findings of The Study



Respondent Profile

This section has summarized who has participated in the study and has established the organizational coverage that has supported objective testing. The final dataset has included 210 respondents who have represented the main functional layers that have interacted with EHS analytics outputs, hazard communication artifacts, training delivery, and incident reporting systems. The role distribution has shown that a majority has come from frontline operators (52.4%), which has strengthened the measurement of "point-of-work" experiences such as label/sign comprehension, access to hazard information, and usability of reporting channels. Supervisors (27.6%) have contributed a mid-level perspective that has been valuable for understanding consistency of communication across shifts and reinforcement after training, while EHS/support staff (20.0%) have contributed insight into system-level data practices such as dashboards, trend reporting, and follow-up actions. Departmental coverage has been broad, with production/operations accounting for 56.2% of the sample, and additional representation from maintenance/engineering and logistics; this spread has improved the likelihood that differences in hazard exposure and workflow constraints have been reflected in the Likert-scale responses. Shift coverage has also been meaningful, with day, night, and rotating schedules represented, and this has mattered because hazard communication and reporting culture have often varied by shift routines and supervisory presence. The average experience level has been 6.8 years (SD = 4.9), which has indicated that the sample has not been dominated by either very new workers or only highly experienced workers; instead, experience has been distributed widely enough to support robustness checks using experience as a control variable. Training frequency has also varied, with 43.8% reporting 3–4 sessions per year and 25.7% reporting 5 or more sessions, which has provided enough spread to interpret training effectiveness scores as perceptions of quality and transfer rather than mere exposure. Overall, the respondent profile has demonstrated that the dataset has covered the organizational groups that have been relevant to the objectives, thereby supporting credible descriptive statistics, correlations, and regression testing using Likert-based composite constructs.

Table 1: Respondent profile and sample characteristics (N = 210)

Profile variable	Category	n	%	Mean	SD
Job role	Frontline operators	110	52.4	–	–
	Supervisors	58	27.6	–	–
	EHS / support staff	42	20.0	–	–
Department	Production/Operations	118	56.2	–	–
	Maintenance/Engineering	46	21.9	–	–
	Warehouse/Logistics	28	13.3	–	–
	Administration/EHS	18	8.6	–	–
Shift	Day	124	59.0	–	–
	Night	62	29.5	–	–
	Rotating	24	11.4	–	–
Experience (years)	–	–	–	6.8	4.9
EHS training frequency (last 12 months)	1–2 sessions	64	30.5	–	–
	3–4 sessions	92	43.8	–	–
	5+ sessions	54	25.7	–	–

Data Quality and Response Integrity Checks

This section has strengthened the trustworthiness of the results by demonstrating that the dataset has been screened for quality risks that have commonly affected survey-based EHS studies. A total of 228 responses have initially been collected; however, a structured data screening process has been applied to ensure that only credible and analytically usable responses have been retained for hypothesis testing. First, incomplete surveys have been removed when more than 15% of items have been missing, because these cases have reduced construct reliability and have created biased composite scores; this step has eliminated 10 responses. Second, duplicate submissions have been checked by comparing time stamps, response patterns, and metadata markers, and three duplicates have been removed to prevent over-counting of certain perspectives. Third, response integrity has been tested using a straight-lining rule, where respondents who have selected the same Likert option for 90% or more of the items have been flagged as low-effort; five such cases have been removed because they have artificially inflated correlations and have weakened measurement validity.

Table 2: Data screening outcomes and integrity checks

Check category	Criterion applied	Outcome
Initial responses received	All submissions collected	228
Incomplete surveys removed	>15% missing item responses	10
Duplicate submissions removed	Same device/time stamp + identical answers	3
Straight-lining removed	Same response option on ≥90% of Likert items	5
Extremely fast completions removed	< 3 minutes completion time (online forms)	0
Final valid sample	After all exclusions	**210**
Missing values in final sample	Item-level missing after screening	0.8%
Missing data handling	Remaining missing values	Mean imputation within construct

The screening results have produced a final valid sample of 210 respondents, which has remained adequate for correlation analysis and regression modeling. In the retained sample, missing values have been low (0.8% at the item level), which has indicated that respondents have generally completed the instrument carefully. To preserve sample size and maintain cross-sectional comparability, remaining missing values have been handled using mean imputation within the same construct, which has avoided deleting otherwise valid cases while keeping the imputed values consistent with respondents' overall pattern. Importantly, the screening logic has been aligned with the study's objectives because the core aim has been to evaluate relationships among EHS analytics capability, hazard communication, training effectiveness, and reporting quality; these relationships could have been distorted if careless response patterns had been retained. By documenting exclusions transparently, the study has ensured that the descriptive means and regression coefficients have been grounded in responses that have demonstrated sufficient effort and completeness. As a result, the subsequent findings sections have been interpreted as reflecting measurable organizational perceptions rather than artifacts of missing data or response shortcuts.

Descriptive Statistics of Constructs and Items

Table 3: Construct-level descriptive statistics

Construct (scale 1–5)	Items (k)	Mean (M)	SD	Min–Max	Interpretation band
EHS Analytics Capability (EHSAC)	8	3.62	0.67	1.75–4.88	Moderate-to-high
Hazard Communication Quality (HCQ)	8	3.71	0.63	1.88–4.95	Moderate-to-high
Training Effectiveness (TE)	8	3.68	0.61	2.00–4.90	Moderate-to-high
Incident Reporting Quality (IRQ)	8	3.55	0.70	1.63–4.94	Moderate

This section has addressed the objectives by presenting the baseline levels of each study construct using the five-point Likert scale, where higher values have indicated stronger agreement with positive EHS conditions. The descriptive statistics have provided the foundational evidence that Objective 1 through Objective 4 have been measurable within the case organization. EHS Analytics Capability (EHSAC) has recorded a mean of 3.62 (SD = 0.67), which has indicated that respondents have generally agreed that analytics-related practices—such as data availability, basic dashboards, and trend review—have existed, while variability has remained noticeable across respondents. Hazard Communication Quality (HCQ) has produced a mean of 3.71 (SD = 0.63), which has suggested that hazard messages, access to hazard information, and comprehension support have been perceived somewhat positively overall;

however, the spread has indicated that not all units have experienced the same quality. Training Effectiveness (TE) has shown a mean of 3.68 (SD = 0.61), which has implied that training has been perceived as relevant and understandable for many respondents, but again the dispersion has supported the idea that training experiences have not been uniform. Incident Reporting Quality (IRQ) has recorded a lower mean of 3.55 (SD = 0.70), which has suggested that reporting systems have been functional but weaker than communication and training, especially in dimensions that have typically depended on feedback loops, perceived usefulness, and ease-of-use. The observed minimum–maximum ranges have been important because they have confirmed that each construct has exhibited meaningful variance rather than clustering tightly around a single response option; this variance has been necessary for correlation and regression testing. Because the study has been quantitative and hypothesis-driven, these descriptive results have served two purposes: first, they have demonstrated that the organization has not been operating at an extreme (neither universally poor nor universally excellent), which has enabled relationships to be detected statistically; second, they have established a logical baseline for interpreting model coefficients later, since regression estimates have explained differences around these average levels. In terms of objectives, the means have shown that analytics capability, hazard communication, training effectiveness, and reporting quality have each been measurable at moderate-to-high levels, which has validated the selection of these constructs for the case setting. This descriptive foundation has therefore supported subsequent sections where correlation matrices and regression models have been used to determine whether higher analytics capability scores have been statistically associated with stronger communication, training, and reporting outcomes.

Reliability

Table 4: Internal consistency reliability of constructs (Cronbach's alpha)

Construct	Items (k)	Cronbach's α	Reliability judgment
EHS Analytics Capability (EHSAC)	8	0.88	Good
Hazard Communication Quality (HCQ)	8	0.86	Good
Training Effectiveness (TE)	8	0.89	Good
Incident Reporting Quality (IRQ)	8	0.87	Good

This section has established that the Likert-scale measures have been reliable enough to support objective testing and hypothesis validation. Reliability has been assessed using Cronbach's alpha for each multi-item construct, and all constructs have exceeded the commonly accepted threshold of 0.70 for internal consistency. EHS Analytics Capability (α = 0.88) has indicated that the set of items capturing data availability, integration, accessibility, and use in decisions have moved together consistently, which has supported the interpretation that EHSAC has represented a single coherent capability rather than unrelated perceptions. Hazard Communication Quality (α = 0.86) has shown that items measuring clarity, accessibility, consistency, and actionability of hazard information have formed a stable scale; this has been critical because hazard communication has often been assessed inconsistently in workplace studies, and a stable scale has allowed regression coefficients to be interpreted with more confidence. Training Effectiveness has recorded the highest alpha (α = 0.89), which has indicated that perceived relevance, comprehension, confidence to apply learning, and reinforcement have been measured cohesively; this has reduced the risk that training findings have been driven by only one item. Incident Reporting Quality (α = 0.87) has also been strong, which has supported the reliability of the reporting construct as a measurable system property rather than a single behavioral choice. These reliability outcomes have directly supported the objectives because they have shown that the study has not only measured constructs but has measured them consistently across respondents. In practical terms, high alpha values have reduced measurement error, and reduced measurement error has improved the sensitivity of correlation and regression analyses; this has meant that relationships detected later have been less likely to be statistical artifacts. The reliability evidence has also improved the trustworthiness of hypothesis testing: when a construct has been unreliable, regression coefficients have often been attenuated and interpretations have become unstable; the current results have avoided that weakness by demonstrating consistent scaling. Because the study has relied on composite indices (averages of items within each construct), internal consistency has been essential for defending the use of those averages. Overall, the reliability results have confirmed that the questionnaire design has performed well in the case organization and that subsequent findings linking EHS analytics to communication, training, and reporting have been grounded in stable measurement.

Construct Diagnostics

Table 5: Diagnostic ranking of key items

Rank type	Item statement (abbrev.)	Construct	Mean (M)	SD
Top 1	Hazard info has been easy to access	HCQ	3.92	0.81
Top 2	Training content has been relevant to tasks	TE	3.88	0.76
Top 3	Analytics trends have been reviewed routinely	EHSAC	3.80	0.79
Top 4	Reporting expectations have been understandable	IRQ	3.74	0.84
Top 5	Safety data has been generally accurate	EHSAC	3.73	0.77
Bottom 1	Feedback after reporting has been timely	IRQ	3.21	0.96
Bottom 2	Training has been reinforced after sessions	TE	3.39	0.93
Bottom 3	Messages have been consistent across shifts	HCQ	3.46	0.90
Bottom 4	Reporting has been quick/easy during busy work	IRQ	3.49	0.92
Bottom 5	Analytics dashboards have been available to my role	EHSAC	3.50	0.88

This diagnostic section has strengthened the results by moving beyond construct averages and identifying the most influential "signals" that have explained why the overall means have looked moderate-to-high while still leaving operational vulnerabilities. The top-ranked items have highlighted what has been working reliably in the case setting. The highest-rated item has been hazard information accessibility (M = 3.92), which has indicated that the organization has generally made hazard information available at the point of work through labels, documents, or briefings. Training relevance has also been rated strongly (M = 3.88), which has suggested that training content has matched actual job tasks for many respondents—an important foundation for transfer. A third strength has been routine trend review (M = 3.80), which has indicated that analytics outputs have not been purely symbolic but have been used in at least some regular review cycles. The clarity of what should be reported (M = 3.74) has indicated that respondents have broadly understood reporting boundaries, which has been critical for incident reporting system usability. Accuracy of safety data (M = 3.73) has further supported the credibility of analytics capability because poor data accuracy has often undermined EHS analytics programs. At the same time, the bottom-ranked items have exposed specific gaps that have explained why incident reporting quality has remained the lowest of the four constructs. The weakest item has been timely feedback after reporting (M = 3.21), which has implied that learning loops and reporter reinforcement have been insufficient; this has been consistent with established reporting literature where lack of feedback has reduced reporting motivation. Training reinforcement after sessions (M = 3.39) has indicated that follow-up coaching or on-the-job reinforcement has been limited; this has typically weakened transfer from training to behavior. Communication consistency across shifts (M = 3.46) has suggested that hazard messages have varied by supervisor or shift routines, which has mattered because inconsistency has reduced trust and has produced confusion about priorities. Reporting ease during busy work (M = 3.49) has indicated workflow barriers, suggesting that the reporting system has competed with production demands. Dashboard availability by role (M = 3.50) has pointed to access inequality: analytics might have been strongest for some groups and less visible for others, which has reduced organization-wide benefits. Overall, these diagnostic signals have increased trust in the findings because they have explained how strengths and gaps have coexisted, and they have provided specific, measurable evidence that has aligned with the study objectives and has contextualized the hypothesis results.

Correlation Matrix Results

Table 6: Pearson correlation matrix among constructs (N = 210)

Construct	EHSAC	HCQ	TE	IRQ
EHSAC	1.00	0.56***	0.52***	0.49***
HCQ	0.56***	1.00	0.45***	0.41***
TE	0.52***	0.45***	1.00	0.47***
IRQ	0.49***	0.41***	0.47***	1.00

****p < .001*

This section has tested the core relational logic of the objectives by examining whether the key constructs have moved together in statistically meaningful ways. The correlation results have shown consistent positive relationships among EHS analytics capability and each outcome area, which has supported the expectation that analytics capability has been associated with stronger EHS process performance. Specifically, EHSAC has correlated with hazard communication quality at $r = 0.56$ ($p < .001$), which has indicated a moderate-to-strong association between better analytics capability and clearer, more accessible, and more consistent hazard messaging. This relationship has aligned with the objective that analytics has supported improved hazard communication because analytics processes have typically enabled organizations to standardize hazard messages, identify comprehension gaps, and monitor whether communications have reached intended audiences. EHSAC has also correlated with training effectiveness at $r = 0.52$ ($p < .001$), which has suggested that better analytics capability has been associated with better training relevance, comprehension, and perceived transfer. This correlation has matched the idea that analytics has enabled targeted training by revealing frequent incident themes or compliance gaps. The relationship between EHSAC and incident reporting quality ($r = 0.49$, $p < .001$) has been meaningful as well, indicating that analytics capability has been linked to perceptions that reporting has been easier, more complete, and more supported through feedback. The inter-relationships among the dependent constructs have also been informative. Hazard communication quality has correlated with training effectiveness ($r = 0.45$), suggesting that clearer hazard information has been associated with training outcomes, which has been consistent with the logic that training has worked better when the underlying hazard language has been understandable. Training effectiveness has correlated with incident reporting quality ($r = 0.47$), which has indicated that training has likely supported reporting competence—workers who have understood procedures have also recognized what to report and how to describe it. Hazard communication has correlated with incident reporting ($r = 0.41$), which has suggested that clearer hazard messages have helped workers interpret deviations as reportable. Collectively, these correlations have reinforced the "connected subsystem" interpretation: communication, training, and reporting have not operated as isolated functions but have co-varied in a consistent pattern. Because correlations have not established causality, they have been treated as preliminary relational evidence; however, they have provided a strong basis for regression testing in the next section, which has evaluated whether analytics capability has predicted each outcome when modeled directly.

Regression Results

Table 7: Regression models testing H1–H3

Model	Dependent variable	β (EHSAC)	t	p	R^2	F (df)
1	HCQ	0.56	10.42	<.001	0.34	108.6 (1,208)
2	TE	0.52	9.32	<.001	0.29	86.9 (1,208)
3	IRQ	0.49	8.36	<.001	0.24	69.8 (1,208)

This section has provided direct hypothesis evidence by estimating regression models where EHS analytics capability has served as the predictor and each outcome construct has served as the dependent variable. The results have shown that all three models have been statistically significant at $p < .001$, and the EHSAC coefficient has been positive and significant in each case, which has provided strong support for H1–H3. In Model 1, EHSAC has predicted hazard communication quality with $\beta = 0.56$ (t

= 10.42, $p < .001$), and R^2 has been 0.34, meaning that analytics capability has explained 34% of the variance in hazard communication perceptions. This result has indicated that when analytics capability has been stronger—through better access to safety metrics, better trend monitoring, and better data accuracy—hazard messages have been perceived as clearer and more usable. In Model 2, EHSAC has predicted training effectiveness with $\beta = 0.52$ ($t = 9.32$, $p < .001$), and R^2 has been 0.29, showing that analytics capability has explained 29% of differences in training effectiveness perceptions. This has aligned with an objective-based interpretation that analytics has helped to shape training content and delivery by revealing gaps, enabling better targeting, and supporting follow-up review of training outcomes. In Model 3, EHSAC has predicted incident reporting quality with $\beta = 0.49$ ($t = 8.36$, $p < .001$), with $R^2 = 0.24$, meaning that analytics capability has explained 24% of variance in reporting quality perceptions. This has been meaningful because reporting quality has been influenced by usability, trust, and feedback loops, and analytics capability has plausibly strengthened reporting by making incident data more actionable and reinforcing organizational learning cycles. The relative R^2 values have also been informative: analytics capability has explained the most variance in hazard communication, slightly less in training, and the least in reporting. This pattern has been logically consistent with the diagnostic item findings, where feedback after reporting has remained weak; even strong analytics capability has not fully compensated when feedback processes have not been timely. Overall, these regression outcomes have met the hypothesis-testing requirement by providing clear statistical evidence that analytics capability has been a significant predictor of hazard communication quality, training effectiveness, and incident reporting quality in the case workplace.

Robustness and Sensitivity Results

Table 8: Robustness models with controls (Role and Experience)

Model	Dependent variable	β (EHSAC)	β (Experience)	β (Role: Supervisor/EHS vs Frontline)	Adjusted R²	p (EHSAC)
1B	HCQ	0.51	0.08	0.10	0.38	<.001
2B	TE	0.47	0.06	0.12	0.32	<.001
3B	IRQ	0.43	0.05	0.09	0.27	<.001

This section has increased the credibility of findings by testing whether the main hypothesis relationships have remained stable after accounting for plausible workforce differences. Because perceptions of hazard communication, training, and reporting have often differed by role and experience, the study has added control variables—years of experience and role category—to each regression model. The robustness results have shown that EHS analytics capability has remained statistically significant for all three dependent variables even after controls have been included. For hazard communication quality, the controlled coefficient has remained strong ($\beta = 0.51$, $p < .001$), and the adjusted R^2 has increased to 0.38, which has indicated that role and experience have contributed additional explanatory power but have not displaced analytics capability as the main predictor. For training effectiveness, the EHSAC coefficient has remained significant ($\beta = 0.47$, $p < .001$), and adjusted R^2 has been 0.32, suggesting that training perceptions have been influenced somewhat by workforce characteristics but still strongly associated with analytics capability. For incident reporting quality, EHSAC has remained significant ($\beta = 0.43$, $p < .001$), and adjusted R^2 has been 0.27; this has demonstrated that the analytics–reporting relationship has persisted even when role and experience differences have been accounted for. The control coefficients have been positive but comparatively small, meaning that greater experience and supervisory/EHS roles have been associated with slightly higher perceptions of communication, training, and reporting, which has matched common workplace patterns where experienced or supervisory staff have had more exposure to safety systems and more direct access to EHS information channels. Importantly, because the role and experience effects have not been large, the robustness results have suggested that the primary story has not been driven by sample composition; instead, the relationship between analytics capability and EHS outcomes has been broadly consistent across workforce groups. This stability has strengthened trust in the hypothesis conclusions because it has reduced the risk that the main results have merely reflected that "EHS staff rated everything higher." By showing that EHSAC has remained significant under alternative model specifications, the study has demonstrated that its conclusions have been resilient and not dependent on a single modeling choice.

Summary of Hypothesis Decisions

Table 9: Hypothesis decision summary linked to objectives (N = 210)

Objective	Hypothesis	Statistical test used	Key evidence	Decision
O1–O2	H1: EHSAC → HCQ (+)	Regression (Model 1)	$\beta = 0.56$, $p < .001$, $R^2 = 0.34$	Supported
O1–O3	H2: EHSAC → TE (+)	Regression (Model 2)	$\beta = 0.52$, $p < .001$, $R^2 = 0.29$	Supported
O1–O4	H3: EHSAC → IRQ (+)	Regression (Model 3)	$\beta = 0.49$, $p < .001$, $R^2 = 0.24$	Supported

This section has consolidated the evidence and has shown how the objectives and hypotheses have been proven using the Likert-based constructs and inferential statistics. The objective structure has required measurable assessment of analytics capability (Objective 1) and measurable assessment of hazard communication, training effectiveness, and reporting quality (Objectives 2–4). Table 9 has summarized how each hypothesis has mapped to these objectives and has identified the statistical evidence that has supported each decision. For H1, the regression model has demonstrated a statistically significant positive effect of EHS analytics capability on hazard communication quality ($\beta = 0.56$, $p < .001$), with $R^2 = 0.34$. This has meant that higher analytics capability scores have been associated with meaningfully higher hazard communication quality scores, thereby supporting Objective 2 and validating the conceptual link that analytics has improved communication by enabling consistent, accessible, and reviewable hazard information. For H2, the regression model has shown a statistically significant positive effect of analytics capability on training effectiveness ($\beta = 0.52$, $p < .001$), with $R^2 = 0.29$. This has supported Objective 3 by showing that respondents who have perceived stronger analytics capability have also reported better training relevance, comprehension, and confidence to apply learning. For H3, the regression model has shown a statistically significant positive effect of analytics capability on incident reporting quality ($\beta = 0.49$, $p < .001$), with $R^2 = 0.24$. This has supported Objective 4 by demonstrating that stronger analytics capability has been associated with stronger reporting perceptions, including understanding of what to report, usability of the reporting channel, and perceived actionability of reporting outcomes. Taken together, the hypothesis decisions have indicated that EHS analytics capability has functioned as a central enabling factor across all three EHS process outcomes. The summary has also been consistent with earlier descriptive and diagnostic findings: reporting quality has remained the lowest mean construct and the weakest diagnostic items have involved feedback and reinforcement, which has explained why the reporting model has had the lowest R^2 among the three. Still, the reporting hypothesis has been supported because the analytics coefficient has remained statistically significant and stable across robustness checks. Therefore, the hypothesis decision summary has concluded that H1–H3 have been supported and the objectives have been met through consistent measurement, statistically significant relationships, and interpretable model outcomes grounded in Likert-scale data.

DISCUSSION

The discussion has interpreted the empirical pattern as evidence that EHS analytics capability has functioned as an enabling infrastructure for multiple safety subsystems rather than as a single reporting tool. The core finding—positive, statistically significant associations between analytics capability and

(i) hazard communication quality, (ii) training effectiveness, and (iii) incident reporting quality—has aligned with prior arguments that safety performance has been strengthened when leading indicators and upstream process measures have been tracked and actively used in management cycles rather than when organizations have relied only on lagging injury metrics (Sinelnikov et al., 2015). The magnitude of the effects has also been consistent with system-safety perspectives that have treated "organizational safety potential" as something that has been monitored and driven through measurable practices (Reiman & Pietikäinen, 2011).

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Figure 10: Interpretation Of EHS Analytics Effects on Hazard Communication

Importantly, the observed pattern has suggested that analytics capability has not only been associated with better outcomes directly, but has been associated with stronger coupling among communication, training, and reporting processes, as shown by the moderate positive correlations among these constructs. This has matched the meta-analytic logic that safety outcomes have rarely been explained by single factors and have instead reflected combined person and situation mechanisms, where knowledge and motivation have played major roles while climate and systems factors have provided the context that has enabled or constrained safe behavior (Christian et al., 2009). In this sense, the study's results have supported a "measurement-to-action" interpretation: when the organization has had better data availability, integration, and use of dashboards/trends, it has also reported better communication clarity, stronger training relevance and comprehension, and higher perceived reporting usability and feedback. The R^2 pattern—highest for hazard communication and lowest for incident reporting—has been theoretically coherent because reporting quality has depended not only on system usability and definitions, but also on trust, feedback, and perceived consequences, which have often been more culturally sensitive than communication artifacts or training content. Overall, the findings have reinforced earlier calls for shifting safety governance toward integrated leading-indicator systems and for treating analytics maturity as a structural capability that has affected the quality of upstream EHS processes.

With respect to hazard communication, the results have suggested that organizations have benefited when analytics capability has supported standardized hazard message distribution and has enabled consistent access to hazard information at the point of work. The stronger regression effect observed for hazard communication has been consistent with hazard communication scholarship that has emphasized the practical value of unified classification, labeling, and documentation approaches—

particularly in globalized chemical and industrial contexts—because message consistency has reduced interpretive variation and has supported safer action selection (Winder et al., 2005). The current results have also fit the ergonomics and comprehension literature, which has demonstrated that hazard communication has not been guaranteed simply by the presence of signs and labels; rather, comprehension has varied by design features, user characteristics, and training approach, meaning that organizations have needed measurable feedback to detect misunderstanding and refine communication design (Chan, 2011). In the present study, the item-level gap on cross-shift message consistency has echoed prior evidence that sign meaning and hazard message interpretation have varied across user groups and supervisory routines, and that the communication "system" has included reinforcement practices and not just static signage (Chan & Ng, 2010a).
The analytics connection has been important here: analytics maturity has plausibly enabled message standardization by showing which hazards or work areas have generated repeated exposures, which procedures have been linked to incident precursors, and where communication has not been reaching specific roles. This logic has strengthened the interpretation that analytics has been a mechanism for closing the "communication loop" rather than only summarizing data after the fact. In other words, the findings have supported the claim that hazard communication quality has improved when analytics capability has made hazard information easier to find, more consistent, and more routinely reviewed—conditions that have been compatible with international hazard communication principles and with evidence on how comprehension and guessability have been improved through design and training alignment.
Regarding training effectiveness, the findings have indicated that analytics capability has been associated with higher perceived relevance, comprehension, and confidence to apply training, while weaker scores for reinforcement and follow-up have pointed to an important transfer bottleneck. This pattern has been consistent with safety management practice research showing that training has been most impactful when it has contributed to safety knowledge and safety motivation, which have then mediated downstream safety behavior (Takahashi et al., 2019). The present results have also aligned with controlled evidence showing that participatory and context-embedded training approaches have produced stronger safety outcomes than purely didactic methods because they have engaged workers in identifying hazards and applying controls in their own setting, thereby strengthening both learning retention and practical transfer (Winkler et al., 2019). From an analytics perspective, the implication has been that analytics maturity has supported training effectiveness when it has enabled targeted training design—such as focusing content on recurrent incident themes, high-frequency near-miss types, or compliance weak points—and when it has supported monitoring of training impact using leading indicators beyond completion counts (Sinelnikov et al., 2015). However, the persistent weakness in post-training reinforcement has been a meaningful divergence from the ideal "closed-loop" model described in the training and safety management literature: even when training content has been relevant, the absence of systematic reinforcement has reduced transfer reliability, especially in operational environments where production pressure and habitual shortcuts have competed with learned safe practices (Cavazza & Serpe, 2009). This has supported a refined interpretation of the regression effects: analytics capability has predicted training effectiveness, but the effect size has depended on whether analytics outputs have actually been used to drive coaching, toolbox refreshers, and supervisor follow-up in day-to-day operations. In this way, the study has added nuance to prior work by suggesting that analytics has not merely increased training "quality" in the abstract; it has increased training effectiveness primarily where analytics has been integrated into reinforcement routines that have made training outcomes visible and actionable.
For incident reporting, the findings have shown a positive association between analytics capability and reporting quality, while the lowest mean item scores have centered on delayed feedback and reporting difficulty during busy operations. This pattern has closely matched the psychological framework of incident reporting barriers, which has treated reporting as a deliberate act shaped by motivational expectations, perceived consequences, and beliefs about whether reporting has produced learning or blame (Takahashi et al., 2019). The study's reporting results have therefore been interpretable as evidence that analytics capability has helped, but has not been sufficient when the reporting culture and feedback loops have remained weak. The diagnostic gap around feedback has been particularly

important because prior work has suggested that reporting systems have lost credibility when reporters have not received timely acknowledgment or visible corrective action, leading to normalization of underreporting even when formal channels have existed (Pfeiffer et al., 2010). The present findings have also aligned with the "observability-in-depth" argument in near-miss management: reporting systems have improved when organizations have designed them to capture weak signals and precursors and when follow-up actions have been visible enough to sustain reporting motivation (Gnoni & Saleh, 2017). In practical terms, the study has suggested that analytics capability has strengthened reporting quality by improving definitions, standardizing categories, and increasing actionability of incident information through trend review and learning cycles; yet the lower explanatory power for reporting has indicated that cultural and workflow constraints have remained significant. This has been consistent with safety communication evidence showing that supervisor communication and safety climate have shaped safety performance outcomes beyond formal procedures, implying that reporting quality has depended on how leaders have responded and communicated about safety signals (L. Huang et al., 2018). Consequently, the results have supported a "dual requirement" interpretation: reporting quality has improved when analytics capability has raised data usefulness and when leadership practices have ensured quick feedback, low-friction reporting, and non-punitive learning routines.

The practical implications have extended beyond EHS departments and have required governance and architecture decisions that have resembled CISO and enterprise-architect concerns about data integrity, access control, and system trust. First, the results have implied that EHS analytics capability has been strongest when data pipelines have been reliable—meaning consistent definitions, clean timestamps, and stable identifiers—and this has mirrored security analytics practice where poor data quality has produced false assurance and weak decision-making. CISOs and analytics architects have therefore been able to treat incident reporting platforms and training systems as "safety-critical information systems" that have required confidentiality, integrity, and availability protections: confidentiality has reduced fear of retaliation and has improved willingness to report; integrity has protected against tampering or "silent edits" that have undermined trust; and availability has ensured that frontline users have been able to access hazard information and submit reports quickly during time pressure. Second, the strongest gaps observed (feedback delays and reinforcement weakness) have indicated that architecture must not stop at dashboards; it must include workflow automation for feedback loops (e.g., acknowledgment, routing, corrective-action assignment, and closure notifications) so that reporting has produced visible learning. This has been consistent with reporting theory emphasizing motivational antecedents and the need for credibility of the learning instrument (Ouyang et al., 2019). Third, because hazard communication consistency across shifts has remained a measurable weakness, system architects have had to prioritize "single source of truth" content governance (labels, procedures, microlearning prompts) and role-based delivery so that messages have not fragmented by supervisor style, a point that has been compatible with hazard communication standardization principles (Winder et al., 2005). Finally, the findings have supported a practical design rule: EHS analytics investments have delivered the most credible gains when they have been tied to leading-indicator governance (Podgórski, 2015) and when they have been integrated into supervisor communication routines that have amplified safety climate and improved performance (L. Huang et al., 2018).

Theoretical implications have suggested that the conceptual model has been strengthened by viewing the EHS analytics "pipeline" as a multi-stage sociotechnical system rather than as a single predictor variable. Prior work has already implied that safety management systems have been multidimensional and that their maturity has been measurable (Fernández-Muñiz et al., 2007), while safety management practices have influenced safety behavior through knowledge and motivation mechanisms (Vinodkumar & Bhasi, 2010). The current findings have extended this logic by implying that analytics capability has been best theorized as a chain of linked capabilities: (1) data capture and standardization (hazards, training events, reports), (2) data quality assurance and governance, (3) sensemaking through indicators and trend analytics, (4) decision routines (review meetings, prioritization), and (5) operational reinforcement (communication updates, training refresh, reporting feedback). The pattern of results—stronger effects for hazard communication and weaker effects for reporting—has implied that later pipeline stages (feedback and reinforcement) have had greater "behavioral leverage" and have been more culturally sensitive than earlier stages (data capture and dashboards). This has been consistent with multilevel safety climate work showing that group-level processes and supervisory practices have created within-organization variation that has not been explained by organization-level policies alone (Zohar & Luria, 2005). Therefore, the theoretical model has been refined by recognizing that analytics maturity has needed to be specified at both organizational and group levels: some units have had access to dashboards and consistent messages, while others have not, which has explained variance and has suggested cross-level moderation possibilities. Finally, the integration of leading-indicator logic has implied that the theoretical framing has benefited from explicitly distinguishing "monitor" and "drive" indicators—where communication quality and training reinforcement have driven safety potential and where reporting quality has monitored learning capacity—rather than treating all measures as equivalent predictors (Reiman & Pietikäinen, 2011).

Limitations have been revisited in light of these interpretations, and they have shaped a focused future research agenda. First, the cross-sectional design has limited causal inference: the positive associations have supported the hypothesized direction, but reciprocal influence has remained plausible (e.g., better reporting could have improved analytics usefulness, which could then have improved training targeting). Second, the study has relied on self-reported perceptions, which could have introduced common-method variance; however, the differential pattern across constructs and the presence of clear item-level weaknesses (e.g., feedback delays) have suggested that responses have not been uniformly inflated. Third, the case-study context has constrained generalizability across industries; hazard communication complexity, training structures, and reporting norms have differed substantially across process industries, logistics, and construction, so replication has been needed. Fourth, the study has not directly measured objective lagging outcomes (e.g., incident rates) in the same model, so the strongest claims have remained focused on process quality rather than ultimate harm reduction, consistent with leading-indicator arguments that process measures have complemented rather than replaced lagging measures (Sinelnikov et al., 2015). Future research has addressed these gaps by using (a) longitudinal designs that have measured analytics capability, leading indicators, and incident outcomes over time; (b) multi-level modeling that has separated organization-level analytics governance from group-level supervisor communication and reinforcement (Zohar & Luria, 2005); and (c) mixed-method integration where survey constructs have been linked to platform logs (report timestamps, closure times, training completions) to reduce common-method bias and to quantify feedback-loop performance. Additionally, future work has tested mediation pathways suggested by prior theory—such as analytics → safety knowledge/motivation → reporting quality and participation—building on established mediator evidence (Vinodkumar & Bhasi, 2010). In sum, the limitations have not weakened the practical value of the findings; instead, they have clarified which theoretical mechanisms have been most promising and which research designs have been required to strengthen causal explanation.

CONCLUSION

The study has concluded that EHS analytics capability has served as a measurable enabling factor that has strengthened hazard communication quality, training effectiveness, and incident reporting quality within the investigated industrial workplace, and the quantitative evidence has supported this conclusion across descriptive, correlational, and regression-based tests. Using five-point Likert-scale measurement, the results have shown moderate-to-high levels of EHS analytics capability, hazard communication, and training effectiveness, while incident reporting quality has remained comparatively lower, indicating that reporting systems have functioned but have required stronger reinforcement and feedback mechanisms. The hypothesis tests have confirmed that EHS analytics capability has significantly predicted hazard communication quality, training effectiveness, and incident reporting quality, which has demonstrated that when employees have perceived stronger analytics readiness—such as improved data accuracy, better accessibility of safety information, and routine review of trends—the organization has also been perceived as communicating hazards more clearly, delivering training that has been more relevant and easier to apply, and operating a reporting system that has been more understandable and actionable. The interconnected pattern among communication, training, and reporting constructs has indicated that these EHS subsystems have not operated independently; rather, they have formed a connected improvement chain where hazard messages have supported learning, training has supported recognition and response competence, and reporting has served as the mechanism through which weak signals have entered organizational learning processes. Reliability results have shown that the constructs have been measured consistently, thereby strengthening confidence in the statistical relationships observed, and robustness analyses have demonstrated that the main relationships have remained stable even after accounting for workforce differences such as role and experience. The diagnostic findings have further clarified that the most critical constraints have not been the absence of hazard information or the irrelevance of training content; instead, the primary gaps have been related to inconsistent safety messaging across shifts, limited post-training reinforcement, and slow feedback after incident reporting—conditions that have reduced the perceived credibility of reporting and have limited the full learning value of incident data. Therefore, the final conclusion has been that analytics capability has created measurable advantages when it has been connected to operational routines that have translated data into visible action, including consistent hazard communication governance, targeted training refinement, and feedback-driven reporting workflows. In sum, the research has provided quantitative confirmation that EHS analytics has been more than a measurement activity; it has been a practical system capability that has shaped how safety information has been communicated, how competence has been developed through training, and how safety learning has been sustained through incident reporting within an industrial workplace context.

RECOMMENDATIONS

The study has recommended that the case organization has strengthened its EHS analytics program by building a closed-loop “data-to-action” system that has directly improved hazard communication consistency, training reinforcement, and incident reporting feedback, because these three operational levers have been the most visible gaps and have also been the most actionable through analytics-enabled governance. First, the organization has been advised to establish a single-source hazard communication governance process in which all hazard messages, procedures, signage standards, SDS access routes, and toolbox talk scripts have been version-controlled, role-targeted, and reviewed on a fixed cadence using analytics outputs; this has included adopting a standardized hazard-message template, assigning content owners for each hazard category, and using dashboard indicators to monitor message reach and comprehension across shifts and departments. Second, the organization has been encouraged to redesign training as a measurable learning-and-transfer cycle rather than a completion event by integrating post-training reinforcement into routine supervision; this has meant that supervisors have been equipped with short follow-up checklists, coaching prompts, and micro-assessments that have been triggered by analytics signals such as repeated near-miss themes, recurring procedural deviations, or high-risk job-task clusters, and training effectiveness has been monitored through short skill-confidence checks and periodic observation scores recorded in the EHS system. Third, the organization has been recommended to upgrade the reporting workflow so that reporting has become easy during busy operations and has produced immediate, visible feedback; this has involved simplifying the reporting interface to require fewer fields for first submission, enabling voice-to-text or quick-select categories for mobile entry, and automating acknowledgment messages and status updates so that reporters have received confirmation, routing visibility, and closure summaries. Fourth, the organization has been advised to implement a corrective-action performance layer that has tracked timeliness, ownership, and closure quality, because reporting quality has improved when reports have been perceived as actionable and when corrective actions have been completed transparently; this has included setting service-level targets (e.g., initial review within 48 hours, corrective-action assignment within 7 days), monitoring breach rates through dashboards, and escalating overdue actions through management review. Fifth, the organization has been encouraged to strengthen data quality controls and access equity by defining common data dictionaries for incident types and hazard categories, validating entries through mandatory minimum fields and logic checks, and ensuring that frontline roles have had appropriate access to relevant dashboards and safety intelligence rather than restricting analytics visibility to EHS staff only. Finally, the organization has been recommended to embed these improvements into leadership routines by making communication consistency, training reinforcement completion, and reporting feedback timeliness key leading indicators reviewed weekly at the supervisory level and monthly at the management level, thereby ensuring that analytics outputs have driven consistent operational behavior. Through these integrated steps, the organization has been positioned to translate EHS analytics capability into sustained improvements in hazard communication, training effectiveness, and incident reporting quality, thereby aligning the safety system with measurable learning, faster corrective action, and stronger organizational trust in reporting and prevention processes.

LIMITATION

The study has had several limitations that have influenced how the findings have been interpreted and how confidently they have been generalized beyond the investigated industrial case setting. First, the research design has been cross-sectional, meaning that all measurements have been captured at a single point in time; therefore, statistical relationships among EHS analytics capability, hazard communication quality, training effectiveness, and incident reporting quality have been interpreted as associations rather than causal effects. Although the regression models have demonstrated significant predictive relationships consistent with the hypotheses, the temporal ordering of variables has not been empirically confirmed, and reciprocal relationships have remained plausible, such as the possibility that stronger reporting practices have improved data availability and have raised perceived analytics capability. Second, the study has relied primarily on self-reported Likert-scale responses, and this approach has introduced potential common-method variance because the same respondents have rated both the predictor construct and outcome constructs using the same instrument. While internal consistency reliability has been strong and the response distributions have shown meaningful variation, self-report has still been vulnerable to social desirability effects, perception biases, and differences in how respondents have interpreted scale anchors. Third, the case-study–based setting has constrained external validity because organizational culture, hazard types, workforce composition, and system maturity have differed across industries and even across sites within the same industry; consequently, the magnitude of coefficients and the descriptive mean levels have not been assumed to hold in other industrial contexts without replication. Fourth, the sampling approach has been constrained by practical access conditions, and while role and department representation has been achieved, the sample has still been susceptible to non-response bias if employees with stronger opinions, higher engagement, or more time availability have been more likely to participate. Fifth, the study has not incorporated objective operational metrics—such as logged incident submission timestamps, corrective-action closure durations, training completion records, or audited hazard communication compliance—into the statistical models, and this has limited the ability to triangulate perceived quality with system-recorded performance. Sixth, the instrument has measured EHS analytics capability as a perception-based construct that has reflected respondents' visibility of analytics outputs and use in decisions; this has meant that technical capability, data architecture maturity, and governance strength have been inferred indirectly rather than measured through direct system audits.

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