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Behavioral Determinants of Occupational Safety Implementation in Indonesian Nickel Mining

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Abstract

The mining industry remains a high-risk sector where the implementation of an Occupational Health and Safety Management (OHSMS) is critical to mitigating workplace accidents. However, the effectiveness of such system is often compromised by human behavioral factors. This study aims to analyze the influence of employee behavior-comprising knowledge, attitudes, and actions on OHSMS Implementation at a nickel mining company in Southeast Sulawesi, Indonesia. A quantitative descriptive-analytic method with a cross-sectional approach was conducted, involving 50 mining personnel as respondents. Data were processed using Partial Least Squares Structural Equation Modelling (PLS-SEM) to examine both measurement and structural models. The results revealed that worker behavior simultaneously influenced OHSMS implementation by 37.6% (R^2 = 0.376). Specifically, attitude exhibited a significant positive influence ($\beta = 1.275, p = 0.030$), whereas knowledge showed a significant negative impact ($\beta = -0.488, p < 0.001$), Interestingly, individual actions did not yield a statistically significant effect. These findings suggest that while positive attitudes are fundamental to safety compliance and procedural non-compliance. This research provides strategic insights for mining management to prioritize behavioral-based safety interventions over purely technical training.

Keywords
Behavioral factors, Nickel mining, OHSMS, PLS-SEM, and Safety Performance

1. Introduction

Occupational Safety and Health (OSH) remains a critical global concern, particularly within high-risk industrial sectors such as mining, where personnel are continuously exposed to hazardous conditions, heavy machinery, and complex operational processes (International Labour Organization 2019). Globally, the extractive industry is recognized as one of the most dangerous sectors due to its high propensity for catastrophic accidents, severe occupational injuries, and debilitating long-term health impacts (Zhang et al. 2024). These operational risks are inherently intensified by the dynamic, non-routine, and unpredictable nature of mining environments, which demand absolute adherence to safety protocols to prevent occupational fatalities and severe operational disruptions. Consequently, the deployment of structured safety frameworks is universally mandated as a strategic priority to minimize workplace incidents and optimize firm-level safety performance (Muiz et al. 2009).

To systematically mitigate these industrial hazards, organizations heavily rely on formal framework standardizations, such as the Occupational Health and Safety Management System (OHSMS), designed to assess operational risks, establish preventative barriers, and drive continuous improvement (ISO 45001 2018). However, an ongoing paradox in industrial safety reveals that the institutionalization of comprehensive, formal safety systems does not automatically guarantee optimal safety outcomes in real working fields (Hmlinen et al. 2006). A substantial execution gap often emerges between documented organizational procedures and actual frontline practices. Empirical safety literature underscores that this gap is predominantly determined by non-technical human dimensions—specifically the cognitive, affictive, and behavioral attributes of the workforce (Carra et al. 2024).

In the specific context of the Indonesian extractive economy, nickel mining has emerged as a hyper-strategic commodity due to the global surge in electric vehicle battery supply chains. This rapid industrial expansion has compelled mining enterprises, including PT Trinusa Dharma Utama in Southeast Sulawesi, to significantly accelerate production rates. This high-productivity pressure frequently intersects with human error, safe behavioral non-compliance, and cultural risk-taking tendencies, transforming behavioral safety into a crucial operational bottleneck. While individual behavioral dimensions (knowledge, attitudes, and actions) are theoretically critical to safety performance, their simultaneous empirical interaction within a multivariate structural model remains highly under-explored in the Indonesian mining literature. Most existing studies utilize superficial, univariate, or direct relationship analyses that fail to capture the latent, multi-dimensional complexities of safe behavior. Therefore, this research is urgently required to close this knowledge vacuum by diagnosing how frontline employee behaviors quantitatively dictate the real-world implementation of OHSMS in a strategic nickel mine.

1.1 Objectives

The primary overarching objective of this research is to evaluate and model the quantitative impact of employee behavioral determinants on the actual execution performance of the Occupational Health and Safety Management System (OHSMS) within the Indonesian mining industry. To achieve this general goal, the study articulates the following specific research objectives:

- To evaluate the quantitative influence of workers' safety knowledge on the structured deployment of OHSMS in the field.
- To analyze the statistical significance of workers' safety attitudes in driving organizational safety compliance and procedural adherence.
- To assess the direct impact of observable safe actions exhibited by personnel on overall OHSMS performance.
- To assess the simultaneous explanatory capacity (R^2) of integrated internal behavioral constructs against external systemic management systems using Partial Least Squares Structural Equation Modeling (PLS-SEM).
- To deliver data-driven, strategic recommendations for mining executives to design target-oriented behavioral safety interventions that bridge the gap between OHS policy and practical site realities.

2. Literature Review

The structural deployment of a comprehensive Occupational Health and Safety Management System (OHSMS) within heavy industries is designed to establish a systematic framework for hazard identification, risk assessment, and continuous safety mitigation. Historically rooted in the engineering paradigm of industrial accident prevention popularized by early safety theorists, traditional models heavily emphasized physical barriers, mechanical compliance, and strict administrative oversight. In the modern era, global standards such as ISO 45001 provide a rigorous framework that codifies organizational policies, regular safety mapping, and structured accountability mechanisms to minimize workplace injuries. Despite the widespread institutionalization of these formal procedures, empirical evidence across high-risk sectors indicates that the mere presence of an administrative system does not inherently guarantee safe working environments. A persistent execution gap frequently emerges between structural protocols and field operational reality, driven primarily by non-technical variables, human error, and systemic organizational failures.

To explain this operational divergence, contemporary occupational research increasingly shifts focus toward behavior-based safety paradigms, which posit that industrial accidents are fundamentally mediated by frontline human behavioral dimensions. This study synthesizes these behavioral determinants by mapping individual human factors into distinct cognitive, affective, and psychomotor domains, operationalized as safety knowledge, safety attitudes, and observable safe actions. Safety knowledge reflects a worker's objective understanding of explicit safety protocols, localized operational hazards, and emergency control mechanisms. Safety attitude encapsulates the internal affective disposition, risk perception, and subjective commitment of personnel toward the validity of safety regulations. Safe actions represent the explicit, measurable execution of safety practices, standard operating compliance, and active participation in localized hazard mitigation programs during daily work activities as follows in Figure 1.

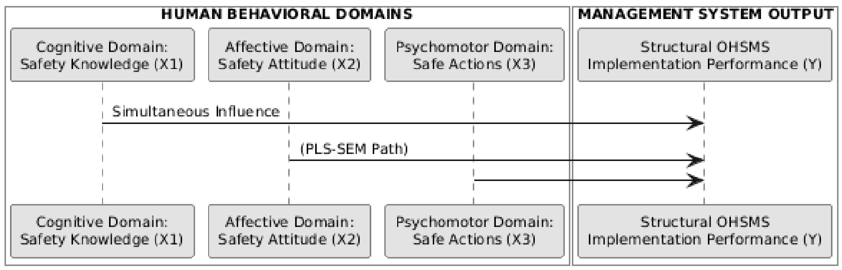

Figure 1: Conceptual framework of behavioral determinants and OHSMS implementation

The underlying theoretical mechanics governing the interaction between these behavioral dimensions are rooted in established psychological frameworks, primarily Ajzen's Theory of Planned Behavior and Bandura's Social Learning Theory. The Theory of Planned Behavior posits that an individual's explicit action is directly guided by behavioral intentions, which are dynamically shaped by cognitive attitudes, subjective norms, and perceived behavioral control. Concurrently, Social Learning Theory highlights the role of observational modeling and environmental conditioning, suggesting that safe or unsafe actions are continually reinforced by the surrounding workplace climate, management commitment, and peer behavior. In industrial settings, safety knowledge is conventionally theorized as the foundational prerequisite that drives positive safety attitudes, which subsequently manifest as consistent, compliant safety actions in the field.

However, empirical literature reveals highly complex, non-linear, and occasionally contradictory relationships when these variables are modeled simultaneously within high-risk extractive operations. For instance, contemporary mining studies demonstrate that while safety literacy is critical, high levels of theoretical knowledge do not automatically yield safe compliance if workers operate under intense productivity pressures or within a permissive safety culture. Furthermore, psychological vulnerabilities such as overconfidence or optimization biases can cause highly knowledgeable workers to bypass formal procedures, mistakenly believing their experience allows them to manage operational risks manually. Conversely, a robust, proactive safety attitude has been consistently validated as a highly stable predictor of procedural compliance, as internally motivated workers view safety protocols as a vital necessity for self-preservation rather than an administrative burden. Observable safe actions are frequently constrained or enabled by external systemic factors—such as the consistency of supervisory enforcement and the immediate availability of personal protective equipment (PPE)—meaning that individual actions cannot be fully evaluated outside the broader organizational ecosystem.

Methodologically, evaluating these latent, multi-dimensional, and simultaneous behavioral pathways presents distinct statistical challenges. Traditional regression techniques often fall short when evaluating complex behavioral models with multiple independent structural paths and relatively small sample sizes. Consequently, contemporary safety literature strongly advocates for the application of Partial Least Squares Structural Equation Modeling (PLS-SEM). PLS-SEM provides superior predictive capacity and analytical flexibility by simultaneously evaluating the measurement model (the relationship between indicators and their respective latent variables) and the structural model (the causal pathways between the behavioral constructs and OHSMS performance) without requiring strict data normality. Recent studies utilizing PLS-SEM in heavy manufacturing and oil and gas operations have successfully identified how underlying safety sub-cultures and behavioral mediators indirectly dictate structural safety compliance.

By adopting this multivariate analytical framework, this study evaluates the distinct empirical pathways through which knowledge, attitude, and action simultaneously influence or constrain the practical implementation of OHSMS within a strategic Indonesian nickel mining facility.

3. Methods

This study deployed a comprehensive quantitative descriptive-analytic research design utilizing a cross-sectional approach to investigate, map, and evaluate the empirical impacts of individual behavioral domains on the institutionalized implementation performance of the Occupational Health and Safety Management System (OHSMS). In occupational safety engineering, a quantitative multivariate framework is considered the most objective methodology to eliminate observational subjectivity, thereby enabling mathematical quantification of the causal trajectories that define human factors within high-risk infrastructure environments (Hair et al. 2019). The structural configuration of this research was explicitly constructed around a cross-sectional horizon, meaning that the operational parameters, behavioral indicators, and system compliance check-logs were captured systematically at a single, un-manipulated point in time (Neal and Griffin 2002). This design was strategically advantageous as it allowed for the rapid extraction of concurrent behavioral baselines across multiple operational divisions—specifically production, processing, and logistics maintenance without introducing experimental treatment interventions that could artificially alter the organic risk-taking or compliance tendencies of the active workforce.

To operationalize the behavioral dynamics under evaluation, this study systematically integrated B.F. Skinner's Behaviorism Theory and Benjamin Bloom's Taxonomy of Educational Objectives, which categorize human functional execution into three interconnected domains: the cognitive domain (operationalized as Safety Knowledge, X_1), the affective domain (operationalized as Safety Attitude, X_2), and the psychomotor domain (operationalized as Safe Actions, X_3). The structural core of this methodological framework is designed to challenge the conventional linear assumption that knowledge automatically dictates attitude, which then perfectly translates into observable action. Instead, this research models these three behavioral dimensions as simultaneous, distinct, and potentially conflicting exogenous drivers that directly intersect with the endogenous management system output, defined here as OHSMS Implementation Performance (Y). By analyzing these three domains simultaneously within a unified structural network, the methodology isolates the unique path coefficient of each individual behavioral component, identifying anomalies such as cognitive overconfidence or administrative friction points that are frequently obscured in basic univariate or bivariate correlation models (Soni and Prasad 2019).

The mathematical modeling and statistical processing of the empirical field data were executed through Partial Least Squares Structural Equation Modeling (PLS-SEM) using the advanced computational engine of SmartPLS 4 (Ringle et al. 2023). Unlike traditional covariance-based structural equation modeling (CB-SEM), which relies heavily on strict assumptions of continuous data normality and large sample sizes ($N > 200$), PLS-SEM was selected for its exceptional statistical power, predictive focus, and mathematical flexibility when handling medium-sized samples and non-normal distribution patterns typical of specialized industrial operations (Henseler et al. 2016). The PLS-SEM algorithm functions by executing a sequence of ordinary least squares (OLS) regressions to maximize the explained variance (R^2) of the endogenous latent variables through a rigorous, two-stage evaluation framework:

3.1 Evaluation of the Measurement Model (Outer Model)

The outer model evaluation was conducted to establish the fundamental psychometric properties, validity, and reliability of the distributed research instrument, ensuring that the empirical indicators precisely represented their underlying latent behavioral constructs. This validation stage is mathematically required before any structural paths can be interpreted, and it involves three primary evaluation metrics:

- Convergent Validity: This parameter measures the degree to which multiple indicators of the same latent variable consistently agree. It was evaluated using two core indices: outer loading factors (λ) and the Average Variance Extracted (AVE). The mathematical formula for calculating the AVE of a latent construct is defined as the sum of squared loadings divided by the sum of squared loadings plus the sum of measurement error variances, which is expressed as follows:

$$AVE = \frac{\sum_{i=1}^{k} \lambda_i^2}{\sum_{i=1}^{k} \lambda_i^2 + \sum_{i=1}^{k} Var\,(\epsilon_i)} \quad (1)$$

  In accordance with strict psychometric standards, an indicator loading $\lambda \geq 0.70$ is preferred, though loadings between 0.50 and 0.70 are acceptable if the overall construct's AVE remains securely above the critical threshold of 0.50. An AVE score ≥ 0.50 mathematically confirms that the latent variable captures more than half of the variance inherent to its operationalized indicators.

- Internal Consistency Reliability: To confirm the structural stability, internal coherence, and replication potential of the measurement scales, this study calculated both Cronbach's Alpha (α) and Composite Reliability (CR). While Cronbach's alpha provides a conservative baseline assumption of reliability by assuming equal weighting across all indicators, Composite Reliability is recognized as a more precise index within PLS-SEM because it accounts for the unique, unequal loadings of each reflective indicator (Hair et al. 2012). For a measurement model to be validated as highly reliable and trustworthy for industrial diagnostic applications, both the Cronbach's alpha and Composite Reliability coefficients must systematically exceed the standard threshold of 0.70.

- Discriminant Validity: This validation ensures that each latent behavioral construct is empirically unique and captures distinct aspects of workforce psychology that are not accounted for by other variables in the model. Discriminant validity was established using the classical Fornell-Larcker Criterion, which requires that the square root of the AVE for any given latent construct (√AVE) must be strictly greater than the highest statistical correlation coefficient (r) existing between that specific construct and any other latent variable within the structural model.

3.2 Evaluation of the Structural Model (Inner Model)
Once the measurement framework was confirmed to be reliable and valid, the analysis proceeded to evaluate the structural model (inner model) to test the hypothesized paths and assess the predictive power of the integrated behavioral framework. This second analytical stage focuses on the following key metrics:

- Path Coefficients (β): These standardized values represent the strength and algebraic direction of the direct relationships between the exogenous behavioral constructs (X_1, X_2, X_3) and the endogenous system output (Y). The path coefficients mimic standardized regression weights, bounded between -1.00 and +1.00, where a positive value indicates a direct supportive relationship and a negative value reveals an inverse structural trajectory.
- Significance Testing via Bootstrapping: Because PLS-SEM does not assume data normality, parametric significance testing cannot be applied. Therefore, the statistical significance of the path trajectories was evaluated using a non-parametric, high-density bootstrapping procedure involving 5,000 sub-sample iterations (Ringle et al. 2023). This computational technique calculates empirical t-statistics and corresponding double-tailed p-values for each structural path. A path is validated as statistically significant if its empirical t-statistic exceeds the critical value of 1.96, corresponding to a p-value below the standard alpha threshold of 0.05 ($p < 0.05$) at a 95% confidence interval.
- Coefficient of Determination (R^2): This metric evaluates the overall explanatory power of the structural model by quantifying the percentage of variance within the endogenous target variable (Y) that can be collectively explained by the simultaneous influence of the exogenous behavioral predictors (X_1, X_2, X_3). Within behavioral safety modeling, R^2 values around 0.25 are categorized as weak, values approaching 0.50 are deemed moderate, and values exceeding 0.75 are classified as substantial (Hair et al. 2019).

4. Data Collection
The field data collection was executed at PT Trinusa Dharma Utama, a strategic nickel ore exploration and production enterprise located in Ganda-Ganda Kolonodale District, Kecamatan Petasia Kabupaten Morowali Utara, Indonesia. The field research timeline and operational data gathering occurred over a three-month window from January to March 2024. The targeted study population consisted of workers actively engaged in frontline mining operations, specifically across production, mineral processing, and maintenance logistics units, as these personnel are directly exposed to daily operational hazards and routinely interact with site safety procedures.

Given the relatively small and specialized nature of the target workforce under 100 individuals, a purposive total sampling approach was deployed, establishing a final sample size of 50 respondents who fulfilled all active inclusion criteria. The inclusion criteria required that participants were actively engaged in frontline operational activities, held a minimum of one year of continuous employment to ensure procedural familiarity, and expressed voluntary willingness to participate. Primary data were gathered via structured questionnaires evaluated using a five-point Likert scale (ranging from 1 for strongly disagree to 5 for strongly agree) alongside direct field observations. Concurrently, secondary data were extracted from official company records, including active employee registers, employment tenure data, documented OHS accident logs, and official OHSMS procedural checklists to support empirical validity. The operationalized measurement items were distributed across four latent constructs as defined in Table 1.

Table 1: Operational variables and indicator layout

Latent Variable	Operational Definition	Number of Indicators	Scale Type
Safety Knowledge (X_1)	Worker comprehension of explicit OHS policies, localized operational risk vectors, and standard safety execution procedures.	5 Indicators	Ordinal (Likert)
Safety Attitude (X_2)	Internal affective disposition, cognitive risk perceptions, and proactive commitment to comply with site safety regulations.	6 Indicators	Ordinal (Likert)
Safe Actions (X_3)	Explicit psychomotor safety execution, procedural compliance during tasks, and active utilization of Personal Protective Equipment (PPE).	7 Indicators	Ordinal (Likert)
OHSMS Implementation (Y)	The institutionalized performance of safety planning, operational execution, evaluation, and continual safety system improvement.	7 Indicators	Ordinal (Likert)

5. Results and Discussion

5.1 Numerical Results

The empirical evaluation of the structural model was performed using a two-stage PLS-SEM approach. First, the measurement model (outer model) was analyzed to confirm that all latent constructs exhibited sufficient structural validity and internal consistency reliability. Convergent validity was assessed by checking the outer loading factors of each indicator and the Average Variance Extracted (AVE) for each construct.

As documented in the structural measurement logs, all indicators retained in the final model exhibited outer loading values exceeding the conservative threshold of 0.50, with the vast majority exceeding 0.70. This indicates that each indicator shared a strong, robust variance with its respective latent variable. Furthermore, the AVE values for all four constructs systematically exceeded the critical cut-off value of 0.50, demonstrating that each latent variable accounted for more than 50% of the variance among its operationalized indicators. The specific numerical breakdowns for the outer model evaluation are compiled in Table 2.

Table 2: Measurement model reliability and convergent validity results

Latent Construct	Indicators Included	Outer Loadings Range	Cronbach's Alpha (α)	Composite Reliability (CR)	Average Variance Extracted (AVE)
Safety Knowledge (X_1)	20 Items ($x_{1.1}$ - $x_{1.20}$)	0.506 – 0.859	0.949	0.953	0.506
Safety Attitude (X_2)	15 Items ($x_{2.1}$ - $x_{2.15}$)	0.771 – 0.964	0.977	0.979	0.759
Safe Actions (X_3)	10 Items ($x_{3.1}$ - $x_{3.10}$)	0.695 – 0.972	0.968	0.968	0.755
OHSMS Implementation (Y)	35 Items (z_1 - z_{35})	0.539 – 0.952	0.989	0.990	0.734

Internal consistency reliability was established through Cronbach's alpha (α) and Composite Reliability (CR) testing. All latent variables produced Cronbach's alpha scores well above the standard 0.70 threshold, ranging from 0.949 to 0.989. Similarly, the CR values fell between 0.953 and 0.990, verifying excellent internal scale coherence and construct trustworthiness. Discriminant validity was also achieved using the Fornell-Larcker criterion, confirming that the square root of the AVE for each construct exceeded its highest correlation with any other latent variable in the structural model.

Following measurement validation, the structural model (inner model) path trajectories were calculated using the bootstrapping algorithm to determine statistical significance. The simultaneous integration of the three behavioral domains explained a moderate-to-substantial proportion of the variance in structural safety system execution, yielding a Coefficient of Determination (R^2) of 0.376. This indicates that safety knowledge, attitudes, and actions together account for 37.6% of the variance in field OHSMS implementation at the nickel mine, while the remaining 62.4% is driven by external systemic variables outside the individual model. The direct path coefficients (β), t-statistics, and exact p-values for each hypothesized pathway are detailed in Table 3.

Table 3: Structural path coefficients and hypothesis testing results

Hypothesis	Path Direction	Path Coefficient (β)	t-Statistic	p-Value	Empirical Decision
H_1	Safety Knowledge (X_1) to OHSMS Implementation (Y)	-0.488	3.876	0.000	Supported (Significant)
H_2	Safety Attitude (X_2) to OHSMS Implementation (Y)	1.275	1.986	0.047	Supported (Significant)
H_3	Safe Actions (X_3) to OHSMS Implementation (Y)	-0.907	1.586	0.113	Rejected (Not Significant)

5.2 Graphical Results

The structural model interactions, loading factors, and path coefficients generated by the PLS-SEM algorithm are visually mapped in Figure 2. This graphical layout illustrates the simultaneous measurement paths linking individual indicators to their latent targets alongside the inner structural model paths that test the primary hypotheses.

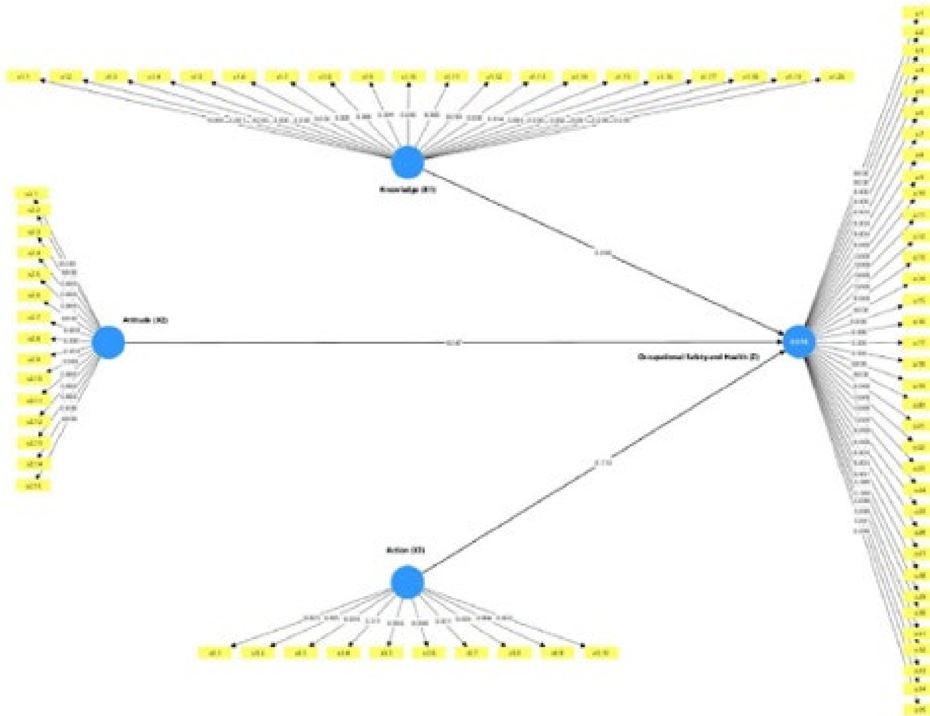

Figure 2: Empirical structural model path coefficients and R-square output

As visually displayed in the model path diagram, the affective domain—represented by Safety Attitude (X_2)—emerges as the most dominant positive driver within the inner model, yielding a high positive path coefficient ($\beta = 1.275$, $p = 0.047$). Conversely, Safety Knowledge (X_1) displays a highly significant negative trajectory ($\beta = -0.488$, $p < 0.001$), indicating a distinct inverse relationship within this specific mining workforce. Safe Actions (X_3) shows a negative path coefficient that fails to achieve statistical significance ($\beta = -0.907$, $p = 0.113$), confirming it does not act as a reliable individual predictor within this structural network.

5.3 Proposed Improvements

The empirical findings reveal a distinct operational paradox: while positive internal safety attitudes strongly support OHSMS execution, elevated scores in theoretical safety knowledge correspond to a significant decline in field system implementation. This inverse knowledge trajectory points to an "overconfidence anomaly" or optimization bias often observed in high-risk industrial settings. Frontline personnel who possess extensive theoretical knowledge regarding safety procedures may develop an inflated sense of situational control. This perceived expertise can lead workers to underestimate routine site hazards, bypass formal administrative checklists, and handle dangerous operational tasks manually based on personal intuition rather than strict procedural compliance.

To bridge this critical gap between cognitive awareness and field execution, the following targeted interventions are proposed for the mining facility's operational architecture:

- Transition to Behavior-Based Safety (BBS) Interventions: Management should shift from conventional classroom-style safety lecturing to field-integrated behavior monitoring. Safety training must incorporate real-world situational testing and peer-led safety reviews to ensure cognitive literacy translates directly into cooperative safety habits.
- Strengthening Supervisory Oversight and Accountability: Because individual safe actions are statistically non-significant on their own, frontline behavior must be supported by strict administrative enforcement. Implementing continuous, short-interval safety field checks by HSE officers will prevent workers from taking shortcuts or bypassing active protocols.
- SOP Optimization and Equipment Accessibility: To turn theoretical safety knowledge into positive field actions, the organization must remove friction points by ensuring that calibrated Personal Protective

Equipment (PPE) is immediately available at all operational sectors and that safety checklists are seamlessly integrated into routine task shifts.

5.4 Validation

To confirm the overall structural validity, explanatory power, and performance of the predictive path model, a global Goodness-of-Fit (GoF) validation was calculated. The mathematical formulation for the absolute GoF index is determined by calculating the geometric mean of the average communality (average AVE) and the average endogenous coefficient of determination (average R^2), expressed as follows:

$$GoF = \sqrt{(AVE \times R^2)} \quad (2)$$

By substituting the validated numerical averages derived from the empirical data model (AVE = 0.689 and $R^2 = 0.376$) into the equation, the absolute index value is verified:

$$GoF = \sqrt{(0.689 \times 0.376)} = \sqrt{0.259} = 0.509$$

According to the established cross-disciplinary evaluation criteria defined by safety modeling theorists, a GoF value of 0.10 indicates small fit, 0.25 signifies medium fit, and values exceeding 0.36 confirm a highly substantial structural model fit. The calculated GoF index of 0.509 establishes that the integrated structural framework possesses a highly substantial level of predictive fit. This confirms a strong, reliable alignment between the outer measurement model and the inner structural pathways, validating that the model is mathematically robust for driving strategic safety management adjustments in the extraction sector.

6. Conclusion

This research successfully modeled and quantified the simultaneous impact of employee behavioral determinants knowledge, attitude, and action on the field implementation of an Occupational Health and Safety Management System (OHSMS) within a strategic Indonesian nickel mine. The empirical modeling validates that the predefined research objectives have been met. The multi-dimensional structural framework explained 37.6% of the overall variance in OHSMS implementation ($R^2 = 0.376$, GoF = 0.509), proving that human behavioral dimensions are key determinants of formal safety system performance.

The primary unique contribution of this study lies in uncovering the divergent pathways through which different behavioral domains operate under intense production environments. While a positive safety attitude is the most powerful internal driver of systematic safety compliance ($\beta = 1.275$, $p = 0.030$), theoretical safety knowledge exhibits a significant inverse relationship ($\beta = -0.488$, $p < 0.001$). This confirms that cognitive safety literacy alone does not guarantee field compliance and can inadvertently trigger procedural bypass due to overconfidence. Furthermore, the non-significant impact of individual actions underscores that frontline safety behaviors are heavily constrained by external variables. Ultimately, optimizing safety performance in high-risk mining environments cannot be achieved through technical instruction alone; it requires aligning individual behavioral interventions with consistent administrative enforcement, supportive management commitment, and a proactive organizational safety culture.

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