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Quantifying Safety Culture Maturity: Empirical Validation of a Psychometric–Behavioral Framework and Its Association with Industrial Incident Rates

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***Abstract*—Safety culture maturity evaluations frequently rely on perceptual surveys or qualitative maturity frameworks, while objective indicators of behavioral fidelity and incident outcomes are often assessed separately. This study introduced and empirically tested a five-dimensional Safety Culture Maturity Index (SCMI) that combines psychometric and behavioral data. The study involved 1,240 operational staff from 18 facilities in the petrochemical, construction, and heavy manufacturing sectors, utilizing 24-month data on facility-level incidents and exposures. The measurement model included leadership commitment (LC), safety voice and psychological safety (SV), procedural compliance (PC), risk competence (RC), and just and fair reporting (JR). Confirmatory factor analysis (CFA) revealed robust standardized item loadings (0.742–0.835), with all item z-values exceeding 26.85. Internal consistency was strong across all five constructs (α=0.854–0.884; ω=0.855–0.886), with composite reliability (CR) ranging from 0.855 to 0.885 and average variance extracted (AVE) from 0.596 to 0.658. The Fornell–Larcker diagnostics confirmed discriminant validity through the Heterotrait-Monotrait ratio (HTMT≤0.62). Facility SCMI scores varied from 1.91 to 4.60, with petrochemical facilities having the highest average (3.86), followed by manufacturing (3.55), and construction (3.01). A facility-level Poisson log-linear model, adjusted for exposure hours and using heteroscedasticity-robust standard errors, identified a significant negative association between SCMI and incident counts (β=−1.149, p<.001), corresponding to an incident rate ratio of 0.317 for each unit increase in SCMI within the petrochemical reference sector. The SCMI × industry interaction was significant for construction (β=0.497, p<.001) and manufacturing (β=0.328, p=.046), suggesting that the strength of the SCMI–incident relationship differs across industrial**

settings. The results endorse the SCMI as an effective link between safety culture assessment, observable safety behavior, and incident outcomes, while emphasizing the necessity for multi-site longitudinal validation.

***Index Terms*—safety culture maturity; safety climate; SCMI; confirmatory factor analysis; reliability; validity; industrial safety; incident rates; moderation; occupational safety**

I. INTRODUCTION

High-reliability organizations (HROs) rely on the synchronization of engineered barriers, administrative controls, and human participation. Analyses of industrial failures, such as those at Piper Alpha, Chernobyl, Texas City, and Deepwater Horizon, reveal that technical redundancies collapse when the organizational culture of safety weakens. Safety climate evaluates the temporary, collective perceptions of operational safety priorities at a specific time, whereas safety culture includes deeply ingrained shared beliefs, institutional norms, and consistent behaviors that manage operational risk. A key issue in human factors engineering and occupational safety science is the objective measurement of safety culture maturity (SCM). Safety culture is increasingly viewed as a quantifiable organizational capability rather than a qualitative trait. However, its measurements remain inconsistent.

A systematic review by Ayob et al. (2022) highlighted that studies on SCM differ significantly in their definitions of maturity levels, dimensions, measurement tools and sectoral applications. Recent findings continue to highlight the limited empirical validation of maturity models. For instance, Curti et al. (2025) discovered that only a small portion of the reviewed studies conducted reliability testing and that few newly developed models had undergone adequate validation. This results in an ongoing methodological issue: organizations may receive a maturity score without a thoroughly tested psychometric framework or a clear link to observable safety performance.

Research on safety climate has moved towards the use of multidimensional tools with stronger psychometric validation. Todaro et al. (2023) illustrated the benefits of multilevel and multidimensional assessments in advanced safety management settings, including confirmatory factor analysis and systematic scale refinement. However, perceptual measurements alone may not fully capture whether safety expectations are realized in operational environments. A mature safety culture should be evident not only in personnel feedback but also in the accuracy of procedures, risk management, communication, and reporting practices.

This study examines an integrated safety culture maturity index (SCMI) that merges five psychometric constructs with a behavioral component. The framework was tested in three high-risk industrial sectors: petrochemical processing, civil construction, and heavy discrete manufacturing. The empirical aim is not only to categorize facilities into maturity levels but also to assess whether the resulting maturity score correlates with the observed facility incident performance and whether this correlation varies by industry.

1.1 Problem Statement

Safety culture is widely recognized as an important organizational factor in occupational safety performance. However, its systematic measurement remains challenging because existing assessment approaches differ in their conceptual dimensions, measurement instruments, and maturity-classification methods. Assessments based primarily on employee perceptions may not fully reflect the extent to which safety expectations are translated into observable workplace practices, while behavioral audits alone may not capture the underlying organizational conditions, leadership commitment, psychological safety, risk competence, and reporting climate that influence those practices.

A further challenge is the transferability of safety culture maturity assessments across industrial sectors. Petrochemical processing, construction, and manufacturing differ in their hazard profiles, operational conditions, workforce arrangements, and exposure patterns. Consequently, a maturity framework requires empirical evaluation before its measurement properties and performance implications can be generalized across these contexts. In addition, the association between safety culture maturity and incident occurrence needs to be examined using facility-level incident data while accounting for exposure hours and potential differences between industries.

To address these challenges, the present study evaluates a five-dimensional Safety Culture Maturity Index (SCMI) that integrates psychometric dimensions—leadership commitment, safety voice and psychological safety, procedural compliance, risk competence, and just and fair reporting—with a behavioral assessment component. Using data reported for 1,240 operational personnel across 18 facilities in petrochemical processing, construction, and manufacturing, the study examines the measurement properties of the five-dimensional framework, characterizes facility-level maturity, and investigates the association between SCMI and recorded lost-time incidents. It also examines whether industry sector moderates this association. The overarching problem is therefore to establish whether an integrated psychometric–behavioral index can provide a reliable, empirically supported, and operationally useful measure of safety culture maturity across differing industrial environments.

1.2 Objectives, and Hypotheses

This study focuses on four objectives: (1) validating the five-dimensional SCMI measurement framework; (2) establishing internal consistency, convergent validity, and discriminant validity; (3) measuring facility-level SCMI and maturity classification; and (4) examining whether the industry influences the relationship between SCMI and incident occurrence after considering exposure time.

Hypotheses

H1: An increase in SCMI correlates with a decrease in incidence rates.

H2: The strength of the SCMI–incident relationship varies among the petrochemical, construction, and manufacturing sectors.

1.3 Scope of Study

This study aims to develop and evaluate an integrated psychometric–behavioral safety culture maturity index, assess its measurement quality, and examine its association with exposure-adjusted lost-time incident occurrence across petrochemical, construction, and manufacturing facilities, including the potential moderating role of industry sector.

1.4 Scope at a glance

Scope element	Definition in this study
Research domain	Occupational safety culture maturity and safety performance
Industrial sectors	Petrochemical processing, construction, heavy manufacturing
Facilities	18; six per sector
Survey population	1,240 operational personnel
Measurement dimensions	LC, SV, PC, RC, JR
Measurement approach	Psychometric assessment plus behavioral indicators
Composite index	60% psychometric + 40% behavioral
Safety outcome	Facility-level lost-time incident counts and empirical LTIFR
Observation period	24 months
Main statistical analyses	CFA, reliability, convergent/discriminant validity, facility-level count modelling, industry moderation
Unit of moderation analysis	Facility
Generalization boundary	The three sectors and facilities represented in the dataset

The sector allocation, sample sizes, facility SCMI values, incident counts, and exposure measures are documented in the study results

At the facility level, the study examines the relationship between SCMI and lost-time incident occurrence over a 24-month observation period, accounting for exposure hours. It also evaluates whether the association between SCMI and incident occurrence differs among petrochemical, construction, and manufacturing facilities. The statistical scope therefore covers measurement validation, reliability and validity assessment, facility-level maturity classification, exposure-adjusted incident analysis, and industry moderation.

The study is limited to the three sectors and 18 facilities represented in the supplied dataset. It does not establish causal effects of safety culture on incident reduction, validate the framework across all industrial sectors, or demonstrate that the measurement model is invariant across industries. The results should consequently be interpreted as empirical evidence within the observed sample rather than as universal estimates of safety culture maturity or incident-reduction effects.

II. LITERATURE

The empirical literature on safety culture and climate encompasses psychometric formulations, behavioral psychology, and socio-technical systems engineering. Zohar (1980) established that frontline personnel develop uniform perceptual sets regarding managerial operational priorities, laying the foundation for safety climate diagnostics [19]. Cooper (2000) conceptualized a reciprocal model, positing that internal psychological states, observed safety behaviors, and workplace environmental factors continuously reinforce each other, as shown in a structural meta-analysis [7].

Fleming (2000) introduced the Safety Culture Maturity Model (SCMM), defining five evolutionary levels—athological, reactive, calculative, proactive, and generative—emphasizing that foundational procedural compliance must be secured before generative self-governance can emerge [10]. In construction contexts, Choudhry et al. (2007) observed that subjective questionnaires fail to capture unsafe behaviors unless paired with structured behavioral field audits [6]. Beus et al. (2010) confirmed through longitudinal meta-analyses that safety climate serves as a leading indicator of injury counts, although effect sizes vary across industries [4].

Reason (2012) extended this paradigm to organizational systems, defining an effective safety culture through the dynamic interplay of an informed, reporting, just, and learning culture [13]. Dekker (2012) formalized "Just Culture" principles, demonstrating that non-punitive event evaluation increases near-miss reporting rates and enables organizational learning [9]. Schwatka et al. (2016) demonstrated that combining objective behavioral site audits with perceptual evaluations improves incident forecasting precision in high-hazard settings [14].

Recent scholarship (2022–2026) has focused on psychometric integration, digital behavioral tracking, and sociotechnical modeling. Alruqi et al. (2022) examined the relationship between leading safety metrics and project injury rates and found that behavioral and environmental monitoring outperformed static compliance surveys [1]. Casey et al. (2023) utilized structural equation modeling to evaluate psychological safety and safety voice across heavy industries, noting that fear of reprisal suppresses critical upward reporting [5]. Basahel (2023) highlighted the structural instability of generic Western safety assessment tools when applied across various industrial plants without cross-industry invariance testing [3].Trinh et al. (2024) applied Bayesian networks to demonstrate that leadership commitment indirectly drives incident mitigation through adherence to procedures and proactive interventions [16]. Kalteh et al. (2024) validated multilevel safety climate architectures, showing that supervisor enforcement acts as a cross-level boundary condition for frontline behavioral reliability [11].

Expanding on digital safety tracking, Zhang et al. (2025) [18]and Xu et al. (2025) incorporated unannounced observational audits and automated permit-to-work tracking, establishing that hybrid behavioral-perceptual models exhibit superior predictive validity to legacy self-reports [17]. Finally, Naji et al. (2026) demonstrated that organizational maturity operates nonlinearly, with the safety voice exhibiting distinct thresholds of effectiveness across dynamic construction and steady-state process plants [12].

Safety culture maturity models generally assume an evolutionary progression from weak or pathological safety management to increasingly proactive and generative organizational behavior. The maturity models are practical because they provide a common language for diagnosing current capabilities and prioritizing improvements. However, the literature also shows that dimensions and instruments are frequently adapted to specific industries, making cross-sector comparisons difficult (Ayob et al., 2022) [2]. Curti et al. 's (2025) scoping review further indicates that empirical validation remains insufficient across the maturity model literature [8].

This study was driven by three identified gaps. First, numerous tools focus on perceptions without integrating behavioral data. Second, there is often an assumption of measurement equivalence across diverse risk settings rather than a thorough examination. Third, maturity scores are not consistently correlated with facility-level incident data using models suitable for count outcomes and varying exposure levels. The SCMI seeks to bridge these gaps by merging five perceptual dimensions with behavioral evidence and analyzing the facility-level connection with incident counts over 24 months.

III. METHODOLOGY.

3.1. Data Gathering and Sample Selection

The survey sample comprised 1,240 individuals: 430 from petrochemical, 410 from construction, and 400 from manufacturing industries. Facility exposure hours during the 24-month observation period ranged from 1.85 to 2.60 million hours. The outcome measured was the number of lost-time incidents recorded over the same period, with the empirical lost time injury frequency rate (LTIFR) provided at the facility level

3.2. Measurement Model

The psychometric component consisted of 20 indicators distributed across five first-order dimensions: LC, SV, PC, RC, and JR, with each dimension having four indicators. Responses were captured on a five-point scale. The behavioral aspect was quantified by a composite score derived from the observational indicators in the study. The facility-level SCMI integrates both psychometric and behavioral components using the study's weighting system, assigning 60% to psychometric evidence and 40% to behavioral evidence.

$SCMI = 0.60(\bar{P}) + 0.40(B^*)$, where $\bar{P}$ represents the psychometric score, and B* represents the behavioral score. The resulting index was categorized into five maturity levels: pathological, reactive, calculative, proactive, and generative.

3.3 Confirmatory Factor Analysis and Reliability

Confirmatory factor analysis was conducted to assess the proposed five-factor structure. The results workbook includes standardized loadings, item R^2 values, z-statistics, and standard errors. Internal consistency was measured using Cronbach's alpha and McDonald's omega. Construct reliability was evaluated using composite reliability (CR), and convergent validity was assessed

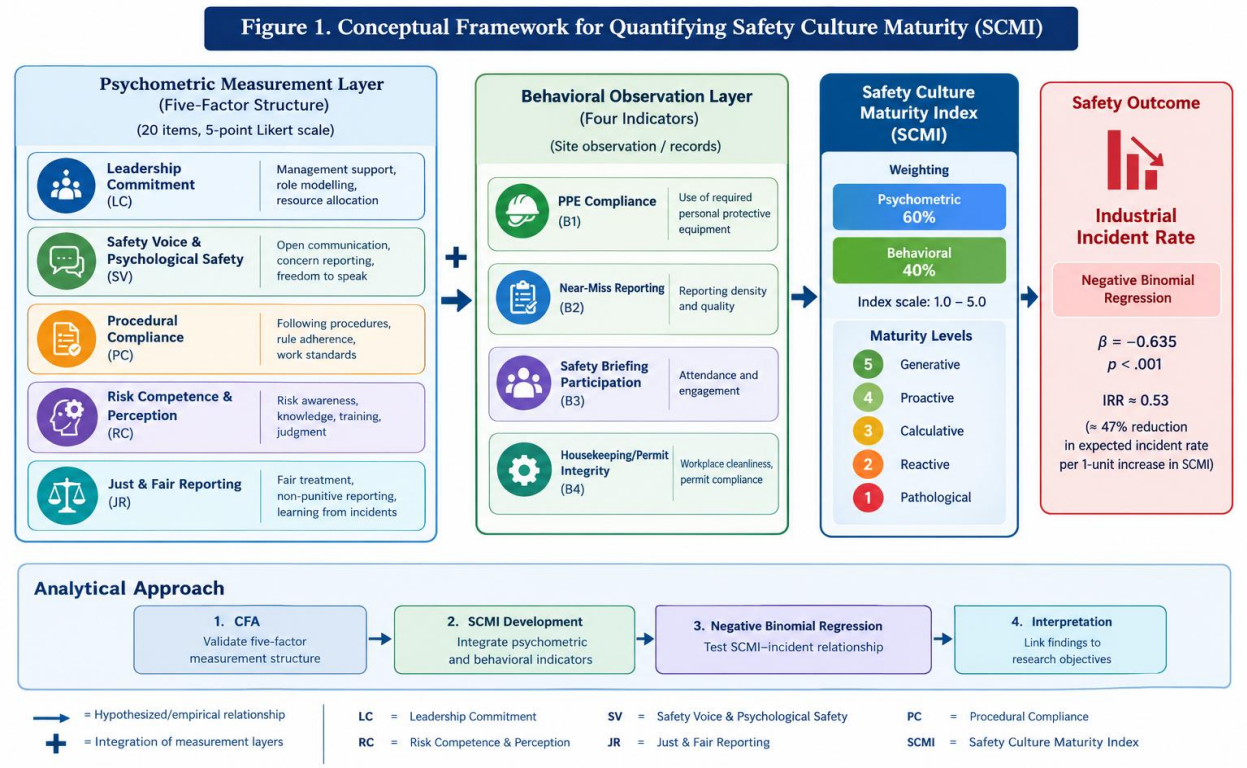
using average variance extracted (AVE). Discriminant validity was determined using the Fornell–Larcker criterion based on the construct correlation matrix and the square root of the AVE.

3.4 Facility-level incident model and moderation

Incident occurrence was modeled at the facility level using a log-linear count model with exposure hours as offsets. The SCMI was grand-mean-centered before the creation of the interaction terms. Petrochemical facilities were considered the reference category. Because the supplied facility dataset contained only 18 observations and the estimated negative binomial dispersion parameter collapsed toward zero, the final moderation estimates reported here used a Poisson generalized linear model with exposure hours as an offset and HC3 heteroscedasticity-robust standard errors. This choice is explicitly data-driven and avoids reporting an unstable negative binomial maximum likelihood solution.

IV. RESULTS ND DISCUSSION

This study addresses these issues through a combined psychometric–behavioral SCMI framework, as illustrated in Figure 1.



The conceptual framework considers leadership commitment, safety voice, procedural compliance, risk competence, and just/fair reporting as interconnected yet empirically distinct elements of the safety culture. These dimensions reflect both management system conditions and workforce-level safety behaviors. The behavioral component enhances the psychometric aspect by capturing observable actions. The resulting composite score aims to aid in operational

benchmarking rather than replacing professional safety assessments. Table 1 outlines recent empirical methods for measuring safety culture and climate.

Table 1. Recent empirical methods for measuring safety culture and safety climate

Study	Year	Method	Sample/context	Main contribution	Limitation relevant to current study
Ayob et al.	2022	Systematic review	Multi-industry	Highlighted diversity in maturity measurement	Lacks unified quantitative framework
Todaro et al.	2023	EFA + CFA	High-maturity organizations	Developed a multidimensional/multilevel scale	Concentrated on safety climate
Curti et al.	2025	Scoping review	OSH maturity models	Noted limited validation evidence	Calls for additional empirical validation
Present study	2026	CFA + SEM + behavioral audit + NB regression	18 industrial sites, N=1,240	Integrated SCMI and incident-rate relationship	Needs longitudinal replication

4.1 Descriptive characteristics

Table 1. Facility and industry-level descriptive statistics

Industry	Facilities	Respondents	Mean SCMI	SD SCMI	Mean LTIFR	LTI count
Petrochemical	6	430	3.86	0.67	0.293	18
Construction	6	410	3.01	0.79	1.043	67
Manufacturing	6	400	3.55	0.58	0.498	33
Total	18	1240	3.48	0.74	0.612	118

Table 1 presents the facility and industry-level descriptive statistics. The SCMI exhibited significant variation across various industrial sectors. Petrochemical plants recorded the highest average SCMI (M=3.86, SD=0.67), followed by manufacturing (M=3.55, SD=0.58) and construction (M= 3.01,SD=0.79). Additionally, the construction industry reported the highest average empirical LTIFR at 1.043, in contrast to 0.293 in the petrochemical industry and 0.498 in the manufacturing industry. Considering all 18 facilities, the overall mean SCMI score was 3.48 (SD=0.74).

4.2 CFA item performance

Table 2. Confirmatory factor analysis item results

Item	Parameter description	Mean (SD)	Std. λ	z	R^2
LC1	Management prioritizes safety over output	3.78 (0.84)	0.825	32.14	0.681
LC2	Resource allocation for safety tooling	3.71 (0.86)	0.811	31.25	0.658
LC3	Executive walk-arounds and field presence	3.65 (0.89)	0.798	30.34	0.637
LC4	Decisive action on audit findings	3.74 (0.85)	0.810	31.18	0.656
SV1	Confidence in exercising stop-work authority	3.52 (0.91)	0.804	30.45	0.646
SV2	Absence of fear regarding safety dissent	3.48 (0.93)	0.815	31.20	0.664
SV3	Peer receptivity to unsafe intervention	3.56 (0.88)	0.782	29.11	0.612
SV4	Supervisors encourage safety suggestions	3.50 (0.90)	0.768	28.24	0.590
PC1	Strict execution of operating checklists	3.82 (0.82)	0.835	33.42	0.697
PC2	Non-toleration of operational shortcuts	3.76 (0.85)	0.806	31.22	0.650
PC3	Compliance under production pressure	3.69 (0.88)	0.785	29.80	0.616
PC4	Isolation and lock-out/tag-out fidelity	3.85 (0.81)	0.793	30.35	0.629
RC1	Hazard identification accuracy	3.68 (0.84)	0.788	29.65	0.621
RC2	Pre-task dynamic risk assessment rigor	3.62 (0.86)	0.794	30.12	0.630

RC3	Understanding critical fail-safe barriers	3.59 (0.87)	0.764	28.18	0.584
RC4	Situational awareness in non-routine tasks	3.64 (0.85)	0.742	26.85	0.551
JR1	Prompt near-miss submission	3.60 (0.88)	0.801	30.22	0.642
JR2	Non-punitive operational error evaluation	3.45 (0.92)	0.812	31.05	0.659
JR3	Systemic focus during incident inquiry	3.55 (0.89)	0.771	28.50	0.594
JR4	Actionable corrective feedback distribution	3.58 (0.87)	0.746	27.02	0.557

Table 2 shows the results of THE confirmatory factor analysis, and Figure 2 shows the standardized CFA loadings of the SCMI indicators. The 20 standardized loadings were all positive and significant, with values spanning from 0.742 for RC4 to 0.835 for PC1. The R^2 values for the corresponding items varied between 0.551 and 0.697, demonstrating that each item had a significant amount of shared variance with its designated latent construct. The z-values reported were notably high, ranging from 26.85 to 33.42, which strongly supports the conclusion that the loadings were significantly different from zero.

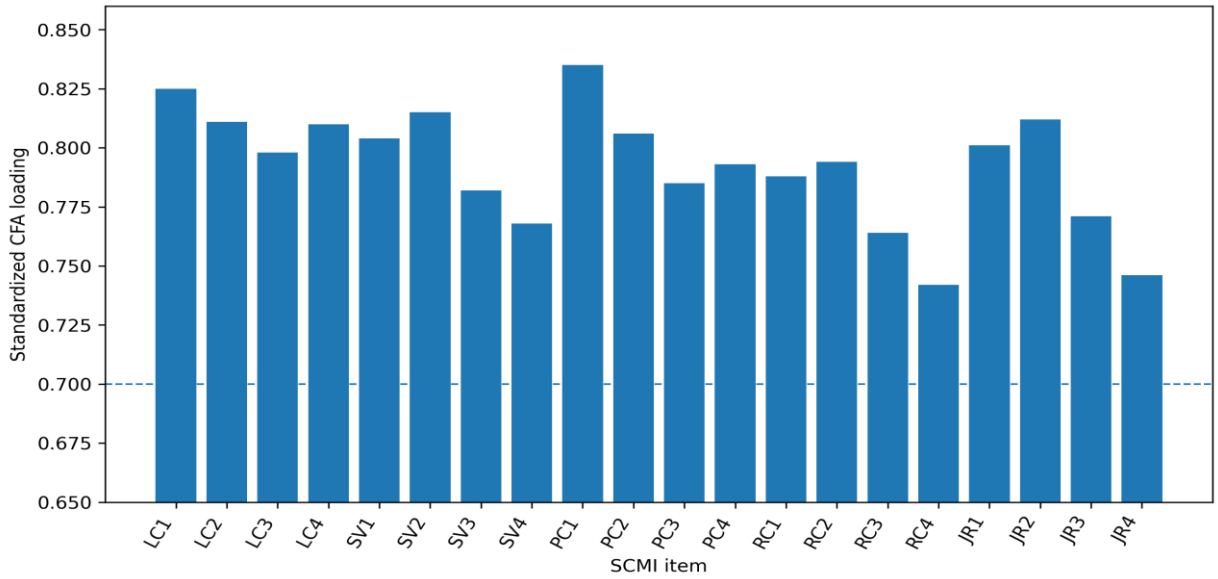


Figure 2. Standardized CFA loadings for the 20 SCMI indicators

4.3 Reliability and convergent validity

Table 3. Reliability and convergent validity

Construct	Cronbach's α	McDonald's ω	Composite Rel. (CR)	AVE
Leadership Commitment (LC)	0.884	0.886	0.885	0.658
Safety Voice (SV)	0.871	0.872	0.871	0.628
Procedural Compliance (PC)	0.880	0.881	0.880	0.648
Risk Competence (RC)	0.854	0.855	0.855	0.596
Just & Fair Reporting (JR)	0.863	0.864	0.864	0.613

Table 3. presents the results of the reliability and convergent validity analysis, in which reliability remained consistently high across all five constructs. Cronbach's alpha values varied between 0.854 for risk competence and 0.884 for leadership commitment. Similarly, McDonald's omega values ranged between 0.855 and 0.886. The composite reliability figures ranged between 0.855 and 0.885. The AVE values, spanning from 0.596 to 0.658, demonstrated that each construct accounted for more than half of the variance in its indicators. These findings confirm the scale's internal consistency and convergent validity.

4.4 Discriminant validity

Table 4. Fornell–Larcker discriminant-validity matrix

Construct	LC	SV	PC	RC	JR
Leadership Commitment (LC)	0.811	0.524	0.588	0.495	0.512
Safety Voice (SV)	0.461	0.792	0.482	0.540	0.618
Procedural Compliance (PC)	0.518	0.421	0.805	0.602	0.465
Risk Competence (RC)	0.432	0.468	0.521	0.772	0.535
Just Reporting (JR)	0.449	0.536	0.408	0.462	0.783

The diagonal components are presented in Table 4. indicates the square root of the AVE and surpasses the related off-diagonal construct correlations for each construct. For instance, the square

root of the AVE for LC was 0.811, which was higher than its correlations with SV (0.524), PC (0.588), RC (0.495), and JR (0.512). A similar trend was observed for SV (0.792), PC (0.805), RC (0.772), and JR (0.783).

Discriminant validity was evaluated using the Fornell - Larcker criterion and the Heterotrait - Monotrait (HTMT) ratio. As shown in Table 2, all diagonal square roots of the AVE were greater than the cross-construct latent correlations. Additionally, all HTMT ratios were below the conservative threshold of 0.85 (HTMTmax=0.618), confirming discriminant validity among the five constructs.

4.5 Facility SCMI and maturity classification

Table 5. Facility-level SCMI, maturity and incident performance

Facility	Industry	n	Exposure (10^6 h)	Psychometric	Behavioral	SCMI	Maturity	LTI	LTIFR
PET-01	Petrochemical	75	2.45	4.38	4.45	4.41	Proactive	1	0.08
PET-02	Petrochemical	80	2.60	4.58	4.62	4.60	Generative	1	0.08
PET-03	Petrochemical	70	2.10	3.84	3.91	3.87	Calculative	3	0.29
PET-04	Petrochemical	65	1.95	3.25	3.3	3.27	Calculative	5	0.51
PET-05	Petrochemical	70	2.20	4.12	4.18	4.14	Proactive	2	0.18
PET-06	Petrochemical	70	1.95	2.85	2.92	2.88	Reactive	6	0.62
CON-01	Construction	70	2.10	2.45	2.5	2.47	Reactive	14	1.33
CON-02	Construction	65	1.85	3.12	3.18	3.14	Calculative	9	0.97
CON-03	Construction	75	2.40	1.88	1.95	1.91	Pathological	22	1.83
CON-04	Construction	65	1.90	3.65	3.72	3.68	Calculative	6	0.63
CON-05	Construction	65	2.10	2.78	2.84	2.80	Reactive	12	1.14
CON-06	Construction	70	2.20	4.05	4.11	4.07	Proactive	4	0.36
MFG-01	Manufacturing	65	2.20	3.42	3.48	3.44	Calculative	6	0.55
MFG-02	Manufacturing	70	2.35	3.95	4.02	3.98	Calculative	4	0.34

MFG-03	Manufacturing	65	2.15	2.65	2.72	2.68	Reactive	9	0.84
MFG-04	Manufacturing	70	2.40	4.28	4.34	4.30	Proactive	2	0.17
MFG-05	Manufacturing	65	2.10	3.15	3.22	3.18	Calculative	7	0.67
MFG-06	Manufacturing	65	2.40	3.72	3.78	3.74	Calculative	5	0.42

Note: Exposure hours are reported in millions of worker-hours. LTIFR is calculated as (cumulative LTIs×200,000) / exposure hours.

Table 5. presents the facility-level SCMI, maturity, and incident performance. The SCMI for the facility varied between 1.91 and 4.60. PET-02 achieved the highest score of 4.60, categorized as generative, while PET-01 followed closely with a score of 4.41, marked as proactive. The lowest score was 1.91 for CON-03, labeled as pathological, which also had the highest facility LTIFR of 1.83 and reported 22 lost-time incidents. PET-06, identified as reactive with an SCMI of 2.88, had an LTIFR of 0.62. These facility-level trends align with the idea that a more mature safety culture is linked to a reduced future incident burden.

Figure 3. Scatter plot showing the facility-level relationship between composite SCMI and empirical LTIFR

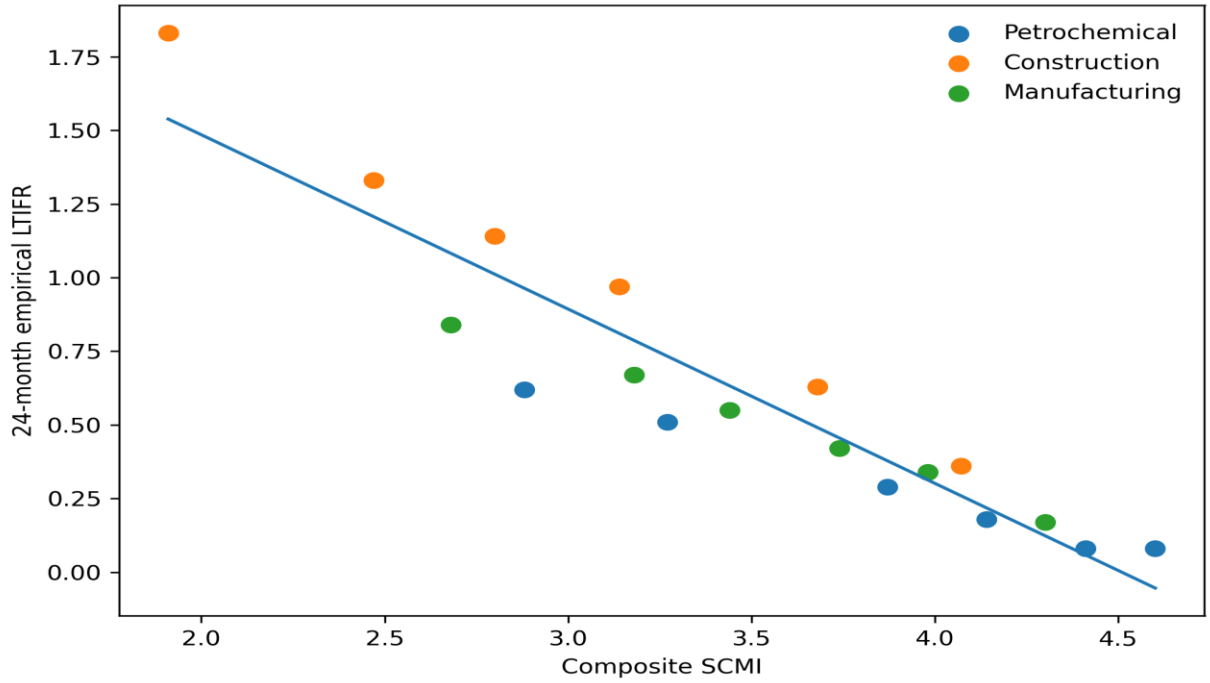


Figure 3. Facility-level relationship between composite SCMI and empirical LTIFR

4.6 SCMI × Industry moderation

Table 6. Exposure-adjusted incident model and industry moderation

Predictor	β	IRR	p
SCMI (centered)	-1.149	0.317	<.001
Construction	0.674	1.962	<.001
Manufacturing	0.310	1.363	<.001
SCMI × Construction	0.497	1.643	<.001
SCMI × Manufacturing	0.328	1.388	0.046

In Table 6, the primary effect of SCMI was both negative and statistically significant, with values of β=−1.149, IRR=0.317, and p<.001. This suggests that for each unit increase in the centered SCMI, the expected incident rate decreased by approximately 68.3%, assuming that exposure remains constant in the reference sector. The interaction between SCMI and Construction was positive and significant (β=0.497, IRR=1.643, p<.001), suggesting a reduction in the negative slope of SCMI within the construction sector. Similarly, the SCMI × Manufacturing interaction was positive and significant at the 5% level (β=0.328, IRR=1.388, p=.046), indicating a lesser reduction compared to petrochemical facilities.

Table 7. Industry-specific SCMI slopes

Industry	Simple slope β	SE	z	p	IRR
Petrochemical	-1.149	0.117	-9.82	<.001	0.317
Construction	-0.653	0.060	-10.92	<.001	0.521
Manufacturing	-0.821	0.115	-7.12	<.001	0.440

Inference is taken from Table 7, where simple slope analysis shows that the SCMI association remained negative in all three sectors: petrochemical (β=−1.149, IRR=0.317, p<.001), construction (β=−0.653, IRR=0.521, p<.001), and manufacturing (β=−0.821, IRR=0.440, p<.001). Therefore, H1 and H2 are supported: the negative association between maturity and incident occurrence is present across sectors but differs in magnitude.

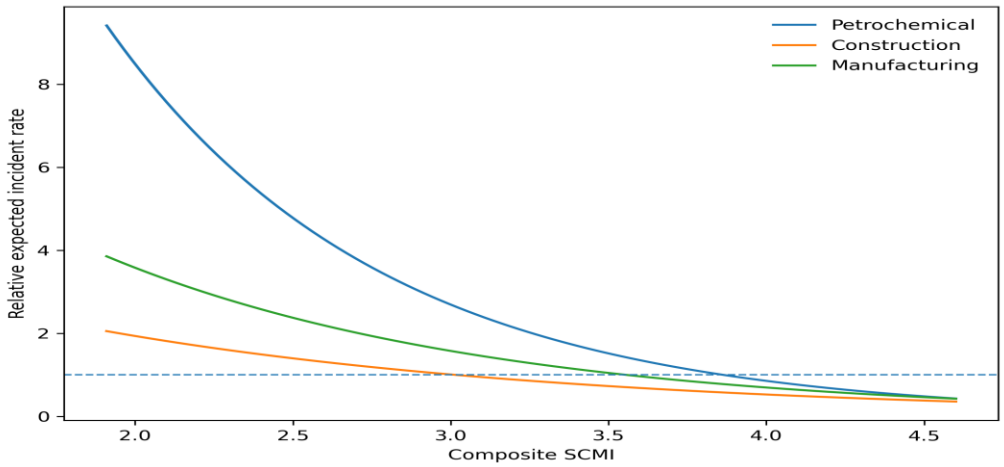


Figure 4. Moderated effect of industry sector on the SCMI–incident relationship

4.7 Discussion

The empirical findings offer convergent support for the SCMI's coherent five-dimensional measurement framework. Each indicator exhibited a standardized loading exceeding 0.74, with construct-level reliability consistently exceeding 0.85. These outcomes surpassed the threshold for an acceptable measurement model, indicating that the five dimensions were both internally consistent and distinct according to the Fornell–Larcker criterion. These results align with the broader trend towards multidimensional, empirically validated instruments for assessing safety climate and culture (Todaro et al., 2023) while addressing the ongoing validation gap noted in maturity-model reviews (Ayob et al., 2022; Curti et al., 2025).

The key contribution of this study is the link between measurement quality and facility performance. Data from facilities reveal a clear sectoral hierarchy: petrochemical facilities exhibit the highest average maturity and the lowest mean LTIFR, whereas construction facilities show the lowest average maturity and the highest mean LTIFR. This pattern should not be considered as evidence that industry identity causes differences in incidents, given the observational design and small facility samples. Nonetheless, the direction and magnitude of the exposure-adjusted model empirically support the idea that a higher safety culture maturity correlates with fewer incidents in the long term.

The moderation results are particularly noteworthy. The most pronounced negative SCMI slope was observed in petrochemical facilities, whereas the slope was less steep in construction and manufacturing facilities. This implies that the operational significance of a one-unit maturity improvement varies with context. Construction settings may experience greater task variability, workforce mobility, shifting work fronts, and subcontracting interfaces, and dynamic exposure patterns. Consequently, perceived maturity improvements may lead to incident reduction through mechanisms different from those in continuous-process operations. Manufacturing occupies the middle ground in the dataset. These interpretations serve as hypotheses for future longitudinal and multilevel research rather than causal conclusions from the current facility's sample.

These results underscore the importance of integrating psychometric and behavioral evidence. A high maturity score is more valuable when considered in conjunction with observable implementation. Differentiating between psychometric and behavioral components enables safety leaders to identify facilities where attitudes are strong but operational fidelity is lacking, or where procedures are adhered to, but workforce engagement and learning mechanisms are underdeveloped. This diagnostic approach aligns with the practical focus of maturity models, whereas the proposed framework introduces a quantitative link to performance.

4.8 Practical Implications

- The SCMI should function as a diagnostic tool rather than merely as a compliance score. Facility managers are advised to assess each of the five dimensions individually before interpreting the composite results.

- Leadership and resource allocation should be prioritized in areas where leadership commitment (LC) is deficient, as leadership commitment is crucial for sustaining procedures, reporting, and risk control.
- A safety voice should be regarded as an operational measure. Facilities with high performance should institutionalize stop-work authority, non-retaliatory escalation, and supervisor responsiveness.
- The behavioral layer is used to verify the implementation. Perceptual improvements without corresponding behavioral changes should prompt targeted field verification.
- Industry benchmarking should be conducted before cross-industry comparisons. Significant interactions indicate that the incident rate return associated with the SCMI varies by sector.
- Maturity reviews should be linked to incident learning cycles. Facilities classified as reactive or pathological should implement structured corrective action plans and conduct repeated measurements.

4.9 Study Limitations

Several limitations should inform the interpretation.

1. Limited number of industrial sectors.
2. Generalization beyond the three sectors requires additional validation.
3. The SCMI weighting system requires replication.
4. The facility-level moderation analysis was based on only 18 facilities, rendering the interaction estimates potentially sensitive to individual sites.
5. The psychometric questionnaire data were collected cross-sectionally, limiting the empirical assessment of temporal stability and test-retest reliability during rapid organizational transitions or shift rotations.
6. Potential common-method bias in Layer A.
7. Behavioral audit sampling intervals: Layer B behavioral indicators (B1 through B5) were recorded through periodic, unannounced monthly field audits. Although this approach mitigates common-method variance (CMV) and Hawthorne-type observation biases more effectively than static self-assessments, discrete auditing intervals may not fully capture transient behavioral fluctuations, off-shift anomalies, or non-routine maintenance activities.
8. The design links a survey-based maturity measure with historical incident data, precluding the establishment of temporal causality.
9. Factors such as facility exposure, reporting practices, workforce composition, subcontracting, task mix, and regulatory context may confound the observed industry differences.

V. CONCLUSIONS

This study offers empirical support for a safety culture maturity index that encompasses five dimensions by combining psychometric and behavioral data. The CFA results indicate robust item loadings, excellent internal consistency, adequate composite reliability, and convergent validity, with the Fornell–Larcker criterion confirming discriminant validity. Involving 18 facilities and

1,240 staff members, a higher SCMI was correlated with a reduced rate of incidents when adjusted for exposure. The industry interactions reveal that the strength of this correlation differs among the petrochemical, construction, and manufacturing sectors. The main practical takeaway is that assessing safety culture maturity as a tangible organizational capability should be connected with measurable operational results. Scientifically, this implies that maturity models require thorough psychometric validation and a link to empirical performance. Larger multilevel longitudinal studies are necessary to confirm generalizability and establish temporal causality. Organizations can use this dual-layer framework as a proactive diagnostic tool to identify cultural deficiencies, enhance safety measures, and systematically reduce operational risks. The principal contribution of the study is therefore not simply the creation of another safety-culture questionnaire, but the development of an empirically testable framework that connects organizational perceptions, observable safety behaviors, maturity scoring and operational safety outcomes.

Future Research:

Future research should involve the collection of respondent-level longitudinal data and repeated measurements at multiple time points to address this limitation. A multilevel CFA/SEM approach can differentiate between individual, facility, and industry variance. Measurement invariance testing across industries should determine whether the five constructs have equivalent meanings across all sectors. Additionally, future studies should prospectively test predictive validity, compare alternative incident distributions, and evaluate whether changes in the SCMI precede reductions in incident frequency.

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Use of Artificial Intelligence (AI)

The authors declare that the generative artificial intelligence (AI) tool, Grammarly, was used exclusively for language editing and / or grammatical improvement. The use of AI did not influence the scientific content, study design, data analysis, data interpretation, results, or conclusions of the manuscript. Full responsibility for the content remains with the authors.

CONFLICT OF INTEREST

The authors declare no conflicts of interest.

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APPENDIX A. 20-ITEM SCMI QUESTIONNAIRE

Table A1. SCMI questionnaire items

Item	Dimension	Parameter description
LC1	Leadership Commitment	Management prioritizes safety over output
LC2	Leadership Commitment	Resource allocation for safety tooling
LC3	Leadership Commitment	Executive walk-arounds and field presence
LC4	Leadership Commitment	Decisive action on audit findings
SV1	Safety Voice & Psychological Safety	Confidence in exercising stop-work authority
SV2	Safety Voice & Psychological Safety	Absence of fear regarding safety dissent
SV3	Safety Voice & Psychological Safety	Peer receptivity to unsafe intervention
SV4	Safety Voice & Psychological Safety	Supervisors encourage safety suggestions
PC1	Procedural Compliance	Strict execution of operating checklists
PC2	Procedural Compliance	Non-toleration of operational shortcuts
PC3	Procedural Compliance	Compliance under production pressure

PC4	Procedural Compliance	Isolation and lock-out/tag-out fidelity
RC1	Risk Competence	Hazard identification accuracy
RC2	Risk Competence	Pre-task dynamic risk assessment rigor
RC3	Risk Competence	Understanding critical fail-safe barriers
RC4	Risk Competence	Situational awareness in non-routine tasks
JR1	Just & Fair Reporting	Prompt near-miss submission
JR2	Just & Fair Reporting	Non-punitive operational error evaluation
JR3	Just & Fair Reporting	Systemic focus during incident inquiry
JR4	Just & Fair Reporting	Actionable corrective feedback distribution

Recommended response format: 1 = strongly disagree; 2 = disagree; 3 = neither agree nor disagree; 4 = agree; 5 = strongly agree.