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Research Article

Towards Safer Workplace: A Survey-Based Study on Developing a Safety Climate Model for the Indonesian Paper Industry

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ABSTRACT

A reliable safety climate model is essential for evaluating safety behavior and predicting risks such as accidents or injuries, yet no research has specifically addressed the safety climate in the paper industry, either globally or in Indonesia. Recognized as high-risk due to its reliance on large machinery and hazardous chemicals, the paper industry has been understudied in this context. This research addresses the gap by developing a safety climate model tailored to the Indonesian paper industry, following a rigorous methodology that included a literature review, model design, validation processes, and Goodness-of-Fit testing. The study identified nine dimensions and 36 initial indicators, with strong content validity confirmed through Aiken's V index, and refined through a survey of 313 employees—including managers, supervisors, and operators—at a paper factory in West Java, Indonesia. Confirmatory factor analysis (CFA) led to the final model, comprising nine dimensions and 32 validated indicators, achieving excellent fit across key criteria. These dimensions include management commitment, safety environment, safety communication, safety involvement, safety rules and procedures, safety training, safety competence, work pressure, and local wisdom. The validated model offers valuable insights into safety practices, providing a practical framework for improving safety performance in the Indonesian paper industry. By fostering a proactive safety culture and addressing sector-specific risks, this model has the potential to significantly reduce workplace accidents and improve overall safety performance, marking an important advancement in industry-specific safety research.

Keywords: Safety climate model, safety risks, workplace accident, CFA, paper industry

INTRODUCTION

A safety climate can be defined as employee perceptions regarding procedures and work practices related to safety factors in the workplace [1][2]. It is a multidimensional concept and is widely recognized as a critical factor in ensuring workplace safety [3]. Since Zohar introduced the safety climate model in 1980, researchers have extensively studied and refined these models across various industrial sectors [4]. Despite significant advancements, there remains no definite consensus in the literature regarding the number of dimensions or the specific labels for safety climate dimensions [4]–[22].

As a subset of safety management, safety climate research contributes to a broader effort aimed at safeguarding employee well-being in the workplace. Safety management involves a systematic approach to identifying, assessing, and mitigating risks to prevent accidents and injuries. This encompasses the development and enforcement of safety policies, the provision of training programs, regular safety audits, and the adoption of advanced safety technologies. Within this broader framework, fostering a strong culture of safety is paramount. Through effective communication, leadership commitment, and active employee involvement, organizations can prioritize safety at all levels. The concept of safety climate highlights the shared perceptions and attitudes of employees toward safety practices, making it a vital component of comprehensive safety management systems. By integrating these elements, safety climate and safety management work synergistically to create a workplace environment where safety is consistently prioritized.

Zohar's model, applied in the metal, chemical, textile, and food processing industries in Israel, identified eight dimensions of safety climate, including safety training, management attitudes, and the impact of safe behavior on promotion [1]. Expanding on this foundational work, Newaz et al. [16] conducted a systematic review of 574 articles and identified five general dimensions: management commitment, safety systems, the supervisor's role, worker involvement, and group safety climate. According to Lin Si-Hao et al. [23], the variation in the selection of dimensions is influenced by several factors, including industry type, organizational culture, policies, and researcher preferences. Additionally, previous studies emphasize the role of contextual factors, such as regional or country-specific influences, in shaping differences in safety climate dimensions and indicators [24][25]. For instance, Bahari and Clarke [10] pointed out that safety climate models developed in Western contexts may not be directly applicable to the Malaysian manufacturing industry, underscoring the importance of cross-cultural research in this field.

A reliable safety climate model is crucial for assessing safety behaviors and predicting safety risks, such as accidents or injuries [26]. Although various safety climate models have been developed globally across diverse sectors, no research to date has specifically addressed safety climate in the paper industry, either globally or in Indonesia. The paper industry, categorized as high-risk due to the use of large, complex machinery and chemicals, remains underexplored in terms of safety climate. This study seeks to develop a safety climate model tailored to the Indonesian paper industry. The paper industry in Indonesia presents unique challenges and risks that necessitate the development of a specialized safety climate model. This industry is inherently high-risk due to its reliance on large, complex machinery and significant quantities of chemicals. Despite the potential for severe accidents, there is a notable lack of specific data and research focusing on the safety climate within this sector. Developing a safety climate model tailored to the paper industry will address these specific risks, offering a framework to improve safety practices, reduce accidents, and enhance overall safety performance. Such a targeted approach bridges the gap in current research while providing practical solutions to the industry's unique safety challenges.

Globally, many safety climate models have been developed across various industrial sectors, demonstrating the diverse applications of safety climate research. There are at least eight safety climate models developed in the last ten years. However, a review of these studies reveals several limitations. Most models, such as those by Ghahramani and Khalkhali [4] for the manufacturing sector in Iran and Milijic et al. [5] for industries in Serbia, focus on generalized industrial categories without addressing the nuances of specific sectors like the paper industry. Similarly, models developed for the construction industry by Newaz et al. [16], Saunders et al. [18], and Wu et al. [6] overlook the unique safety challenges posed by industries reliant on both machinery and hazardous chemicals. Even sector-specific models, such as those by Kongsvik et al. [22] for aquaculture, Liu et al. [13] for manufacturing in China, or Lestari, et al. [21] for construction sector, do not account for the interplay of industry-specific risks and cultural factors that can vary significantly between regions and industries.

Given the gaps in existing research, this study provides a novel contribution by focusing on the safety climate in the paper industry, a high-risk sector that remains underexplored in safety climate research. This research uniquely addresses the specific risks associated with Indonesia's paper industry, while incorporating regional and cultural

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considerations that influence safety perceptions and practices. By doing so, it not only complements existing models but also advances safety climate research by applying a tailored, context-sensitive approach to a previously neglected sector.

To achieve this, the study adopts a survey method combined with a Confirmatory Factor Analysis (CFA) approach to develop a validated safety climate model for Indonesia's paper industry. A conceptual model was proposed based on insights from previous studies to explain the theoretical relationships between safety climate dimensions and indicators. The assumption is that each dimension corresponds to specific indicators, enabling the confirmation of the model theory using empirical data. Statistical analyses were performed using SPSS version 25.0 and SmartPLS version 4.0.9.9, ensuring robust data processing and interpretation. By the end of this research, a validated and industry-specific safety climate model will be established, providing a much-needed framework for improving safety outcomes in Indonesia's paper industry.

Developing a safety climate model specific to the Indonesian paper industry will contribute to the broader body of knowledge on safety climate by addressing the contextual differences specific to this sector and region. It will provide a theoretical framework that can be tested and refined in future studies, thereby enhancing our understanding of how safety climate operates in high-risk industries in developing countries. Practically, this model will offer a valuable tool for industry practitioners to assess and improve safety practices within the paper industry. By identifying specific dimensions and indicators relevant to the Indonesian context, companies can tailor their safety interventions more effectively, potentially reducing the incidence of workplace accidents and improving overall safety performance. Additionally, this model can guide policymakers in developing targeted safety regulations and initiatives, ultimately fostering a safer work environment in the paper industry.

METHODS

Research Methodology

This study employed a cross-sectional quantitative design using a survey method. The research process was conducted in several stages, beginning with the construction of a safety climate model. Existing instruments were thoroughly reviewed, and relevant dimensions and indicators of safety climate were selected and integrated into a comprehensive framework. The subsequent phase focused on content validity, wherein the relevance and adequacy of the instrument were evaluated through expert advice, ensuring it met the required validity index. Following this, a pilot study and reliability testing were conducted to measure the consistency of the instrument, ensuring the results aligned with the desired reliability coefficients. The construct validity and factor analysis phase were then performed to validate the theoretical model and refine it by eliminating items with low factor loadings, thereby enhancing the model's robustness. Finally, the model fit was assessed using goodness-of-fit indices to confirm that the safety climate model accurately represented the data, resulting in a validated model.

Data collection was conducted using a questionnaire, a widely accepted tool for developing safety climate models [27]. The study was carried out at one of Indonesia's largest paper companies, located in West Java Province. The research framework, illustrated in Figure 1, comprised five systematic steps to develop a safety climate model tailored to the paper industry. These steps ensured the selected dimensions and indicators were relevant and comprehensive.

1. Construction of the Safety Climate Model

The initial step involved identifying various measurement models and instruments used in prior research through an extensive literature review. This review generated 471 safety climate indicators from questionnaires in published articles [4]–[22]. A filtering process reduced these indicators to 32, aligning them with the research objectives. All

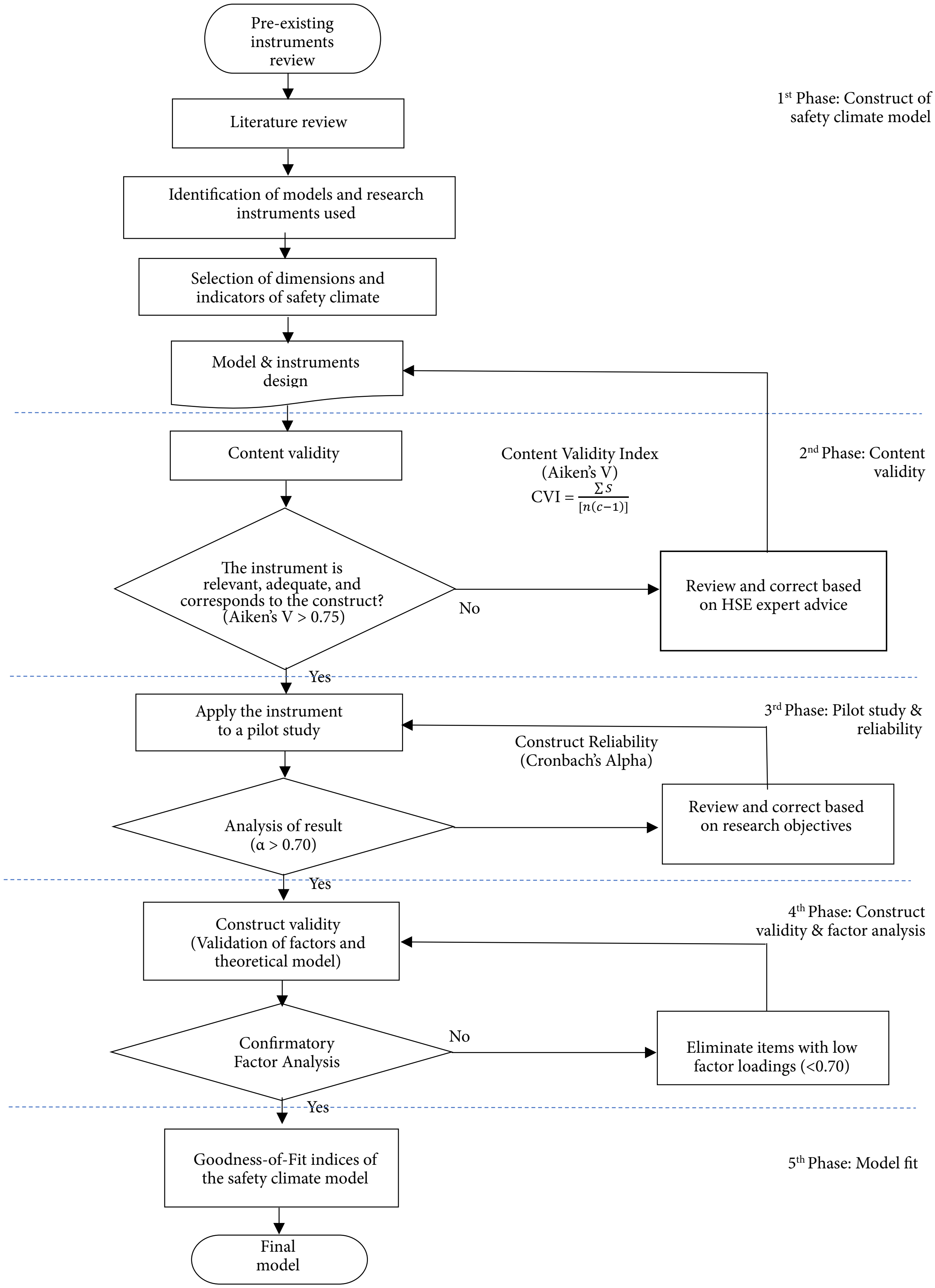

Figure 1. Methodology Flowchart

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indicators were assessed using a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree) [28]. To streamline the selection, dimensions with different labels but similar attributes were grouped under common dimension labels [6]. Dimensions with a usage frequency of more than 30% and consistent application across studies were selected to construct the safety climate model for the paper industry.

2. Content Validity

Content validity was assessed using a quantitative approach, aligning with the chosen research methodology. This phase employed Aiken's V content validity coefficient or Content Validity Index (CVI), which evaluates the level of expert agreement on the instrument items [29], as shown in equation (1). Content validation criteria included input from eight expert panels using a 4-point rating scale, with a CVI threshold of > 0.75 [29]. Many researchers have applied similar quantitative methods to validate safety climate scales [4].

$$CVI = \frac{\Sigma S}{[n(c-1)]} \tag{1}$$

where

CVI Content-validity index Aiken (score 0-1);

S R - Lo, where R represents the raters assigned score within the category (range: 1-4), and Lo is the lowest score in that category (=1);

n Number of raters;

c Number of categories that raters can choose (=4)

3. Pilot Study and Reliability

The reliability of the measurement method was assessed through internal consistency, evaluated using Cronbach's alpha in a pilot study. A Cronbach's alpha value of ≥ 0.70 is typically considered acceptable [4][5][18]; however, values below 0.7 may be acceptable for exploratory research [30].

4. Construct Validity and Factor Analysis

Construct validity was established to determine the extent to which the test measured the intended constructs, a critical component of overall validity. Confirmatory Factor Analysis (CFA) was used to evaluate construct validity by identifying factor loadings greater than 0.70 [31]. CFA was chosen because the dimensions had been predefined based on prior models or research [17][18][32].

5. Model Fit

Model fit was evaluated to assess the alignment of the theoretical model with observed data [33]. Following the recommendations of Hair et al. [34], multiple goodness-of-fit indices were used, including Chi-square/df (χ^2/df) < 3 for a good fit, RMSEA < 0.05 for a good fit and < 0.08 for an acceptable fit, CFI > 0.95 for a good fit and > 0.90 for an acceptable fit [4][5][17]. Additional criteria included SRMSR < 0.05 (good fit) and < 0.08 (acceptable fit) [18]; TLI > 0.95 (good fit) and > 0.90 (acceptable fit); PGFI > 0.50 (good fit); and PNFI > 0.50 (good fit) [6]. These indices were grouped into three categories: absolute goodness-of-fit (GoF), incremental GoF, and parsimonious GoF.

Sampling Technique

This study employs probability sampling, a method that ensures each member of the population has an equal opportunity to be selected for the sample [35]. The respondents for this survey consisted of workers at a paper factory located in West Java Province, Indonesia. The inclusion criteria for respondents specified individuals working in the production section, encompassing managers, supervisors, and operators.

To conduct Confirmatory Factor Analysis (CFA), a sample size of 200 to 300 respondents is generally recommended [4]. Larger sample sizes, such as N = 250 or more, enhance the measurement consistency of each construct [36] and optimize the results of factor analysis. To further improve the robustness of the factor analysis, power analysis was applied to determine the appropriate sample size. Power analysis is increasingly recommended in contemporary studies as a method for accurately determining sample requirements.

For this research, power analysis was conducted using the GPower application (version 3.1.9.7). The analysis type used was a-priori power analysis, performed at the study's outset to calculate the minimum required sample size. The parameters set included a significance level (α) of 0.05, an effect size of 0.15 (medium effect), and a power value (β-1) of 80%, which is considered the minimum acceptable threshold in research [37]. With nine predictors (reflecting the number of latent variables), the GPower analysis determined that a minimum of 114 respondents was required.This study adopted the sampling methodology of Zakaria et al. [7], utilizing simple random sampling to select respondents. This technique ensures an unbiased representation of the target population. Each respondent was expected to take approximately 10–15 minutes to complete the survey.

RESULT AND DISCUSSION

The results of the systematic review identified eight general safety climate factors or dimensions with a frequency above 30%. Among these, four dimensions demonstrated a particularly high level of consistency: management commitment (71%), safety environment (59%), safety communication, and safety involvement (53%). These findings, summarized in Figure 2, provide a foundational understanding of the commonly used dimensions in safety climate research, setting the stage for further exploration. Building on this foundation, the research introduces a new dimension, local wisdom, which encompasses a community's collective knowledge, beliefs, insights, customs, and ethical practices that guide human behavior within an ecological context. According to research by Gaya et al. [38], local wisdom significantly and positively impacts employee performance. Incorporating this dimension represents a key innovation of the study, aimed at enriching traditional safety climate models. To ensure consistency and reliability in measurement, each dimension, including local wisdom, is assessed using four indicators. The use of four or more indicators enhances the reliability of construct measurement [36]. Table 1 provides a detailed summary of the dimensions and indicators that comprise the paper industry safety climate model.

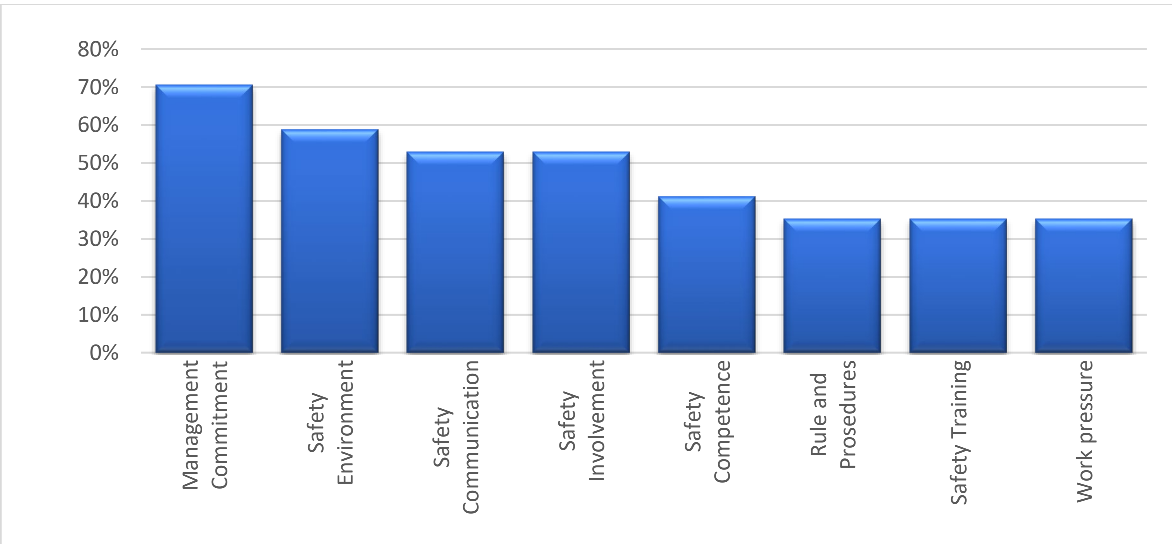

Figure 2 Frequency of use of safety climate dimensions in literature studies

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Table 1 Demographics of the study sample (N=313)

Variables	Position in the company			Total Respondent
	Manager 41 (13.1%)	Supervisor 72 (23.0%)	Operation 200 (63.9%)	313 (100%)
Gender				
Male	39 (12.5)	65 (20.8)	124 (39.6)	228 (72.8)
Female	2 (0.6)	7 (2.2)	76 (24.3)	85 (27.2)
Age (years)	**48.02 (6.19)***	**44.76 (6.07)***	**34.37 (9.21)***	**38.55 (9.97)***
≤25	-	1 (0.3)	46 (14.7)	47 (15.0)
26-35	2 (0.6)	5 (1.6)	52 (16.6)	59 (18.8)
36-45	5 (1.6)	18 (5.8)	64 (20.4)	87 (27.8)
46-55	29 (9.3)	46 (14.7)	36 (11.5)	111 (35.5)
≥56	5 (1.6)	2 (0.6)	2 (0.6)	9 (2.9)
Education level				
Junior high school	-	5 (1.6)	12 (3.8)	17 (5.4)
High school	9 (2.9)	28 (8.9)	126 (40.3)	163 (52.1)
Bachelor	30 (9.6)	39 (12.5)	62 (19.8)	131 (41.9)
Master	2 (0.6)	-	-	2 (0.6)
Work experience (years)	**23.73 (7.07)***	**20.57 (7.75)***	**12.75 (8.51)***	**15.99 (9.26)***
<5	-	2 (0.6)	53 (16.9)	55 (17.6)
5-10	2 (0.6)	11 (3.5)	34 (10.9)	47 (15.0)
11-15	6 (1.9)	8 (2.6)	46 (14.7)	60 (19.2)
16-20	2 (0.6)	5 (1.6)	17 (5.4)	24 (7.7)
21-25	11 (3.5)	17 (5.4)	28 (8.9)	56 (17.9)
>25	20 (6.4)	29 (9.3)	22 (7.0)	71 (22.7)
Accident involvement				
Yes	6 (1.9)	11 (3.5)	42 (13.4)	59 (18.8)
No	35 (11.2)	61 (19.5)	158 (50.5)	254 (81.2)

To validate these dimensions and indicators, the study conducted a content validity assessment. The results indicated that the 36 safety climate indicators demonstrated strong validity, with individual content validity indices (i-CVI) ranging from 0.75 to 1.00 and an overall content validity index (s-CVI) of 0.89. These findings confirm the excellent validity of the questionnaire, enabling its progression to the pilot study phase. The pilot study was conducted with 313 paper industry workers from the production section, including 41 managers (13.1%), 72 supervisors (23.0%), and 200 operators (63.9%). This group was chosen specifically because production workers are closely involved in daily occupational safety and health activities and are exposed to higher risks than non-production workers [7]. Consequently, their insights offer valuable perspectives on the safety climate. Remarkably, the survey achieved a 100% participation rate, reflecting strong engagement. Simple random sampling was used to ensure an unbiased selection of participants, and the sampling process was facilitated by the company's Health, Safety, and Environment (HSE) team.

Detailed demographic information about the respondents is presented in Table 1. The majority of respondents were male (72.8%), with most employees falling within the 46–55 years age group (35.5%). In terms of education, 52.1% of respondents had completed high school. Work experience among employees was found to be relatively balanced across different levels, providing a diverse and representative perspective within the production section. These demographic insights highlight the diversity of the workforce, which contributes to a comprehensive understanding of their perceptions regarding occupational safety and health.

This study builds on the demographic indicators identified by Ghahramani and Khalkhali [4] by adding three new variables: position within the company, educational level, and accident involvement. Including these additional variables enhances the completeness and structure of the demographic data, providing a more detailed understanding of the characteristics of the respondents. This expanded scope of information not only enriches the analysis but also ensures a more comprehensive exploration of the factors influencing safety climate perceptions. Furthermore, data on respondents' occupational safety and health background were collected to assess their experiences with workplace accidents. Respondents were asked whether they had ever experienced a work accident, categorized as light, moderate, or severe. Among the 313 respondents, 59 individuals (18.8%) reported having experienced a work accident. This information adds valuable context to the study, linking respondents' personal experiences with workplace safety to their perspectives on the safety climate.

Safety Climate Perception

A Respondent data, including average values, standard deviation (SD), skewness, and kurtosis for each safety climate item or indicator, are presented in Table 2. Most kurtosis values fall within the range of -1 to 1, indicating that the data follows a normal distribution [15]. Skewness values can be positive, negative, or zero. Notably, all skewness values in this study are negative, suggesting a left-skewed distribution where the majority of the values are concentrated on the right side of the curve [15]. These findings provide a comprehensive overview of the distribution characteristics of the data, offering valuable insights into respondents' assessments of their safety climate perceptions.

The internal consistency reliability of the safety climate scale was assessed using Cronbach's alpha, with an overall coefficient of α = 0.927. Cronbach's alpha was also calculated for each safety climate dimension, yielding the following results: management commitment (0.897), safety environment (0.863), safety communication (0.854), safety involvement (0.880), safety rules and procedures (0.896), safety training (0.844), safety competence (0.906), work pressure (0.850), and local wisdom (0.869). These values exceed the commonly accepted threshold of 0.70 for internal consistency reliability [4][5][18], confirming the robustness of the measurement instrument. Furthermore,

Table 2 Safety climate perception of sample study (N=313)

Safety Climate Indicators	Mean	SD	Kurtosis (0.270)	Skewness (-0.754)
Management Commitment - MC (Cronbach alpha = 0.897)				
My company management acted quickly to correct the safety issue	4.243	0.529	0.389	-0.877
My company management focuses on safety at all times, not just after an accident	4.230	0.511	0.465	-0.828
My company management places employee safety as a top priority	4.342	0.524	0.592	-1063
My company management expressed concern if safety procedures were not followed	4.304	0.500	0.324	-0.839
Safety Environment – SE (Cronbach alpha = 0.863)				
My work location is protected from potential safety hazards and work accidents	4.115	0.585	0.241	-0.866
The available machines and work equipment meet safety standards	4.109	0.583	0.117	-0.795
There are always enough people to complete the job safely	4.163	0.619	0.047	-0.897
There is sufficient and adequate personal protective equipment to protect workers	4.003	0.567	0.175	-0.712

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Table 2 Safety climate …. (cont.)

Safety Climate Indicators	**Mean**	**SD**	**Kurtosis (0.270)**	**Skewness (-0.754)**
Safety Communication – SC (Cronbach alpha = 0.854)				
Communication about safety between superiors and workers is considered to be effective	4.093	0.536	-0.395	-0.455
The methods used to communicate safety information are considered adequate	4.077	0.538	-0.085	-0.547
I received a lot of information about safety	4.188	0.532	0.331	-0.806
I accept suggestions and reprimands if I work unsafely	4.236	0.556	0.552	-1017
Safety Involvement – SI (Cronbach alpha = 0.880)				
I play an active role in identifying potential hazards at work sites	4.000	0.549	0.197	-0.661
The company encourages all workers to submit suggestions on how to improve workplace safety	4.204	0.525	0.231	-0.761
I am strongly encouraged to report unsafe conditions in my workplace	4.380	0.538	1183	-1232
I am actively involved in implementing work safety	4.038	0.543	0.218	-0.671
Safety Rule and Procedure – SRP (Cronbach Alpha = 0.896)				
Existing safety regulations and procedures are easy to understand	4.109	0.550	0.210	-0.651
Existing safety regulations and procedures are practical	3.888	0.586	-0.320	-0.770
Safety regulations and procedures have been implemented by all parties	4.109	0.550	0.462	-0.708
Safety regulations and procedures protect workers from work accidents	4.112	0.528	-0.256	-0.896
Safety Training – ST (Cronbach alpha = 0.844)				
Safety training is appropriate for my job	3.984	0.565	0.103	-0.739
The safety training provided is practical	4.086	0.565	0.214	-0.457
I take part in safety training regularly and periodically	4.147	0.543	0.113	-0.856
With safety training, I can work safely	4.329	0.492	0.473	-0.497
Safety Competence – SCo (Cronbach alpha = 0.906)				
I am able to identify potentially dangerous situations	4.105	0.443	0.591	-0.465
I have the necessary competencies to safely handle my job duties	4.144	0.491	0.147	-0.540
I am familiar with relevant safety and risk control procedures	4.141	0.499	0.308	-0.631
I fully understand the applicable and relevant laws regarding occupational safety and health	4.204	0.525	0.348	-0.805
Work Pressure – WP (Cronbach alpha = 0.850)				
I have a fairly balanced workload	4.157	0.546	0.378	-0.840
I have enough time to complete the job safely	4.070	0.585	0.120	-0.777
I don't have to work in a hurry	4.029	0.586	0.028	-0.696
No matter how big the work pressure is, I don't take shortcuts at the expense of safety	4.326	0.498	1065	-0.994
Local Wisdoms – LW (Cronbach alpha = 0.869)				
I understand the importance of learning about the culture and customs of my work environment	4.342	0.431	0.464	-0.632
I believe that workplace safety policies need to be aligned with local cultural values and norms	4.335	0.458	0.219	-0.691
I feel that local cultural practices such as safety rituals can increase awareness of work safety	4.153	0.531	0.172	-0.700
I feel that recognition and appreciation for workers can increase awareness of work safety	4.428	0.428	0.299	-0.756

the findings of this study surpass those reported by Ghahramani and Khalkhali [4], highlighting the instrument's superior reliability and comprehensiveness in capturing safety climate dimensions.

Measurement Model

Confirmatory Factor Analysis (CFA) was conducted using Covariance-Based Structural Equation Modeling (CB-SEM) to evaluate the fit of the proposed model with the survey data. CFA was selected over exploratory factor analysis due to the model's foundation on a pre-established hypothesis, which defined a set of latent constructs and their associated items [33]. This approach focuses on estimating how latent variables (factors) relate to observed variables, with the observed variables serving as indicators of broader latent constructs. By employing CFA, the study was able to assess how well the proposed theoretical model aligns with the empirical data, thereby validating the constructs.

The CFA was implemented using the SmartPLS4 covariance-based SEM model, a recently introduced technique in SmartPLS [32]. This method evaluates the reflective measurement model through three key indicators: Standardized Loading Factor (LF), Construct Reliability (CR), and Average Variance Extracted (AVE). The LF value represents the correlation of indicator validity, with higher values (closer to 1) indicating a stronger validity level [32]. Hair et al. [34] recommend a minimum acceptable LF value of > 0.70. These LF values, which reflect the correlation between each indicator and its corresponding latent variable, are detailed in Table 3. This comprehensive analysis provides a robust evaluation of the model's validity and reliability, confirming the appropriateness of the proposed framework. The output above provides an estimate of the standardized parameters or Standardized Loading Factors (LF) for the indicators. The LF values for management commitment indicators are as follows: MC1 = 0.829, MC2 = 0.867, MC3 = 0.815, and MC4 = 0.802, among others. These values allow for a comparative analysis of the indicators' contributions within their respective dimensions. Notably, the SCo2 indicator exhibits a higher LF value compared to SCo1, SCo3, and SCo4, suggesting that SCo2 holds greater importance in measuring the safety competence dimension.

The evaluation of the model's measurement results identified four LF values below the threshold of 0.70, indicating a low or invalid level of indicator validity. These indicators are SE3 ← SE = 0.677, SC3 ← SC = 0.695, SRP4 ← SRP = 0.558, and LW4 ← LW = 0.692. As these low LF values can negatively impact the model's goodness-of-fit, these indicators must be removed from the measurement model. The removal of these indicators is critical to improving the model's validity and ensuring the robustness of the measurement results. Following this adjustment, the model

Table 3 List of standardized loading factors (LF)

Reflection	LF	Reflection	LF	Reflection	LF
MC1 ← MC	0.829	SI1 ← SI	0.802	SCo1 ← SCo	0.787
MC2 ← MC	0.867	SI2 ← SI	0.808	SCo2 ← SCo	0.901
MC3 ← MC	0.815	SI3 ← SI	0.783	SCo3 ← SCo	0.838
MC4 ← MC	0.802	SI4 ← SI	0.824	SCo4 ← SCo	0.850
SE1 ← SE	0.844	SRP1 ← SRP	0.860	WP1 ← WP	0.732
SE2 ← SE	0.842	SRP2 ← SRP	0.816	WP2 ← WP	0.718
SE3 ← SE	0.677	SRP3 ← SRP	0.806	WP3 ← WP	0.742
SE4 ←SE	0.783	SRP4 ← SRP	0.558	WP4 ← WP	0.857
SE1 ← SE	0.844	SRP1 ← SRP	0.860	WP1 ← WP	0.732
SSC1 ← SC	0.798	ST1 ←ST	0.838	LW1 ← LW	0.866
SSC2 ← SC	0.784	ST2 ← ST	0.888	LW2 ← LW	0.851
SSC3 ← SC	0.695	ST3 ← ST	0.853	LW3 ← LW	0.692
SSC4 ← SC	0.798	ST4 ← ST	0.744	LW4 ← LW	0.771

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was re-evaluated by excluding the four low-validity indicators, and the analysis was re-run. The results of the final Confirmatory Factor Analysis (CFA) and the updated measurement model are illustrated in Figure 3, reflecting the improved validity and fit of the model.

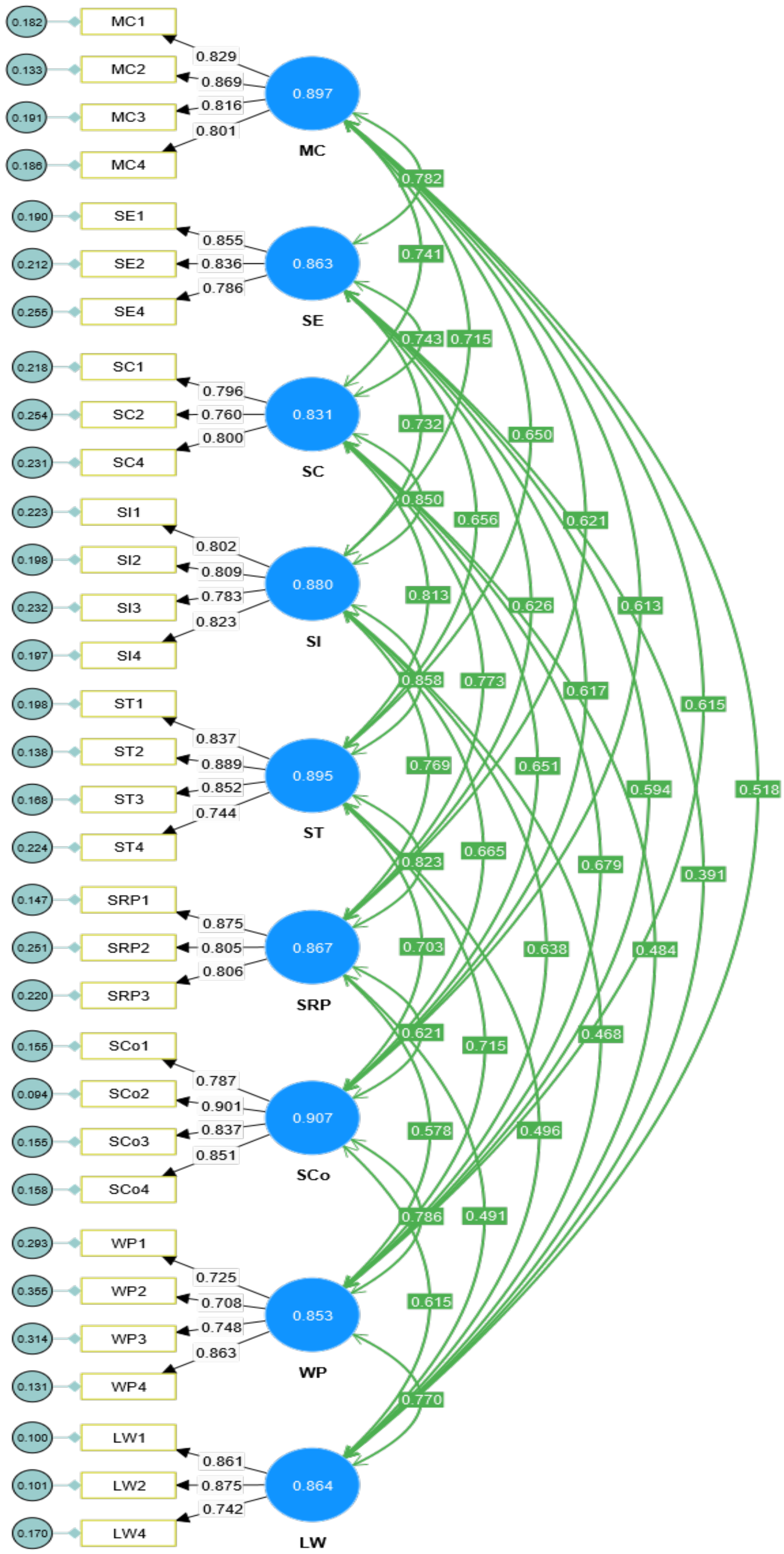

Figure 3 Confirmatory factor analysis of safety climate model

The re-run results confirm that all indicators of the safety climate measurement model are valid, with Standardized Loading Factors (LF) meeting the threshold of ≥ 0.70. For example, the MC1 measurement item has an LF value of 0.829, indicating that any change in management commitment will be reflected in the MC1 indicator ("My company management acted quickly to correct the safety issue") by 0.829 x 0.829 = 68.7%. The indicator with the highest LF value remains SCo2 = 0.901, which measures safety competence through the statement, "I have the necessary competencies to safely handle my job duties." This underscores that SCo2 is the most important indicator for measuring the safety competence dimension. The LF values reflect how well each measurement indicator represents the corresponding factor or dimension, with higher values indicating more significant contributions to the measurement of the dimension.

In addition to LF values, the Construct Reliability (CR) and Average Variance Extracted (AVE) were evaluated to further assess the model. The results of these calculations, conducted using CB-SEM, are detailed in Table 4. The CR

Table 4. Standardized loading factor, construct reliability, and average variance extracted

Indicator	←	**Dimension**	**Loading Factor (LF)**	**Construct Reliability (CR)**	**Average Variance Extracted (AVE)**
MC1	←	Management Commitment	0.829	0.897	0.687
MC2	←	Management Commitment	0.869		
MC3	←	Management Commitment	0.816		
MC4	←	Management Commitment	0.801		
SE1	←	Safety Environment	0.855	0.863	0.683
SE2	←	Safety Environment	0.836		
SE4	←	Safety Environment	0.786		
SC1	←	Safety Communication	0.796	0.831	0.617
SC2	←	Safety Communication	0.760		
SC4	←	Safety Communication	0.800		
SI1	←	Safety Involvement	0.802	0.880	0.647
SI2	←	Safety Involvement	0.809		
SI3	←	Safety Involvement	0.783		
SI4	←	Safety Involvement	0.823		
SRP1	←	Safety Rule and Procedure	0.875	0.867	0.688
SRP2	←	Safety Rule and Procedure	0.805		
SRP3	←	Safety Rule and Procedure	0.806		
ST1	←	Safety Training	0.837	0.895	0.693
ST2	←	Safety Training	0.889		
ST3	←	Safety Training	0.852		
ST4	←	Safety Training	0.744		
SCo1	←	Safety Competence	0.787	0.907	0.714
SCo2	←	Safety Competence	0.901		
SCo3	←	Safety Competence	0.837		
SCo4	←	Safety Competence	0.851		
WP1	←	Work Pressure	0.725	0.853	0.582
WP2	←	Work Pressure	0.708		
WP3	←	Work Pressure	0.748		
WP4	←	Work Pressure	0.863		
LW1	←	Local Wisdoms	0.861	0.864	0.686
LW2	←	Local Wisdoms	0.875		
LW4	←	Local Wisdoms	0.742		

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Table 5 Discriminant validity – Fornell Larcker criterion

	LW	MC	SC	SCo	SE	SI	SRP	ST	WP
LW	**0.828**								
MC	0.518	**0.829**							
SC	0.484	0.741	**0.785**						
SCo	0.615	0.613	0.651	**0.845**					
SE	0.391	0.782	0.743	0.617	**0.826**				
SI	0.468	0.715	0.850	0.665	0.732	**0.805**			
SRP	0.491	0.621	0.773	0.621	0.626	0.769	**0.829**		
ST	0.496	0.650	0.813	0.703	0.656	0.858	0.823	**0.832**	
WP	0.770	0.615	0.679	0.786	0.594	0.638	0.578	0.715	**0.763**

values for all constructs exceed 0.70, indicating strong reliability, while AVE values are above 0.50, demonstrating good convergent validity [18]. For instance, the AVE value for management commitment is 0.687, which means that 68.7% of the variance in the indicators MC1, MC2, MC3, and MC4 is captured within the management commitment construct. These findings confirm that the latent variable scores extracted from the variance of each measurement item are above 50%, ensuring robust representation of the constructs. The results also highlight that convergent validity is fulfilled, as different indicators measuring the same variable, construct, or dimension are strongly correlated with one another [32]. Based on these evaluations, it can be concluded that the measurement model meets the criteria for convergent validity, confirming the reliability and validity of the proposed safety climate measurement model.

Discriminant validity assesses the degree to which a variable or construct is distinct from others and is evaluated statistically [32]. According to Fornell and Larcker [39], a model demonstrates strong discriminant validity when the square root of the Average Variance Extracted (AVE) for each dimension (presented along the diagonal) exceeds its correlations with other dimensions. This approach is particularly relevant as it addresses the need for discriminant validity evaluation, as emphasized by Ghahramani and Khalkhali [4], in the development of safety climate models. Table 5 presents the Fornell-Larcker criterion applied to the development of a safety climate model for the paper industry sector in Indonesia. Based on the Fornell-Larcker criterion, the root of AVE for local wisdom (LW) is 0.828, which is higher than its correlations with management commitment (MC) at 0.518, safety communication (SC) at 0.484, and safety competence (SCo) at 0.615, among others. Overall, the root AVE for each variable or dimension exceeds 0.05, indicating acceptable discriminant validity. However, there are three correlations that do not meet the Fornell-Larcker criterion: SC-SI, SC-ST, and SI-ST. These exceptions suggest potential multicollinearity issues, requiring further examination. Multicollinearity can undermine the reliability and stability of a variable's predictive power when it is excessively correlated with other variables in the model [18].

To address potential shortcomings of the Fornell-Larcker criterion, Henseler and Sarstedt [40] introduced the Heterotrait-Monotrait Ratio (HTMT) as an alternative and more sensitive measure of discriminant validity. HTMT evaluates the mean of all indicator correlations between different constructs (heterotrait-heteromethod correlations) relative to the geometric mean of the average correlations of indicators within the same construct. It is recommended to report HTMT values, with a threshold below 0.90 indicating strong discriminant validity [32][41]. Table 6 presents the HTMT values for the variables in the safety climate model. The HTMT values shown in Table 6 are all below 0.90, confirming strong discriminant validity. This indicates that each measured variable is conceptually distinct and empirically validated through statistical analysis. Additionally, the correlation between measurement items within the same variable is stronger than correlations between items of different variables. These results demonstrate that

Table 6 Discriminant validity – Heterotrait-Monotrait ratio (HTMT)

	LW	MC	SC	SCo	SE	SI	SRP	ST	WP
LW									
MC	0.533								
SC	0.485	0.737							
SCo	0.630	0.624	0.660						
SE	0.395	0.789	0.751	0.629					
SI	0.469	0.717	0.841	0.676	0.739				
SRP	0.487	0.625	0.775	0.634	0.632	0.769			
ST	0.527	0.671	0.822	0.718	0.672	0.867	0.853		
WP	0.747	0.619	0.665	0.771	0.591	0.628	0.569	0.713	

Table 7 Summary of the overall fit test results using SEM

Statistics	Fitness Criteria	Value	Fitness Judgment (Yes or No)
Absolute fit indices			
Chi Square/df (χ^2/df)	< 3.0 (good fit)	2.121	Yes
RMSEA	< 0.05 (good fit) and < 0.08 (acceptable fit)	0.060	Yes
SRMR	< 0.05 (good fit) and < 0.08 (acceptable fit)	0.041	Yes
Incremental fit indices			
TLI	> 0.95 (good fit) and > 0.90 (acceptable fit)	0.927	Yes
CFI	> 0.95 (good fit) and > 0.90 (acceptable fit)	0.937	Yes
Parsimonious goodness of fit			
PGFI	> 0.50 (good fit)	0.683	Yes
PNFI	> 0.50 (good fit)	-	-

Notes: RMSEA: Root Mean Square Error of Approximation, SRMR: Standardized Root Mean Square Residual, TLI: Tucker–Lewis Index; CFI: Comparative Fit Index, PGFI: Parsimonious Goodness-of-Fit Index, PNFI: Parsimonious Normed Fit Index.

the discriminant validity of the model is robust, with both the Fornell-Larcker and HTMT evaluations providing consistent and reliable evidence of distinct conceptualization and measurement for each construct.

Goodness-of-Fit CFA model

A The goodness-of-fit (GoF) assessment was conducted using the CB-SEM method to evaluate the suitability of the proposed model. Following the recommendations of Hair et al. [34], several GoF indices were employed to assess the adequacy of the CFA model, including Chi-square/df (χ^2/df), RMSEA, SRMSR, TLI, CFI, PGFI, and PNFI. The results of these tests, along with their recommended thresholds for satisfactory fit, are presented in Table 7.

Overall, the GoF results indicate that the proposed CFA model achieves a good fit. Given the limitations of relying on a single GoF index, a combination of indices was utilized for a comprehensive assessment. While the Chi-Square test results for the CFA model indicated statistical significance, it is well-documented that Chi-Square values are highly sensitive to minor specification errors in the model structure [42] and large sample sizes [43]. To address these limitations, alternative indices such as RMSEA, which incorporates a correction for sample size, are highly recommended for confirmatory construct validity testing. Other indices, such as CFI and TLI, serve as cross-checks to identify any potential inconsistencies in the estimation process [44]. Additional indices, PNFI and PGFI, provide further comparative insights, with higher values (ranging from 0 to 1) indicating a better model fit [15][39]. Thus,

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this study used a combination of indices to confirm the suitability of the model, even with significant Chi-Square results.

The final CFA results yielded a safety climate model with nine dimensions and 32 indicators that successfully passed the tests for content validity, construct reliability, and construct validity. This outcome is consistent with prior studies identifying dimensions such as management commitment, safety environment, safety communication, safety involvement, safety rules and procedures, safety training, safety competence, and work pressure as critical components of the safety climate and vital for improving employee safety performance [18][20][22][6][9][13]. A notable contribution of this research is the addition of the local wisdom dimension, a new factor in the safety climate model, which also met the required validity and reliability criteria.

To implement the developed safety climate model within paper factories, it is crucial to integrate it into existing safety management systems. Strategies could include conducting periodic safety climate surveys to identify specific areas for improvement, using the results to design targeted safety interventions, and fostering continuous employee engagement in safety practices. Expected benefits include enhanced employee participation in safety measures, reduced workplace incidents, and overall improved safety performance. To strengthen key dimensions such as management commitment, safety communication, and safety training, it is recommended to establish clear safety policies, provide ongoing safety education, and encourage open communication between management and employees. While this model was specifically tailored for the paper industry in Indonesia, its principles may also apply to other industries or regions facing similar safety challenges, though further research is necessary to confirm its broader applicability.

CONCLUSION

This study presents pioneering research in developing a safety climate model tailored to the paper industry sector in Indonesia, addressing a gap that had not previously been explored. The resulting model consists of nine dimensions—management commitment, safety environment, safety communication, safety involvement, safety rules and procedures, safety training, safety competence, work pressure, and local wisdom—and 32 measurement indicators, all of which demonstrate satisfactory validity and reliability. Developed to meet the specific needs of the Indonesian paper industry, this model systematically assesses employees' perceptions of safety, identifying strengths and areas for improvement in safety practices and policies. Its impact is multifaceted: first, it provides a customized tool for addressing the unique challenges and conditions of the sector; second, its standardization enables comparative studies across paper manufacturing sites, promoting a deeper understanding of safety dynamics and fostering best practices industry-wide; and third, it lays a foundation for future research by establishing a validated and reliable instrument that supports ongoing monitoring and continuous improvement of safety culture. Practitioners can use this model to design targeted interventions, improve safety training programs, and reduce workplace incidents and accidents, bridging academic insights with practical applications in occupational safety. However, the cross-sectional nature of the study limits the ability to assess the consistency of respondents over time, presenting a potential weakness. Future research should validate and refine the model with samples from multiple paper industries, and explore correlations between safety climate dimensions and other organizational factors to enhance its applicability and impact.

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CONFLICT OF INTEREST

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