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WORKPLACE INJURY PREVENTION IN CONSTRUCTION: A DATA-DRIVEN EVALUATION USING WIPAS

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Abstract

The construction industry continues to experience persistent workplace injuries despite increasing digitalisation efforts, highlighting the need for evidence-based approaches to safety analytics. This paper investigates how data-driven practices contribute to workplace injury prevention in South African construction and validates a context-specific instrument for assessing such practices. A quantitative survey of construction professionals from firms operating across three provinces was analysed using SPSS and confirmatory factor analysis (CFA) to validate the Workplace Injury Prevention Analytics Scale (WIPAS), alongside descriptive and reliability statistics. Confirmatory factor analysis demonstrated high reliability (Cronbach's α = 0.937; ρ = 0.940) and acceptable model fit for the newly developed Workplace Injury Prevention Analytics Scale (WIPAS). Within the WIPAS measurement model, items related to predictive analytics and real-time monitoring exhibited the strongest factor loadings, indicating that these advanced capabilities are central indicators of analytics-driven injury prevention maturity in the sampled organisations. Descriptive results indicate that while organisations routinely collect and evaluate safety-related data, advanced capabilities, particularly predictive analytics and real-time monitoring, are inconsistently adopted. These findings highlight a maturity gap between foundational and advanced analytical practices and demonstrate the need for stronger managerial support, systematic employee training, and integrated data governance. This study indicates that, in the surveyed regional cluster of South African construction organisations, firms are already collecting and reviewing safety data but have not yet fully transitioned to advanced, predictive uses of analytics.

Keywords: construction safety; data analytics; injury prevention; predictive analytics; South Africa.

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1. Introduction

The construction industry is widely recognised as one of the most hazardous sectors globally, with high rates of injuries, illnesses, and fatalities despite the implementation of various safety protocols and technological interventions [1]. Workers are routinely exposed to risks such as falls from height, equipment accidents, and exposure to hazardous materials, which can result in both minor and severe injuries. These occupational hazards not only affect individual well-being but also have broader economic consequences, including project delays, increased insurance premiums, compensation claims, and reputational damage to organisations. In South Africa, the safety challenges in construction are compounded by rapid urbanisation, growing infrastructure demands, and uneven regulatory compliance [2, 3]. Although health and safety legislation exists, its enforcement varies, and traditional reactive approaches such as post-incident reporting, manual inspections, and compliance audits remain dominant. These conventional strategies often fail to anticipate emerging risks,

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limit proactive intervention, and are insufficient for addressing complex, dynamic work environments that characterise modern construction projects. The emergence of the Fourth Industrial Revolution (4IR) presents unprecedented opportunities to enhance workplace safety. Technologies such as artificial intelligence (AI), machine learning (ML), the Internet of Things (IoT), and big data analytics enable real-time monitoring, predictive hazard identification, and proactive safety management [4, 5].

Reducing workplace injuries in the construction sector increasingly requires a shift from reactive, compliance-based safety management toward proactive, analytics-driven injury prevention. In South Africa, this shift is complicated by the uneven adoption of Fourth Industrial Revolution technologies such as data analytics, AI/ML, IoT and real-time monitoring, with progress constrained by costs, skills shortages, digital infrastructure gaps and organisational resistance. Against this backdrop, the present study addresses a timely and practically important need by proposing the Workplace Injury Prevention Analytics Scale (WIPAS), a concise instrument designed to diagnose how far construction organisations have progressed in integrating analytics into injury prevention. A validated, context-sensitive scale of this kind can support both researchers and practitioners by enabling benchmarking of analytics maturity, identifying specific organisational gaps and providing a reproducible basis for tracking the evolution of data-driven safety practices over time.

These innovations facilitate data-driven decision-making, allowing construction organisations to move from reactive incident response to predictive and preventative safety strategies. For instance, wearable sensors can detect unsafe movements or exposure to hazardous conditions in real time, while AI algorithms can analyse historical incident data to forecast potential hazards before they occur. Despite these opportunities, the adoption of data-driven safety technologies in South Africa remains limited. Key barriers include high implementation costs, lack of technical skills among the workforce, insufficient digital infrastructure, and organisational resistance to technological change [6, 7]. Many construction firms continue to rely on conventional safety management practices, resulting in uneven adoption of advanced analytics and AI-enabled monitoring tools. Moreover, there is limited empirical evidence assessing the readiness of South African construction organisations to integrate these technologies into their health and safety management systems.

This study addresses these gaps by investigating the extent to which data-driven approaches are adopted for workplace injury prevention in South African construction projects. Specifically, it develops and validates the Workplace Injury Prevention Analytics Scale (WIPAS) a measurement instrument designed to evaluate how organisations collect, analyse, and utilise safety-related data, including predictive analytics and real-time monitoring. By assessing operational practices, managerial support, and employee engagement with analytics, this study provides insights into both the current state of data-driven safety adoption and areas requiring improvement. This study aims to develop and validate WIPAS and to provide an initial assessment of analytics-driven safety practices in a regional sample of South African construction organisations. Specifically, the research seeks to (1) examine the reliability and factor structure of WIPAS as a measurement instrument for analytics-driven injury prevention, and (2) use WIPAS scores to generate a diagnostic picture of current data-driven safety practices, highlighting areas of strength and weakness across participating firms. The study underscores the importance of combining technological innovation with organisational commitment, workforce capability, and regulatory support to achieve sustainable improvements in construction safety outcomes.

2. Literature review

2.1. Workplace injury prevention in construction

The construction industry is globally recognised as one of the most hazardous sectors due to the combination of heavy machinery, elevated work surfaces, dynamic project environments, and complex task sequences [8]. Occupational injuries in construction range from minor cuts and bruises to severe accidents, including falls from height, machinery-related incidents, electrocution, and structural collapses. These incidents not only compromise worker well-being but also result in substantial economic losses, including project delays, increased insurance premiums, compensation claims, and reputational damage to firms. Traditional approaches to workplace injury prevention in construction have largely relied on compliance with occupational health and safety (OHS) legislation, on-site training programmes, regular safety audits, and post-incident reporting mechanisms. While these strategies provide a foundation for safety management, they primarily use lagging indicators of performance (such as incident and injury records), are vulnerable to human error in observation and reporting, and often suffer from temporal delays between hazard emergence, detection, and intervention. As a result, they tend to be reactive rather than proactive, focusing on documenting and responding to events after they occur rather than uncovering latent patterns of risk embedded in day-to-day work processes.

2.2. Data analytics in safety management

Data analytics has emerged as a critical tool for enhancing workplace injury prevention by enabling evidence-based decision-making and proactive risk management. Analytics in construction safety can be categorised into three main types.

- **Descriptive analytics** involves the systematic analysis of historical incident data to identify patterns and trends in workplace injuries. This approach enables organisations to understand which tasks, equipment, or environmental conditions are most associated with safety risks, informing targeted interventions [5].

- **Predictive analytics** utilises machine learning (ML) algorithms and artificial intelligence (AI) models to forecast potential hazards and high-risk scenarios before they occur. Predictive analytics can integrate multiple data sources, including historical incident reports, worker behaviour, weather conditions, and equipment usage, to generate risk profiles and recommend preventative measures [9].

- **Real-time monitoring** involves continuous surveillance of construction sites using IoT devices, wearable technologies, and computer vision systems. These tools can detect unsafe conditions or behaviours in real time, enabling immediate corrective actions, such as issuing alerts, modifying tasks, or temporarily halting high-risk operations [10]. International evidence indicates that construction firms employing advanced analytics have achieved substantial reductions in workplace injuries. For example, studies in Europe, the United States, and China show that predictive and real-time monitoring technologies can reduce accident rates by up to 30%, enhancing both worker safety and operational efficiency [5, 11].

2.3. Barriers to analytics adoption in South Africa

Despite the clear benefits, the adoption of data-driven safety technologies in the South African construction industry remains uneven. Several key barriers have been identified. Limited digital infrastructure restricts the use of IoT devices, real-time monitoring systems, and analytics platforms on many construction sites [12, 13]. High implementation costs for software, hardware, and digital tools present significant challenges, particularly for small and medium-sized enterprises (SMEs), which dominate the sector [5, 11]. Skills shortages also impede effective adoption, as personnel trained in data analytics, AI, and digital tools are limited, resulting in underutilisation of available technologies [14]. Finally, organisational resistance and cultural inertia further constrain uptake; traditional work practices, reluctance to change, and limited awareness of analytics benefits lead many firms to prioritise regulatory compliance over innovative injury prevention strategies [6, 12].

2.4. Workplace injury prevention analytics scale (WIPAS)

Despite emerging insights on data-driven safety, existing safety management tools and assessment frameworks remain largely geared toward regulatory compliance and incident reporting rather than capturing the maturity, integration, and practical impact of analytics-based injury prevention strategies [14]. Most available instruments focus on observable safety behaviours, safety climate, or generic management practices, but do not evaluate the organisational capability to collect, analyse, and operationalise safety-related data using predictive analytics and real-time monitoring technologies. This limitation is particularly pronounced in the South African construction sector, where digital adoption is uneven and empirical measures of analytics readiness are scarce. The development of the Workplace Injury Prevention Analytics Scale (WIPAS) therefore addresses a critical gap by providing a contextually grounded mechanism to assess how construction firms internalise and operationalise analytics-driven safety practices. WIPAS enables a systematic evaluation of both technological and organisational dimensions of analytics integration, creating a platform for linking digital capability to measurable improvements in safety performance. To evaluate the operational integration of data analytics in construction safety management, this study developed the Workplace Injury Prevention Analytics Scale (WIPAS).

The nine WIPAS items were derived by integrating existing constructs from safety climate and safety management scales (e.g. items on safety data collection and integration into H&S protocols), analytics maturity models (e.g. use of predictive analytics and real-time monitoring), and organisational support and training frameworks, and then tailoring them to the South African construction context through expert review.

WIPAS was deliberately designed as a parsimonious diagnostic tool focusing on nine core dimensions repeatedly highlighted in the literature as central to analytics-enabled safety (data collection, multi-source analysis, evaluation of outcomes, practical analytics tools, real-time monitoring, predictive analytics, integration into protocols, management support, and employee training). We acknowledge that additional variables such as organisational culture, inter-organisational data sharing, or regulatory pressure may also influence analytics adoption, and we now identify these as promising constructs for extension in future versions of the scale.

3. Methodology

3.1. Research design

This study used a cross-sectional, quantitative survey design with mixed-mode administration. The survey was distributed both online (using snowball sampling through email and professional networks) and manually on construction sites and in offices, in order to include respondents with limited digital access. Manual surveys were also conducted on construction sites and in offices to include individuals without digital access. This method ensured diverse representation across different organizational contexts and helped reduce bias related to survey access, considering the varying levels of technological adoption in the industry.

3.2. Participants and sampling

A total of 210 responses were received, with 192 complete and consistent responses analyzed. Participants came from Mpumalanga (66.1%), KwaZulu-Natal (18.2%), and Gauteng (15.6%), with a regional bias towards Mpumalanga, which could affect the generalizability of the findings. Because the online survey relied on snowball sampling through professional networks and the total number of individuals who received the survey link is unknown, a conventional response rate could not be calculated. This limitation means that potential non-response bias cannot be quantified, as those who chose not to participate may systematically differ from respondents in their engagement with data-driven safety practices.

Respondents held diverse roles, with contractors making up the largest group (44.8%), followed by clients (19.8%), consultants (13%), suppliers (13%), and regulators (9.4%). The sample also included various professional backgrounds such as health and safety practitioners (29.7%), project managers (21.9%), quantity surveyors (18.8%), civil and structural engineers (16.1%), and construction managers (13.5%). Most respondents (66.7%) had 5–15 years of experience, ensuring a mix of early- and mid-career professionals. Due to snowball sampling and multiple distribution channels, the overall population reached could not be determined, limiting statistical generalizability. The regional concentration and non-probability sampling approach also suggest that the findings should be seen as indicative, not fully representative. Future studies could improve representativeness by using probability-based sampling and collaborating with industry bodies.

Given the dominance of respondents from Mpumalanga, the findings are best interpreted as indicative of data-driven safety practices in this regional cluster rather than statistically representative of the entire South African construction sector.

3.3. Instrumentation

The Workplace Injury Prevention Analytics Scale (WIPAS) was developed to evaluate the operational integration of data analytics in construction safety management. The initial item pool was generated from the literature on data-driven safety, organisational analytics maturity, and 4IR technologies in construction, and then refined through expert review with health and safety practitioners and construction management academics to ensure content relevance and contextual fit. The resulting instrument comprised nine items rated on a 5-point Likert scale (1 = strongly disagree; 5 = strongly agree), covering the following aspects of analytics-driven safety practice: frequency of safety data collection, analysis of diverse data types, evaluation of analytics outcomes, use of practical analytics tools, real-time hazard monitoring, predictive analytics for risk forecasting, integration of data into health and safety protocols, management support for analytics implementation, and employee training in analytics techniques.

The final WIPAS instrument consisted of nine Likert-type items (1 = strongly disagree; 5 = strongly agree). The exact wording of all items, as administered, is provided in Appendix A to support reproducibility.

3.4. Data analysis

The analysis used a multi-stage approach combining descriptive, reliability, and confirmatory factor analysis (CFA) to assess the Workplace Injury Prevention Analytics Scale (WIPAS). Descriptive statistics (mean, standard deviation, skewness, kurtosis) provided an overview of organisational practices. Reliability testing (Cronbach's alpha and composite reliability) confirmed internal consistency. CFA was used to validate the measurement model and assess model fit (CFI, TLI, RMSEA). Data analysis was performed using SPSS for descriptive and reliability analyses and EQS for CFA

Conceptually, the nine items capture three interrelated domains of analytics-driven injury prevention: (1) data practices (frequency of safety data collection, analysis of multiple data sources, evaluation of analytics outcomes, use of practical analytics tools), (2) advanced capabilities (predictive analytics and real-time monitoring), and (3) organisational integration and support (integration into health and safety protocols, management support, and employee training). Treating these as indicators of a single higher-order construct reflects the idea that injury-focused analytics maturity depends on the combined presence of technical, procedural and organisational elements.

4. Results

4.1. Descriptive statistics – WIPAS

Table 1. WIPAS descriptive statistical findings

WIPAS Variables	Mean	Std	Skewness	Kurtosis	Rank
Q1. Health and Safety-related data are collected frequently in my organisation (e.g. daily, weekly, monthly).	4.0	1.16	−1.18	0.68	1
Q2. My organisation analyses various data types (e.g. incident reports, employee feedback, environmental data, wearable technology data) for safety purposes.	3.7	1.13	−0.60	−0.42	2
Q3. My organisation regularly evaluates the outcomes of data analytics efforts to reduce workplace injuries.	3.5	0.95	−0.38	0.32	3
Q4. My organisation utilises practical data analytics tools for safety analysis (e.g. predictive analytics software and real-time monitoring systems).	3.5	1.16	−0.12	−1.15	4
Q5. My organisation employs real-time data analytics to monitor workplace conditions and detect hazards immediately.	3.4	1.10	−0.16	−1.10	5
Q6. Data analytics is integrated into my organisation's health and safety protocols and practices.	3.4	1.14	−0.26	−0.81	6
Q7. My organisation's management actively supports the implementation of data analytics in health and safety initiatives.	3.3	0.95	−0.04	−0.30	7
Q8. Predictive analytics is used to forecast hazards and risks in my firm.	3.3	1.25	−0.18	−1.15	8
Q9. Employees in my organisation are trained in data analytics techniques relevant to health and safety management.	3.2	1.22	0.23	−1.15	9

The descriptive findings in Table 1 show that respondents report relatively strong engagement in basic data-oriented safety practices such as frequent health and safety data collection and analysis of diverse safety data sources, whereas employee training in analytics techniques receives the lowest mean score. This pattern points to a capability gap: organisations are beginning to institutionalise data routines, but investment in workforce skills has not kept pace, potentially constraining the effective adoption of more advanced predictive and real-time analytics. From a practical standpoint, the mean scores and ranks in Table 1 highlight where organisations appear relatively strong and where they lag in analytics-driven safety. High means and pronounced negative skewness for frequent data collection (Q9), multi-source data analysis (Q10) and evaluation of analytics outcomes (Q17) indicate that many firms have institutionalised basic data-oriented routines, such as logging incidents, reviewing reports and monitoring compliance. In contrast, the more moderate means and greater variability for predictive analytics (Q14), real-time monitoring (Q15), management support (Q16) and employee training (Q12) reveal an uneven transition toward advanced, capability-intensive practices, suggesting that only a subset of organisations are currently able to exploit the full potential of data-driven injury prevention.

The descriptive results of the WIPAS indicated that organisations showed strong commitment to basic data-driven safety practices, particularly in frequent collection of health and safety data, analysis of diverse safety data, and regular evaluation of analytics outcomes. High mean scores and negative skewness for these variables suggested that such practices are generally well established and widely accepted, reflecting a proactive approach to data-driven health and safety management. In contrast, lower-ranked variables employee training in data analytics, use of predictive analytics, and active management support revealed notable gaps in more advanced aspects of analytics adoption. These areas showed moderate mean scores, greater variability, and more neutral response patterns, indicating inconsistent implementation and uneven organisational maturity. Overall, the findings point to a moderate level of engagement with workplace injury prevention analytics: while data collection is well embedded, the integration of predictive tools, skills development, and strong managerial support remains uneven and aspirational across the sector.

4.2. Reliability and Confirmatory Factor Analysis (CFA)

The reliability analysis of the Workplace Injury Prevention Analytics Scale (WIPAS) showed excellent internal consistency, with Cronbach's alpha (α) of 0.937 and composite reliability (rho) of 0.940, indicating that the scale reliably measures analytics-driven injury prevention. The very high internal consistency coefficients (Cronbach's $\alpha = 0.937$; $\rho = 0.940$) imply that the nine WIPAS items cohere strongly as indicators of a single underlying construct of analytics-driven injury prevention, and that the instrument is unlikely to suffer from random measurement error in this context. The CFA results further support this interpretation: all factor loadings exceeded the recommended threshold of 0.50, while fit indices (CFI and TLI greater than 0.90 and RMSEA below 0.08) indicate that the specified higher-order model reproduces the observed covariance structure well. Taken together, these findings suggest that WIPAS not only captures a conceptually meaningful construct, but does so with sufficient psychometric quality to justify its use in both research and organisational self-assessment.

WIPAS was modeled as a higher-order construct with nine first-order indicators reflecting key aspects of data-driven safety practices. Confirmatory Factor Analysis (CFA) confirmed the validity of the measurement model, with all factor loadings above the acceptable threshold (≥ 0.50), and strong model fit indices (CFI, TLI > 0.90; RMSEA < 0.08), supporting the scale's structural integrity. Among the WIPAS items, predictive analytics and real-time monitoring had the strongest factor loadings, highlighting these advanced capabilities as core indicators of organisational readiness for data-driven injury prevention.

Overall, the results provide three interrelated contributions. First, they demonstrate that WIPAS functions as a reliable and structurally valid, context-specific instrument for assessing analytics-driven workplace injury prevention in South African construction organisations. Second, the descriptive and CFA findings together offer empirical evidence of a maturity gap: while basic practices such as frequent data collection and incident analysis are widely embedded, more advanced capabilities such as predictive analytics and real-time monitoring are adopted inconsistently and remain aspirational for many firms. Third, both the descriptive rankings and the latent structure highlight management support and employee training as persistent bottlenecks, indicating that organisational leadership and workforce capability are crucial levers for realising the safety benefits of data analytics.

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Table 2. Confirmatory factor analysis results for WIPAS

Item	Standardised loading	Cronbach's α	ρ (composite reliability)	R^2
WIPAS3	0.6614	0.937	0.94	0.435
WIPAS4	0.8777			0.764
WIPAS5	0.823			0.685
WIPAS6	0.922			0.858
WIPAS7	0.8882			0.792
WIPAS8	0.7887			0.612
WIPAS9	0.8039			0.639

The higher-order WIPAS measurement model demonstrated good fit to the data (χ^2/df = 2.41, CFI = 0.94, TLI = 0.93, RMSEA = 0.056), with all standardised loadings exceeding 0.60, thereby supporting convergent validity. Note: CFA model fit indices: χ^2/df = 2.41, CFI = 0.94, TLI = 0.93, RMSEA = 0.056; Cronbach's α = 0.937; ρ = 0.94.

5. Discussions

The findings point to a construction sector that is developing basic analytics capabilities but has not yet achieved the predictive, intelligence-driven safety management envisioned under the broader 4IR agenda [15]. Foundational practices such as routine safety data collection, incident analysis, and monitoring of compliance suggest that many firms are moving beyond ad hoc safety management toward more formalised, data-informed processes [16]. However, the weaker adoption of predictive analytics, real-time monitoring, and structured training indicates that these practices remain largely descriptive and backward-looking, rather than anticipatory [17]. From a socio-technical systems perspective, this pattern reflects a partial alignment where data infrastructures exist, but organisational structures, skills, and routines have not fully evolved to support higher-order, AI-enabled safety capabilities [18]. Interpreted through diffusion of innovation and high-reliability organisation lenses, the results suggest that analytics-driven safety in South African construction is in an early to mid-adoption phase [19]. Innovator and early-adopter firms appear to be experimenting with real-time and predictive tools, but the majority remain anchored in conventional, compliance-focused practices that emphasise incident recording over risk foresight [20].

This coexistence of strong descriptive analytics and weak predictive maturity indicates that the innovation-decision process is constrained by perceived complexity, uncertain relative advantage, and limited trialability of advanced systems in fragmented, project-based environments [21]. In high-reliability terms, the sector has begun to institutionalise learning from past events but has not yet embedded the preoccupation with failure and sensitivity to operations that characterise organisations that use predictive signals to intervene before incidents occur [19]. Contextually, the uneven uptake of advanced analytics aligns with structural features of the South African construction ecosystem [22, 23]. The dominance of SMEs with tight margins and limited capital, combined with uneven digital infrastructure and connectivity across provinces, helps explain why relatively low-cost practices such as incident logging and basic data analysis are widespread, while resource-intensive predictive tools and real-time monitoring lag behind [24]. Fragmented project structures and extensive subcontracting diffuse responsibility for long-term technology investment, making it harder to justify analytics platforms whose benefits accrue across projects and over time [25]. These contextual constraints mean that even organisations with strong technical awareness may struggle to move beyond foundational analytics, reinforcing the "data-rich but insight-poor" condition observed in the descriptive results [17]. Management support emerges as a critical bottleneck in this transformation [25].

The relatively low scores for managerial advocacy and investment in analytics reflect a broader pattern in which safety is often subordinated to cost and schedule imperatives [24]. When senior leaders perceive analytics as an optional cost rather than a strategic capability, resources for predictive tools, training, and integration into core processes remain limited [**?**]. This reinforces a reactive safety culture focused on satisfying minimum regulatory requirements rather than leveraging data to prevent harm [16]. The hesitancy to commit to analytics can also stem from uncertainty about return on investment, lack of clear success cases in comparable local firms, and misalignment between digital initiatives and existing performance metrics, all of which slow the transition toward predictive injury prevention [20–25]. Finally, the findings highlight that workforce capability and human factors are central to the success of data-driven safety initiatives [**?**]. Limited employee training scores suggest that digital competence and analytics literacy are uneven, which can manifest as discomfort with new tools, fear of surveillance, or concern that data-driven monitoring might be used punitively rather than for learning [**?**]. In such environments, even well-designed predictive systems risk underuse or active resistance if workers and supervisors do not trust the technology or understand its value for their own safety [18]. This underscores the importance of coupling technological investment with targeted training, participatory implementation, and clear communication that positions analytics as a support for safe work rather than a threat to autonomy [**?**]. Overall, the discussion indicates that improving workplace injury prevention in South African construction will require coordinated attention to technology, leadership, and human factors, with WIPAS offering a structured lens for tracking how these intertwined capabilities evolve over time [16].

Although SEM was initially planned to examine structural relationships between WIPAS dimensions and organisational readiness variables, model diagnostics led us to restrict the analysis to CFA to ensure a robust measurement model; accordingly, SEM results are not reported in this study. Overall, the discussion indicates that improving workplace injury prevention in the surveyed regional cluster of South African construction organisations will require coordinated attention to technology, leadership, and human factors.

6. Conclusions

This study shows that many South African construction organisations are already collecting and reviewing safety data but have not yet fully transitioned to advanced, predictive uses of analytics. In doing so, the study moves beyond generic discussions of "digital safety" by providing a validated, context-specific scale (WIPAS), empirical evidence of a maturity gap between foundational and advanced analytics practices, and clear identification of management support and training as key constraints on the effective use of predictive and real-time safety tools. WIPAS is validated as a reliable instrument and offers a new way to diagnose how far firms have progressed toward genuinely data-driven injury prevention.

Beyond its statistical validation, WIPAS offers practical value as a benchmarking and self-assessment tool that construction organisations can use to identify gaps in their analytics-driven safety practices, particularly in areas such as predictive analytics, real-time monitoring, management support and employee training.

- Study contribution

The study examined the use of data-driven methods for workplace injury prevention in South Africa's construction sector and validated the Workplace Injury Prevention Analytics Scale (WIPAS) as a dependable measurement tool for analytics maturity. Key findings reveal that, although organisations regularly gather and analyse safety data, the adoption of more advanced practices such as predictive analytics and real-time monitoring remains uneven, with notable variation in capability and uptake across firms. The analysis also identified limited managerial support and inadequate employee training as major obstacles to fully implementing analytics-based safety strategies, reinforcing earlier evidence of skills gaps and reactive safety cultures in the sector.

- Recommendations

Based on the findings, several practical recommendations arise. First, construction organizations should develop comprehensive training programs focused on predictive analytics and real-time monitoring to equip employees with the skills needed for effective use of advanced safety technologies. Second, analytics should be systematically incorporated into organizational H&S protocols, supported by active managerial support to emphasize the importance of data-driven decision-making and foster a culture of accountability. Third, using IoT devices and wearable technologies is encouraged to enable real-time hazard detection, allowing for quick intervention and reducing the risk of incidents. Fourth, organizations should use WIPAS as a benchmarking tool to evaluate the maturity of their analytics practices, identify areas for improvement, and track progress over time. Lastly, future research should include longitudinal studies to explore the causal relationship between analytics adoption and reductions in workplace injuries, providing stronger evidence of the effectiveness of data-driven approaches interventions.

- Limitations

Several limitations inherent in this study should be recognized. The use of snowball sampling for the online survey made it impossible to determine an exact response rate, which may affect the sample's representativeness and prevents formal assessment of non-response bias; non-participants may differ from respondents in ways that influence analytics adoption and safety practices. Additionally, the regional concentration of respondents in Mpumalanga (66.1%), with fewer participants from KwaZulu-Natal and Gauteng, may restrict the generalizability of findings to the broader South African construction industry or other international contexts. The cross-sectional design of the survey captures perceptions and practices at a single point in time, preventing the assessment of changes over time or long-term outcomes of analytics adoption. Finally, relying on self-reported data introduces potential response bias, as participants may overstate their engagement with safety practices or underreport gaps. Despite these limitations, the study offers valuable insights into the current state of data-driven injury prevention practices and provides a solid foundation for future empirical research and policy development. While the present study validates the internal consistency and structural fit of WIPAS and provides descriptive evidence of its diagnostic utility, it does not yet test the instrument's predictive validity in relation to actual injury outcomes; future longitudinal research is required to evaluate the practical impact of WIPAS scores on recorded workplace injuries.

Future research should validate the WIPAS across a broader and more balanced national sample and test measurement invariance across provinces and role categories (e.g. contractors, clients, regulators) to assess the stability of the scale structure.

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Appendix A. Workplace Injury Prevention Analytics Scale (WIPAS) Items

The WIPAS instrument consists of nine items designed to measure the maturity of data-driven injury prevention practices. Respondents rated each statement on a 5-point Likert scale (1 = strongly disagree; 5 = strongly agree).

1. Health and safety-related data are collected frequently in my organisation (e.g. daily, weekly, monthly).

2. My organisation analyses various data types (e.g. incident reports, employee feedback, environmental data, wearable technology data) for safety purposes.

3. My organisation regularly evaluates the outcomes of data analytics efforts to reduce workplace injuries.

4. My organisation utilises practical data analytics tools for safety analysis (e.g. predictive analytics software and real-time monitoring systems).

5. My organisation employs real-time data analytics to monitor workplace conditions and detect hazards immediately.

6. Data analytics is integrated into my organisation's health and safety protocols and practices.

7. My organisation's management actively supports the implementation of data analytics in health and safety initiatives.

8. Predictive analytics is used to forecast hazards and risks in my firm.

9. Employees in my organisation are trained in data analytics techniques relevant to health and safety management.