

Digital Safety Technology Adoption and Construction Accident Risk: A Multivariable Analysis Using Logistic and Negative Binomial Models

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Abstract

Digital innovations increase visibility of and shorten the response time to dangers. However, they do not ensure safer outcomes. This paper analyzes a subset of a Ph.D. construction safety framework and uses appropriate models based on the outcomes to analyze accident frequency and occurrence. The analysis employs the fixed data (n=450, Chennai=250, Coimbatore=200) as reported in the author's article. Measurement of the adoption of technology was done as a multi-item construct along with proxies of BIM, IoT, wearables, computer vision, mobile safety applications, digital permits, real-time monitoring, drones, RFID, proximity warnings, smart helmets and smart helmets and immersive training. The binary accident experience was modeled with logistic regression, and the accident count was modeled with Poisson and negative binomial regression. Technology adoption was found to decrease accident odds (OR=0.508, 95% CI 0.333–0.775, p=0.002). Safety training (OR=0.433) and PPE (OR=0.554) were protective, whereas financial constraints (OR=1.847) and scaffolding exposure (OR=1.735) were found to increase odds. The logistic model achieved AUC=0.785. For accident frequency, the negative binomial model was found to be better than Poisson (AIC 915.93 vs. 931.69) and protective associations of technology adoption (IRR=0.597), safety culture (IRR=0.647), training (IRR=0.668) and PPE (IRR=0.606) were found along with an increase in expected counts due to financial constraints, height exposure and hazard exposure. The findings indicate a socio-technical meaning, where "Digital tools used to provide visibility of and reduce response time to dangers must be coupled with governance, competence, maintenance and controls such as rapid human response and privacy." The data are and meant to be presented as a modeling demonstration rather than field data.

Keywords: construction safety technology; accident risk; logistic regression; negative binomial regression; BIM; IoT; computer vision; wearables

Table 1:- Abbreviation used in the article

Abbreviation / Symbol	Full form / Meaning
AI	Artificial Intelligence
AIC	Akaike Information Criterion
AR	Augmented Reality
AUC	Area Under the Curve
BIM	Building Information Modeling
CI	Confidence Interval
CV	Computer Vision
GPS	Global Positioning System
HIRA	Hazard Identification and Risk Assessment
IoT	Internet of Things
IRR	Incidence Rate Ratio
OR	Odds Ratio
PPE	Personal Protective Equipment
RFID	Radio Frequency Identification
ROC	Receiver Operating Characteristic

TA	Technology Adoption Construct
VR	Virtual Reality
N	Total number of observations/sample size
n	Number of observations in a subgroup
p	Statistical significance (p-value)

Introduction

Digital technologies are increasingly being adopted to strengthen safety management in the construction industry. Wearable devices, computer vision, building information modelling (BIM), the Internet of Things (IoT), radio-frequency identification (RFID), drones, mobile safety applications, electronic permit-to-work systems, and real-time monitoring can improve hazard visibility and accelerate communication and response. However, the availability of digital information does not automatically produce safer outcomes. Safety benefits depend on reliable technology, competent users, effective supervision, maintenance, data governance, and timely corrective action.

Computer vision is widely investigated for construction-safety applications, including personal protective equipment detection, unsafe-behaviour recognition, worker equipment interaction monitoring, hazard identification, and construction-progress assessment (Akinosho et al., 2020; Guo et al., 2021; Zhang et al., 2020). BIM, digital twins, IoT platforms, and wearable devices can further connect planned work activities with real-time information about work zones, worker location, environmental exposure, and movement (Adjei and Jin, 2026; Kim et al., 2020; Liu, 2025; Pereira et al., 2025; Saif et al., 2024). Drones can support remote inspection of roofs, façades, excavations, and other hazardous areas, whereas virtual reality and augmented reality can provide immersive hazard-recognition training without exposing trainees to physical risks (Van Der Heijden, 2023; Xu et al., 2023). Nevertheless, changing site conditions, poor data quality, interoperability problems, privacy concerns, limited digital competence, implementation costs, and weak organizational support can reduce the effectiveness of these systems (Abioye et al., 2021; Arshad et al., 2023; Buniya et al., 2021; Chong et al., 2023; Regona et al., 2022).

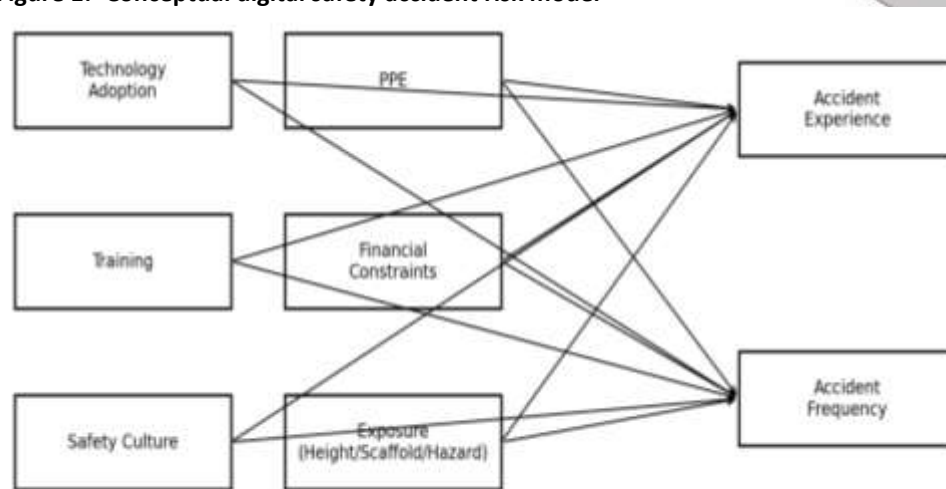
A further limitation is that digital safety technologies are often assessed according to their novelty or technical capability rather than their relationship with measurable safety outcomes. Installing cameras or wearable devices is insufficient when organizations lack clear operating procedures, maintenance schedules, privacy safeguards, and response mechanisms (Alkaissy et al., 2020; International Organization for Standardization, 2018). Technology should therefore be considered as one element of a broader socio-technical safety system that includes safety culture, training, personal protective equipment (PPE), hazard identification and risk assessment (HIRA), supervision, and financial capacity.

This study aims to examine whether technology adoption is associated with accident occurrence and accident frequency after accounting for safety training, safety culture, PPE, HIRA, financial constraints, construction experience, work-at-height exposure, scaffolding exposure, and other hazards. A dataset of 450 observations, comprising Chennai (n = 250) and Coimbatore (n = 200), is analyzed as a modelling demonstration rather than as field evidence. Logistic regression is used for the binary accident-experience outcome, while Poisson and negative binomial regression are compared for accident counts. The study evaluates whether technology adoption, training, safety culture, and PPE are associated with safer outcomes and whether financial constraints and physical hazard exposures are associated with increased risk. Because the data are , the estimates are interpreted as methodological demonstrations rather than causal or generalizable empirical effects.

Hypotheses

- H1: Higher technology adoption leads to lower accident odds.
- H2: Higher technology adoption leads to lower accident frequency.
- H3: Safety training leads to reduced accident occurrence and frequency.
- H4: Higher PPE is associated with a reduced occurrence and frequency of accidents.
- H5: A stronger safety culture leads to a reduced frequency of accidents.
- H6: Financial constraints lead to increased accident risk.
- H7: Work-at-height, scaffolding and/or hazard exposure lead to increased accident risk.

Figure 1:- Conceptual digital safety accident risk model



Binary outcome assessed with logistic regression; count outcome assessed with Poisson/negative binomial models

Methodology

The study uses dataset on N=450 observations, allocated to Chennai (n=250) and Coimbatore (n=200). The records were created using a fixed random seed and were designed to create realistic, but non-deterministic, safety constructs, technology indicators and accident outcomes. These records should not be interpreted as field observations or as estimates of actual occurrences.

The primary predictor is the Technology Adoption Construct (TA), which consists of seven Likert items. The broader article contains 18 technology indicators which include functions and services related to Building Information Modeling (BIM) / BIM safety planning, Internet of Things (IoT) sensors, wearables, Radio Frequency Identification (RFID), Global Positioning System (GPS) / location monitoring and computer vision, and Artificial Intelligence (AI) based hazard recognition and smart virtual assistance systems to detect Personal Protective Equipment (PPE) and issue proximity warnings, as well as smart helmets, drones, Safety Apps, digital permits, real time monitoring, digital dashboards and safety training in Virtual Reality (VR) and Augmented Reality (AR). The high adoption indicator was applied to 52.2% of the sample employing a clear preference rather than a universally high adoption level.

The binary outcome is accident experienced (0/1). The count outcome is accident_count_12m. Safety training and safety culture, PPE, Hazard and Operability Study (HIRA), exposure to height and to scaffolding, construction experience, financial constraints and a hazard-exposure score; are the covariates. The rate of accident experienced is 37.6% and the mean of accident_count_12m is 0.691. These values are only for testing the modeling framework. Binary logistic regression calculates odds ratios (ORs) and 95% confidence intervals, and model discrimination is assessed using the receiver operating characteristic area under the curve (AUC). Accident frequency is first modeled using Poisson regression and subsequently using negative binomial regression. Model selection is based on overdispersion and the Akaike Information Criterion (AIC). Incidence rate ratios (IRR) are used for substantive interpretation. ORs and IRRs are conceptually differentiated: Ors pertain to the odds of any accident, and IRRs pertain to the expected count of accidents (Stata Corp, 2023).

Table 2: - Digital Technology Portfolio

Technology	Primary safety function
BIM / BIM safety planning	Spatial hazard planning, design-for-safety and coordination
IoT sensors	Environmental and equipment sensing
Wearables / smart helmets	Location, exposure and physiological monitoring
RFID / GPS	Tracking of workers, assets and zones
Computer vision / AI recognition	PPE, proximity, activity and hazard detection
Automated PPE detection	Continuous compliance monitoring

Proximity warning	Worker–equipment collision prevention
Drones	Remote inspection of large or hazardous areas
Mobile safety apps / digital permits	Communication, permits and corrective-action traceability
Real-time monitoring / dashboards	Leading indicators and rapid decision support
VR / AR training	Immersive hazard-recognition and task learning

Results

The heterogeneous adoption of technology indicators was noted. The article reports that 52.2% of the observations were considered high-adoption indicators. The technologies were used at varying levels from relatively high-usage of mobile devices and digital tools, to smart helmets and AR training, which was used less. This is in line with the expectation of risk-specific and staged adoption.

The binary logistic model achieved pseudo- R^2 of 0.195 and AUC of 0.785. Technology adoption was found to be associated with lower accident odds (OR = 0.508, 95% CI 0.333 – 0.775, $p = 0.002$). Similar results were found for safety training (OR = 0.433, 95% CI 0.285 – 0.657, $p < 0.001$) and PPE (OR = 0.554, 95% CI 0.374 – 0.821, $p = 0.003$). Safety culture was not significant (OR = 0.672, $p = 0.072$), which supports the importance of reporting non-significant results. HIRA was not significant (OR = 0.964, $p = 0.862$).

Exposure and resource variables demonstrated the opposite pattern. Scaffolding exposure was associated with an increase in accident odds (OR = 1.735, 95% CI 1.111 – 2.709, $p = 0.015$). Height exposure was also associated with an increase in accident odds, although this result was considered marginal (OR = 1.515, $p = 0.071$). Financial constraints were associated with an increase in accident odds (OR = 1.847, 95% CI 1.239 – 2.752, $p = 0.003$). Construction experience and hazard-exposure scores were not significant in the binary model.

The accident count exhibited a right-skew distribution with a large number of zero values. The Poisson model yielded an AIC of 931.69 and a dispersion indicator of 1.266. A significant overdispersion parameter was estimated for the negative binomial model (AIC = 915.93, $\alpha = 0.439$, $p = 0.002$), supporting this specification.

In the negative binomial model, technology adoption was estimated to reduce average accidents by 40% (IRR=0.597, 95% CI 0.458–0.778, $p<0.001$). Safety culture (IRR=0.647, $p=0.001$), safety training (IRR=0.668, $p=0.001$) and PPE (IRR=0.606, $p<0.001$) were also found to be protective. Financial constraints led to an increase in expected counts (IRR=1.546, $p<0.001$), as did height exposure (IRR=1.366, $p=0.030$) and hazard exposure (IRR=1.171, $p=0.040$). There was no significant impact of experience and working hours showed an elevated but non-significant IRR=1.121 ($p=0.078$).

Table 3: - Accident Profile

Measure	Value
N	450
Chennai / Coimbatore	250 / 200
Accident experienced	37.6% ()
Mean accident count (12 months)	0.691
High technology-adoption indicator	52.2%
Logistic AUC	0.785

Table 4: - Binary Logistic Regression

Predictor	OR	p	95% CI
Safety training	0.433	<0.001	0.285–0.657
Safety culture	0.672	0.072	0.435–1.037
Technology adoption	0.508	0.002	0.333–0.775
PPE	0.554	0.003	0.374–0.821
HIRA	0.964	0.862	0.640–1.452

Height exposure	1.515	0.071	0.966–2.378
Scaffolding exposure	1.735	0.015	1.111–2.709
Experience	1.008	0.745	0.959–1.060
Financial constraints	1.847	0.003	1.239–2.752
Hazard exposure	1.173	0.203	0.917–1.501

Model summary: pseudo- $R^2=0.195$; AUC=0.785. Odds ratios below 1 indicate lower modelled odds, whereas odds ratios above 1 indicate higher modelled odds, holding the other variables constant.

Figure 2:- Odds ratios and 95% confidence intervals for the accident-experience model

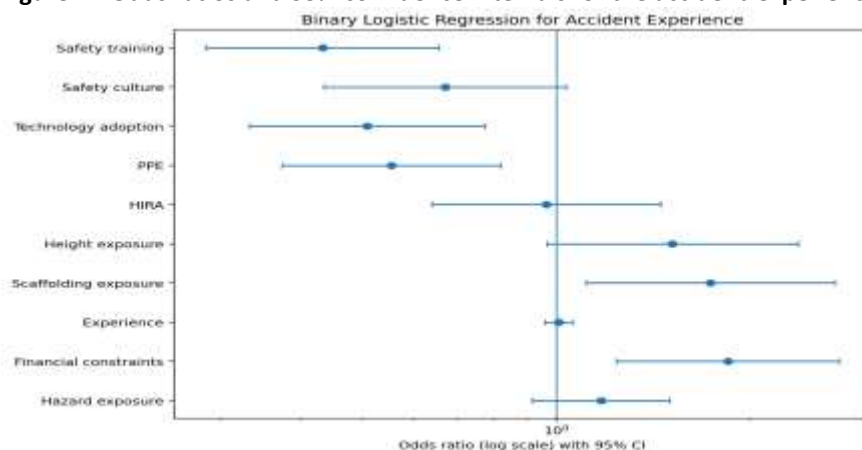


Table 5: -Poisson versus Negative Binomial Models

Model/diagnostic	Value	Interpretation
Poisson AIC	931.69	Higher
Dispersion indicator	1.266	Evidence of overdispersion
Negative binomial AIC	915.93	Lower / better fit
Negative binomial alpha	0.439 (p=0.002)	Significant overdispersion parameter

Figure 3:- AIC comparison between Poisson and negative binomial accident-count models

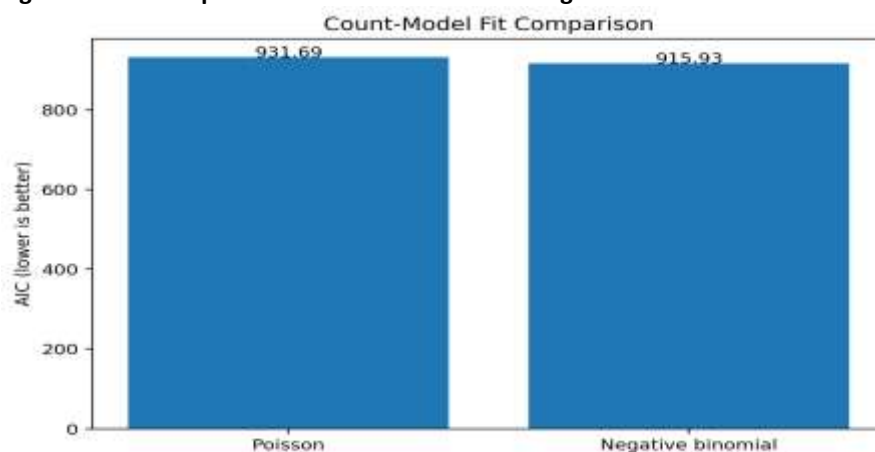


Table 6:- Negative Binomial Regression

Predictor	IRR	p	95% CI
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Safety training	0.668	0.001	0.520–0.857
Safety culture	0.647	0.001	0.495–0.845
Technology adoption	0.597	<0.001	0.458–0.778
PPE	0.606	<0.001	0.476–0.772
Height exposure	1.366	0.030	1.030–1.810
Experience	1.013	0.396	0.983–1.045
Working hours/day	1.121	0.078	0.987–1.273
Hazard exposure	1.171	0.040	1.008–1.360
Financial constraints	1.546	<0.001	1.208–1.979

Figure 4:- Incidence rate ratios and 95% confidence intervals for the negative binomial model

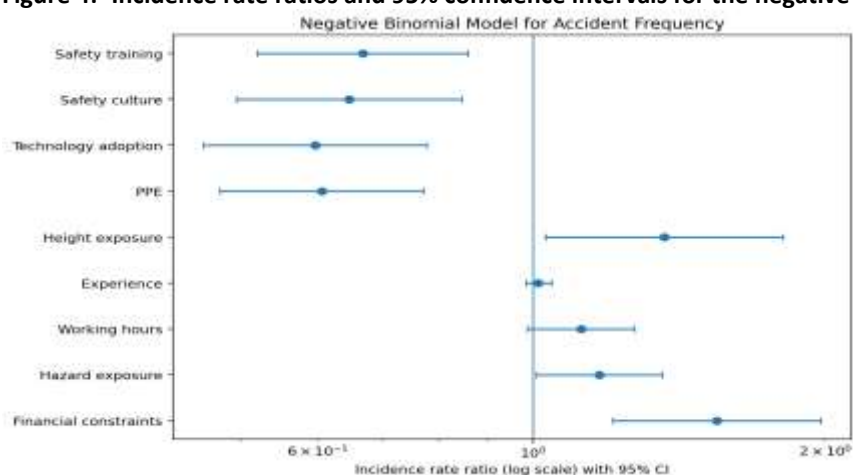


Table 7:- Hypothesis Summary

Hypothesis	Evidence	Decision
H1 Technology → accident odds	OR=0.508, p=0.002	Supported
H2 Technology → accident frequency	IRR=0.597, p<0.001	Supported
H3 Training protective	OR=0.433; IRR=0.668	Supported
H4 PPE protective	OR=0.554; IRR=0.606	Supported
H5 Safety culture lowers frequency	IRR=0.647, p=0.001	Supported for count outcome
H6 Financial constraints adverse	OR=1.847; IRR=1.546	Supported
H7 Exposure increases risk	Scaffold OR=1.735; height IRR=1.366; hazard IRR=1.171	Partially supported

Discussion

Adoption of higher levels of technology resulted in significantly lower odds of binary accidents and accident frequency across both outcome scales. The agreement between OR and IRR directions helps better understand the components of the model, but it doesn't imply a causal relationship. Technology may likely include or involve many of the following: earlier detection of hazards, automated PPE detection, proximity alerts, remote inspections, more accurate location awareness, digital permit systems within the bounds of the system and accelerated corrective actions.

The AUC of 0.785 suggests good discrimination in the dataset. This should not be described as perfect predictive accuracy. In real-world deployments, the accuracy of the model will depend on the quality and quantity of available

data, the type of deployment, sensors, and if they are calibrated. An external validation of the model would be required before it could be deployed for an accident risk assessment.

There are a strong distinction and emphasis on the adoption of technology versus the effectiveness of technology. Computer vision has the ability to monitor a work zone, but the presence of false positives, blind spots, occlusions, and domain shifts may adversely affect trust and the system (Guo et al., 2021; Zhang et al., 2020). Wearables have the potential to create detailed location or exposure data, but may suffer broad adoption due to privacy concerns (Chong et al., 2023). IOT systems need reliable connectivity, battery power, and ongoing maintenance, and safe data. BIM adds valuable context, but needs periodic, accurate model updates, and ongoing integration of changing conditions. These constraints encourage a socio-technical perspective as opposed to a technology-centric view (Mostafa and Hegazy, 2021; Okonkwo et al., 2025; Santoso et al., 2025).

The models show that PPE and safety training maintained their protective role, suggesting that digital systems will not substitute for traditional safety controls. An employee still needs task competency and a functioning hierarchy of controls and the appropriate PPE for residual risk. In addition, in the count model, safety culture was significant, whereas in the binary model, it was not. It is reasonable to consider safety culture relevant in the case of repeated exposure management and the accumulation of incidents more than in a situation of a binary yes/no accident.

Both models showed financial constraints to be adverse. This shows that digital systems may be correlated with an organization's capacity. Evaluating and acquiring the technology requires consideration of the costs associated with its acquisition, calibration, software, connectivity, and training as well as safety and cybersecurity. Financial constraints may lead to a reduction in the basic controls and staff. Therefore, safety technology should be introduced only after evaluating lifecycle risks and costs and not based on technology novelty.

According to the models, exposure to heights increased the expected number of accidents, and exposure to scaffolding increased the odds of a binary accident. This further solidifies the need for temporary structures and systems to prevent falls. Digital systems can help with safety inspection, tagging and monitoring as well as the placement of exclusion zones, but they cannot substitute for design, erection, and edge protection as well as safe access and planning for fall-arrest and rescue stand-by.

Digital Safety Implementation Framework

A practical digital safety system consists of multiple steps that happen in a closed loop. Each step has to be explicitly the responsibility of someone. If a step doesn't have an owner, then the other, preceding steps provide control. A sensor without a response owner, a dashboard without thresholds, or an alert without closure of corrective action, provides information, but not control (Elrifaee and Zayed, 2025; Fang et al., 2020; Liu, 2025).

The selection of technology that involve risk assessment should be done in an order that makes sense. That is, if safety hazards are observable by computer vision, then these would be the technologies chosen for that given risk. For safety hazards of a predominately location and interaction risk, wearables paired with proximity systems could be used. Drones can be used to reduce the risk of an inspection to workers. BIM and digital twins can also be used to plan in a digital environment. VR/AR can be used for training to improve hazard recognition. Privacy by design, cyber safety, worker input, and the least amount of data should also be considered within this framework. The framework should also include alternative measures to be taken if there is a failure of equipment or loss of connectivity.

Theoretical and Practical Implications

There are three implications from this analysis. The first of these is that digital safety should be more about the capabilities that an organization has, rather than the measures it has available. The second is that in modeling accidents, one has to take into account the type of distribution that would result from the outcome of the accident (Li et al., 2026; Zhang et al., 2020). Analyzing accident results that are binary or results that are of a count are different, and may also affect the patterns of significance. The third of these is that the protective technology effect relies on the controls that are human and organizational. Hence, the best strategy is integrating people, process, and technology.

For practitioners, the aim is not to deploy every available technology. Projects should focus on main hazards, appropriate technology, performance verification in local conditions, protocols for response, and scalability. Safety managers should monitor alert accuracy, response time, closing of corrective actions, and acceptance of workers as

leading indicators. When procuring technology, maintenance cost, interoperability, and cybersecurity, and the training cost over the life cycle of the technology should be considered.

Limitations and Future Research

Since the dataset is , the reported accident rate, technology-adoption rate, odds ratios, incidence rate ratios and AUC cannot be used to provide evidence on Chennai, Coimbatore, or any other company. The analysis is cross-sectional and cannot demonstrate causality. Technology adoption is represented primarily with construct scores and binary indicators, rather than device-level performance logs.

Field research should validate the framework with real incident data and timestamped technology data. Future models could include project-level clustering, repeated measures, exposure hours, and zero-inflated count models, as appropriate. Device-level studies should report sensitivity, specificity, false-burden of alarm, latency and uptime, along with behavioral and organizational outcomes. Comparative cost-effectiveness analysis is also needed to define the point at which digital controls can achieve risk reduction compared to alternative engineering controls.

Conclusion

For the final model, the use of technology in construction accidents was analyzed along with training, safety culture, PPE, finances, and exposure. From the results of the analysis, it was shown that the use of technology is associated with a lower risk of accidents and a lower accident rate. Financial constraints and exposure variables were associated with a greater risk of accidents. The negative binomial model was able to fit the data better than the Poisson model, due to overdispersion. The overall conclusion of the accidents is that the use of technology on construction sites does not eliminate the risk of accidents, rather that the use of technology in a controlled manner has the potential to improve the safety and the ease of responding to hazards associated with construction. It is important to emphasize that the data, analysis, and results presented require on-site verification before they can be adapted to a given construction project.

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