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An Evidence-Driven Approach to Slip and Fall Prevention in Large Campus Facilities

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Abstract: We developed an evidence-based risk assessment and benchmarking framework towards pedestrian safety. Pendulum slip resistance tests were conducted on 23 sites within a large campus facility covering ceramic tiles, pebbles, tactile indicators, and metal coverings for manholes and drainage. The results show frictional resistance can be reduced when tested wet and exacerbated when it is on a slope. The results were further verified via laboratory tests under controlled conditions. The perceived affordance of certain features such as tactile indicators providing a better grip or traction requires urgent attention. Therefore, a data-driven approach not only enhances the accuracy of slip risk assessments but also establishes empirically grounded benchmarks for surface safety, ensuring effective and resource-efficient interventions. The findings contribute to the existing body of knowledge and future research agenda in pedestrian safety, offering a robust foundation for benchmarking and risk management efforts in diverse environments.

Keywords: slip and fall; pedestrian; slipperiness; tactile pavement; frictional resistance; public safety and health; random forests

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1. Introduction

Slips and falls are a leading cause of injuries globally and its prevention remains a pressing public safety and health challenge. While studies on hazards and risk control measures of slips and falls due to environmental and human factors have been widely conducted [1], little has been reported on the risk for pedestrians when stepping over coatings and features such as tactile indicators, metal covers for ramps and manholes, and drainage metal grills, etc., during wet days (see Appendix A for examples from the case study). Understanding this relationship, particularly concerning slip and fall incidents, is a critical issue in urban environments. In tropical cities, where weather conditions and urban infrastructure present unique challenges, understanding and mitigating the risks associated with slip and fall accidents is essential.

In tropical cities, frequent rainfall can significantly impact surface slipperiness leading to pedestrian slips and falls. This necessitates a thorough understanding of slip resistance. The research by [2] highlights the role of surface roughness in measuring slipperiness, advocating for reliable methods such as stylus-type profilometers and laser scanning confocal microscopes to characterise slip resistance properties. The interaction between shoe–floor surfaces is also emphasised [3], which is crucial for accurate slip resistance assessment. These techniques are essential for designing safer pedestrian pathways.

Tropical cities experience heavy and frequent rainfall, which can create slippery conditions similar to icy environments. There are numerous studies regarding slips and falls over icy conditions; a dearth exists when it comes to tropical environments. For example, ref. [4] discusses the effectiveness of weather warning services in Finland. This research underscores the importance of timely weather warnings to mitigate slip and fall incidents. Extrapolating these findings for tropical cities, enhancing weather prediction systems, and communicating potential hazards to the public can play a significant role in preventing accidents. Similarly, ref. [5] focuses on skid-resistant measurements in cold climates. Their findings suggest that permeable pavements, which allow water to drain through, could reduce surface water accumulation and improve skid resistance in wet conditions, which does provide insights relevant to tropical cities, whereby implementing permeable pavement solutions may help mitigate the risks associated with heavy rainfall.

Workplace injuries due to slips, trips, and falls in Singapore [6] highlight the ongoing safety concerns in urban environments. These data underscore the necessity for the continuous monitoring and improvement of pedestrian surfaces. Additionally, the assessment of concrete finishes in community settings reveals that rougher textures do not always guarantee better traction in wet conditions [7]. This finding suggests that tropical cities should prioritise innovative surface treatments and maintenance practices to enhance pedestrian safety [7]. Similar work was performed in temperate countries; for example, a Slip and Fall Index (SFI) was developed recently in Canada [8], which alerts the public about slippery conditions and improves pedestrian safety.

Further research indicates that elderly populations are particularly vulnerable to falls and preventive strategies should include designing pedestrian pathways with appropriate textures, ensuring good drainage, and educating the public, particularly the elderly, about the hazards [9,10]. In tropical cities, heavy rains and wet surfaces pose similar risks.

A rougher surface provides a better grip or traction to walk on but, at the same time, it increases stainability and reduces cleanability. Other considerations include aesthetics, glossiness, surface coolness, etc. The choice of floor surface roughness depends on the usage with different priorities, e.g., dance floors, sports halls, wet kitchens, shopping centres, and outdoor pavements [11]. Anti-slip treatment, a process which removes soft particles and exposes hard particles on the flooring surface, may be used to alter the mineral structure of the floor surface which in turn increases the slip resistance properties and makes the floor safer when wet or lubricated.

An approved pavement material is usually safe from skids and falls when it is in a dry and clean condition. However, when it is wet or lubricated, the effect of hydroplaning or aquaplaning (loss of traction when a layer of water builds up between the sole of the footwear and the surface of the pavement) may take place. The friction between the sole of the footwear and the pavement surface depends on the ability of the sole's grooves to disperse water beneath. Hydroplaning or aquaplaning occurs when the sole of the footwear encounters more water than it can dissipate, in which case, this can lead to a slip and fall. Tactile ground surface indicators were devised in Japan in 1965 to facilitate the safe movement of people with impaired vision. It has been widely accepted and used globally since then. The two types of tactile indicators found in practice are (a) warning blocks that indicate the location of hazards, and (b) directional blocks that indicate the direction of travel (Figure 1). Among the issues raised in the guide for the proper installation of tactile indicators is the use of the feature on slopes [12,13]. One of the main concerns is the slipperiness [13].

ASTM E303 [14] is the international standard test method for measuring the skid resistance of pavements and other surfaces using the British Pendulum Tester. The standard is primarily used to determine the slip resistance of flooring materials, especially in terms of pedestrian safety. The standard defines the test, which involves swinging a pendulum device over a wetted surface to measure the friction (or slip resistance) of that surface. The pendulum's arm is equipped with a rubber slider that contacts the tested surface. The results are reported as the British Pendulum Number (BPN), also known as the skid resistance value (SRV). The higher the BPN, the greater the slip resistance. The ASTM E303 standard itself does not specify a single minimum value of BPN required for pedestrian safety because the acceptable value depends on the specific conditions of use and the level of slip resistance desired. However, industry practices and safety guidelines generally use BPN values as a guideline depending on their geographical or functional requirements. For example, standards in Australia, New Zealand, and Singapore [15,16] (AS/NZS 4586:2004, SS 485:2022), specify the slip resistance classification of pedestrian surface materials [17] (AS/NZS 4663:2004), defining the notional contribution of the floor surface to the risk of slipping when wet (see Table 1).

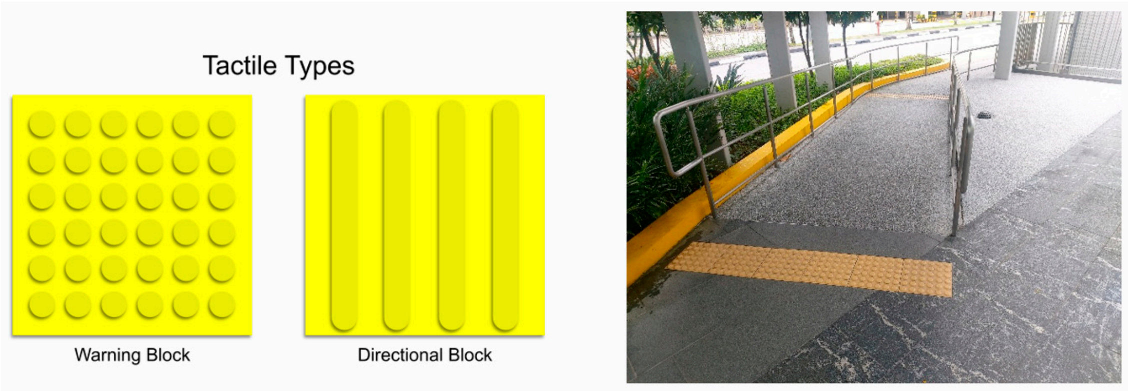

Figure 1. The two basic types of tactile ground surface indicators.

Table 1. Wet pendulum test classification (sources: [16,17]).

Mean BPN	Classification	Notional* Contribution of Floor Surface to the Risk of Slipping When Wet
>54	V	Very low
45 to 54	W	Low
35 to 44	X	Moderate
25 to 34	Y	High
<25	Z	Very high

* The term "notional" has been used to highlight the need to consider all potential contributing factors to a slip incident.

In the context of developing evidence-driven risk assessment frameworks for slip and fall prevention, random forests (RFs) emerge as a particularly effective methodology when compared to other machine learning techniques like support vector machines (SVMs) and artificial neural networks (ANNs). Random forests, an ensemble learning approach, construct multiple decision trees and aggregate their predictions, reducing overfitting through the random sampling of data subsets and features [18]. This leads to high accuracy and robust performance in handling complex, non-linear relationships, which are typical in pedestrian safety scenarios. Unlike SVMs, which can be sensitive to specific parameters like the ε-insensitive zone [19], and ANNs, which often require extensive tuning and are prone to overfitting [20], random forests offer strong generalisation capabilities with relatively straightforward implementation, making them a compelling choice for assessing and mitigating slip and fall risks in large campus facilities.

Adapting an evidence-driven approach for pedestrian safety in tropical cities such as Singapore involves the accounting of pavement operational surface slip resistance, which is a gap found in the literature in this field. Thereby to reduce slip incidents, inform public behaviour, and enable targeted maintenance efforts, further exploration is needed in the tropics. To that end, the aim of this paper is to develop an evidence-based risk assessment and benchmarking framework towards pedestrian safety by empirically evaluating the frictional resistance of some common pavement features when wet in a large campus facility.

2. Materials and Methods

Pendulum slip tests according to SS 485:2022 were conducted on various floor surfaces (Figures 2 and 3) across a large campus facility in a hot humid tropical city. Tests were conducted under the following conditions: (1) as is—original state with no intervention; (2) dry (clean)—a simple cleaning of the surface with a wet towel and dried before testing;

(3) ASTM E303—ASTM standard condition; and (4) flow—with a flow of streaming water from a bottle. Laboratory tests were further conducted under controlled conditions to verify the results of some of the field tests (Figure 4).

Figure 2. Wet pendulum slip resistance test.

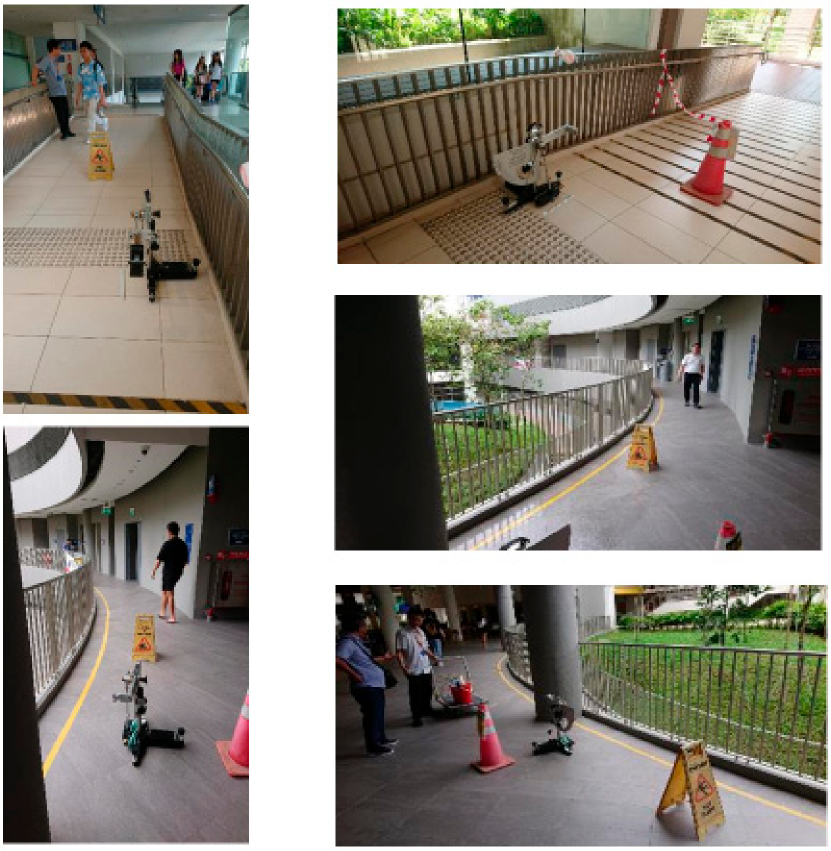

Figure 3. Examples of pendulum slip tests conducted on various sites.

All tests were conducted using a portable skid resistance tester (i.e., British Pendulum Tester) using a four S rubber. The equipment was calibrated at the site prior to each observation. Testing for different types of conditions was performed with an initial test shot followed by four-times actual observations under the four conditions as above. Twenty-three tests were conducted at various locations across the large campus facility (see Table 2), as well as ten tests conducted in the laboratory to test different tactile products under controlled conditions. The tests were conducted from October 2023 to May 2024. The recorded BPN numbers, pendulum travel (in mm), ambient temperature, weather data, qualitative comments on floor usage, exposure conditions, and human traffic levels were recorded for each test.

Figure 4. Laboratory pendulum tests.

Table 2. Locations of portable skid resistance testing.

Code	Floor Surface	Location	Exposure	Travel (mm)	Human Traffic
A	Tile	Toilet	Indoor	127	High
B	Tile	Footpath	Indoor	127	High
C	Tactile	Footpath	Outdoor	127	Low
D	Tile	Disability ramp	Indoor	127	Low
E	Tile	Bridge	Indoor	125	High
F	Tile	Toilet	Indoor	127	High
G	Tile	Canteen	Indoor	127	High
H	Tile	Lobby	Outdoor	125	Low
J	Tile	Stairs	Outdoor	124	Low
K	Tactile	Lobby	Indoor	124	High
L	Granite	Stairs	Indoor	125	High
M	Pebble wash surface	Footpath	Outdoor	127	Low
N	Pebble wash surface	Lobby	Indoor	127	Low
O	Red brick	Footpath	Outdoor	125	Low
P	Pebble wash surface	Footpath	Outdoor	127	Low
Q	Asphalt	Carpark	Outdoor	125	Low
R	Metal grate	Footpath	Outdoor	125	Low
S	Tile	Stairs	Outdoor	125	High
T	Metal grate	Carpark	Outdoor	127	Low
W	Concrete	Carpark	Outdoor	125	Low
X	Tactile	Lobby	Outdoor	127	Low
Y	Manhole	Footpath	Outdoor	124	Low
Z	Concrete	Footpath	Outdoor	126	High

The data gathered are subjected to a thorough statistical analysis to understand the potential differences between the data collected at various locations and under different conditions. Descriptive statistics were calculated for each location and condition. Once the statistics are computed, the mean BPN value for each location is used as the baseline for that location. The standard deviation will give you an idea of the variability in surface performance. Box plots were created to visualise the distribution of BPN values across different locations. This is used to observe the spread and identify outliers in the dataset.

A one-way ANOVA test was carried out to compare means across multiple groups (i.e., different locations or conditions). Cohen's d was computed to calculate the effect size which is used to understand the magnitude of differences between the samples gathered at different locations. This is used to draw insights into the magnitude of the differences between different pairs of locations. The understanding of the skid performance over different locations is useful in developing statistical model performance standards in that local context. The observed performance is then compared against the requirements classified in Table 1.

A pedestrian slip and fall risk assessment framework is developed using a random forest classification of this dataset. Random forests are employed to develop a predictive model for assessing slip and fall risks in large campus facilities. They are used in this study due to their capability of handling non-linear relationships, robustness to noise and outliers, feature importance analysis, and avoidance of overfitting. Recent studies in the construction and infrastructure sectors have highlighted the efficacy of random forests in similar contexts [21–23]. The random forest algorithm utilises historical incident data, environmental factors (e.g., floor material and environmental conditions), and foot traffic patterns as input features. By constructing multiple decision trees trained on randomly selected subsets of the data, the random forest algorithm aggregates the outputs of these trees to determine the risk score for different facility zones through majority voting. This ensemble approach effectively captures complex interactions between variables, enabling the accurate identification of high-risk areas. The model's robustness to overfitting and its capability to handle both categorical and continuous variables make it well suited for this evidence-driven analysis, enhancing the predictive accuracy of the slip and fall risk assessment framework.

The classifications (V, W, X, Y, Z) correspond to varying degrees of slip potential, with "V" indicating a very low risk and "Z" representing a very high risk. The data are preprocessed to include the categorical labels based on standard thresholds: V (>54), W (45–54), X (35–44), Y (25–34), and Z (<25). Feature engineering is conducted to include relevant contextual information, such as location, surface type, and environmental conditions. A random forest classifier is used to train the model on the preprocessed data. The model is designed to predict the slip risk category (V, W, X, Y, Z) based on BPN values and additional contextual features. The model is then evaluated to assess the model's performance using cross-validation, focusing on metrics such as accuracy, precision, recall, and F1 score. The programming language Python in a Jupyter environment was used to execute these tasks.

To validate the classification model's effectiveness in predicting slip and fall risks, the dataset was split into training and testing sets to assess model performance and generalisation. K-fold cross-validation was applied to further reduce variability and enhance reliability across different data partitions. Additionally, scenario analysis was used to consider various real-world conditions, such as changes in weather and foot traffic, to evaluate mode robustness, providing a comprehensive validation of the proposed framework.

3. Results

Observations were made across 23 locations, thus establishing a dataset comprising BPN values and contextual information (i.e., surface type, location, weather, and environmental data). A variety of these locations are shown in Appendix B.

The box plots drawn for the different locations and conditions are given in Figures 5 and 6. The same observations made for different tactile surfaces in the laboratory are given in Figure 7. The box plots show that at some locations, the observations are consistently closer to the central tendency, whereas at other locations it varies largely. In some locations, the spread is also wide indicative of a higher variability of the BPN values. Therefore, locations with high medians and narrower spreads can be considered as high-performing surfaces. Interestingly, these observations also show the most consistency in the observations for wet conditions using water flow during testing, followed by the observations made using the ASTM E303 method. Variability during as-is surface conditions and once the surface is cleaned and dried are similarly sporadic.

The ANOVA calculations show low *p*-values, suggesting statistically significant differences between the means of the locations being compared. This indicates t significant differences across locations. Cohen's d results quantify the magnitude of these differences, with large values indicating a substantial effect size. The results suggest differences that are not just statistically significant but also practically significant. Of these observations, many pairwise comparisons show statistically significant differences (small *p*-values), indicating that BPN values vary significantly between different locations. Additionally, overall, the effect sizes (Cohen's d) vary widely, with some comparisons showing large differences in surface performance as discussed above, while others show minimal differences (small Cohen's d).

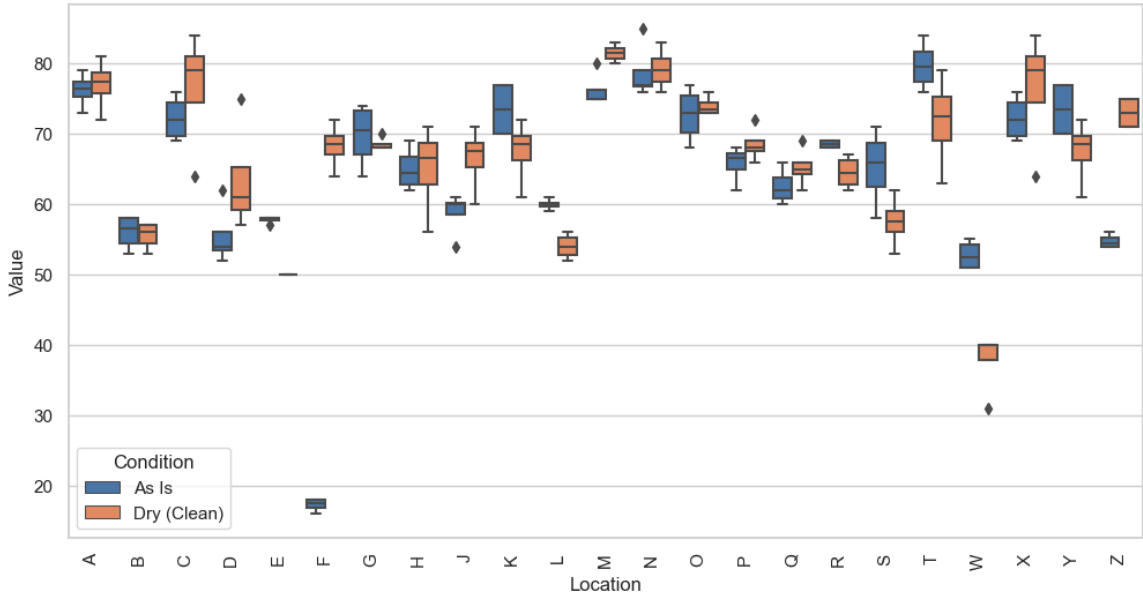

Figure 5. Box plot of values by location and condition (as is, dry (clean)).

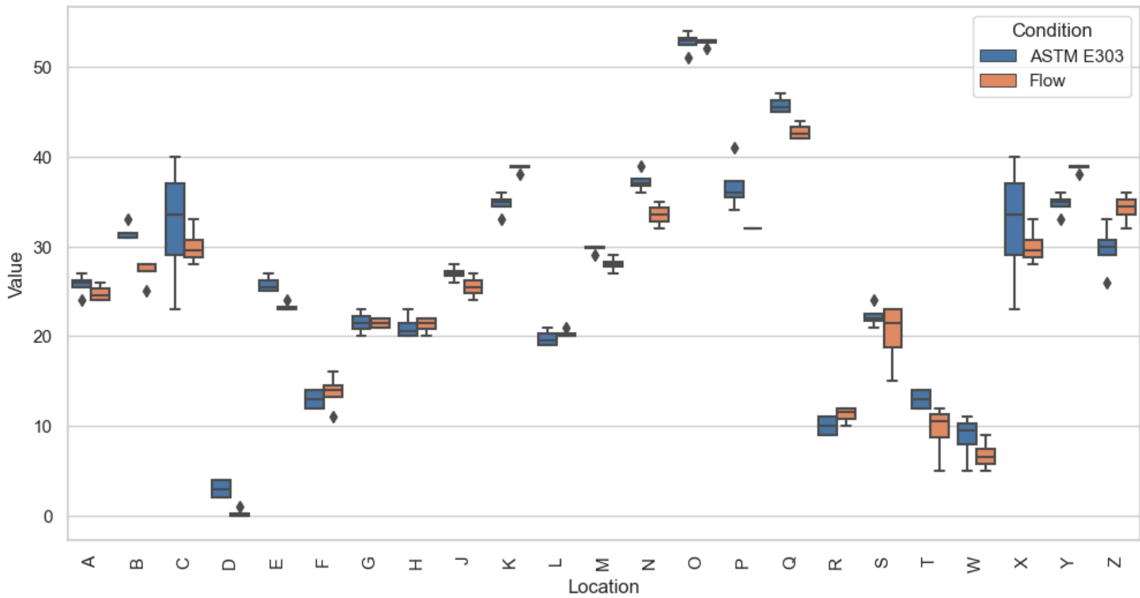

Figure 6. Box plot of values by location and condition (ASTM E303, flow).

Large effects were observed with significant *p*-values between pairs O–W, F–O, E–O, B–O, N–W, C–F, A–W, D–K, G–O, and A–F, in descending order of effect. Locations O and W appear multiple times with very high Cohen's d values compared to others, indicating that they have significantly different means from other locations. Location O with the red brick pavement shows significant differences in many comparisons, often with a very large effect size, suggesting it has distinct characteristics compared to other locations. Whilst it could be due to the substrate materials' properties, locations O and W warrant further examination to understand the difference from the others. These results can be used to isolate and initiate targeted improvements of locations, i.e., to conduct risk assessments. For example, locations with large effect sizes and significant differences in BPN values should be prioritised for intervention to reduce slip risk. The analysis can also help establish performance baselines by identifying which locations have consistently better or worse BPN values, guiding maintenance efforts. The large variability in the current dataset suggests that performance differs across different surface types, making it more suitable for setting differentiated benchmarks. This has a key implication for achieving study objectives, as these statistics can inform data-driven policies and guidelines to enhance pedestrian safety across different campus locations.

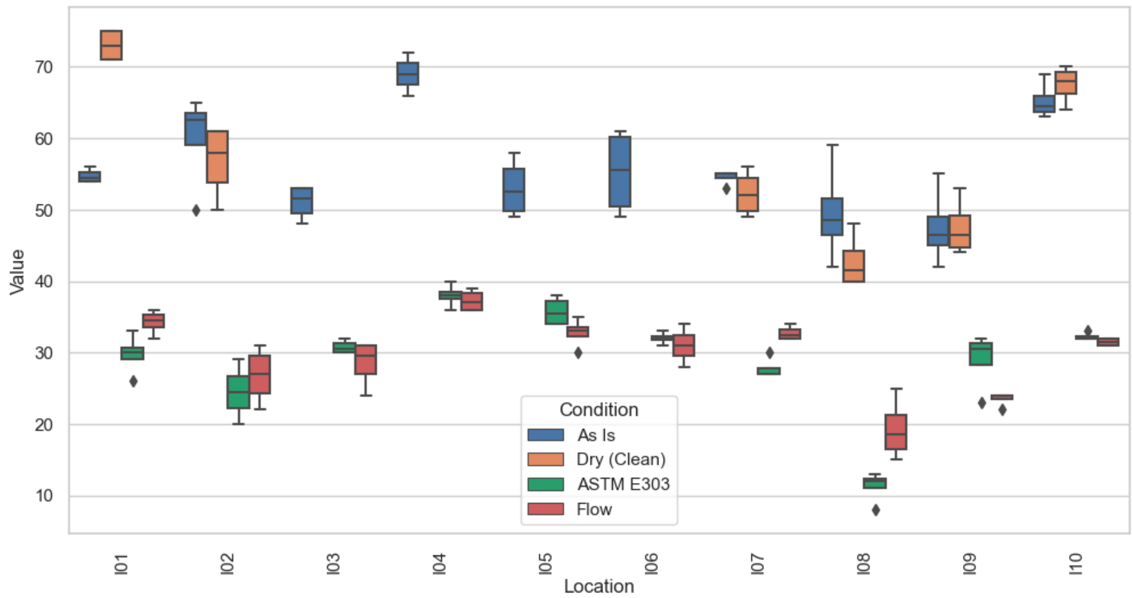

Figure 7. Box plot of values for laboratory observations.

Once the statistics verified the suitability of the dataset for setting differentiated benchmarks, the on-site observation dataset (n = 368) was used to train a random forest classifier model. The dataset was divided into training (70%) and testing (30%) sets to evaluate the model's performance on unseen data. The classifier was trained to classify locations into five risk categories (V, W, X, Y, Z) using the training data. Then, it was used to make predictions on the test set. The results of which are used to assess the model's performance using metrics such as precision, recall, F1 score, and support (see Table 3).

Table 3. Random forest classification model performance.

Mean BPN	Classification	Precision	Recall	F1 Score
>54	V—very low	0.93	0.96	0.95
45 to 54	W—low	0.75	0.67	0.71
35 to 44	X—moderate	0.56	1.00	0.71
25 to 34	Y—high	0.88	0.78	0.82
<25	Z—very high	1.00	0.94	0.97
Accuracy				0.90
Macro average		0.82	0.87	0.93
Weighted average		0.91	0.90	0.90

The results indicate that the model performs exceptionally well for class V (very low risk). This means that almost all the predictions for V were correct, and the model identified instances of class V correctly. The model struggled to identify instances with class W (low risk), likely due to having fewer observations. For class X (moderate risk), the model correctly identifies all instances with perfect recall, but there were false positives. The reason why the model did not make many correct predictions for these classes is possibly due to the small number of samples or overlap in features between these classes and others among the overall datasets. The model's performance for class Y (high risk) is good, which indicates the model makes some correct predictions; it also misclassifies some instances. Excellent metrics were observed with class Z (very high risk), with perfect precision and high recall indicating the model identifies Z instances correctly. The overall accuracy indicates the model will correctly classify 90% of the test instances. The overall performance is good for classes with more data (i.e., V and Z), and relatively poor performance is observed in classes W and X, which is common in datasets with imbalances.

The above metrics for the trained random forest classifier suggest that there might be an imbalance in the dataset, with certain classes like V being overrepresented and others like W and X underrepresented. This imbalance can lead to the model being biased towards the majority class. The model also might be struggling with feature overlap for classes W and X. This occurs when the features distinguishing the classes are similar or overlapping. To overcome this, additional features and more complex interactions between features can be considered to improve overall classification accuracy. However, random forests are known for being able to handle imbalanced datasets more effectively than many other classifiers [24]. Given the potential imbalance in the distribution of BPN observations (e.g., more surfaces may fall into the "V" category than the "X" or "Z" categories), this is a critical advantage. Random forests can also effectively manage the noise and variability of the data to smooth out erratic predictions [18]. Pedestrian surfaces vary widely in terms of material, usage, and environmental exposure. Using the random forest classifier's ability to use categorical data with numerical data improves the adaptability to these variations between multiple features [25], leading to the more accurate classification of slip risks under diverse conditions.

An analysis of the feature importance shows that the condition of the surface and temperature were the most influential factors contributing to the model's decisions, while human traffic (high or low) and exposure (whether indoor or outdoor) contributed the least. This emphasises which variables are important in risk assessment and safety management. In the context of a large campus facility located in a hot–humid tropical climate, surface conditions and temperature emerged as the most influential factors in predicting slip risks. The surface condition is particularly critical in such environments, as the combination of frequent rainfall and high humidity can lead to wet, slippery surfaces, especially on outdoor walkways and entrances. Current findings emphasise the need for constant monitoring and maintenance, from regular cleaning to surface modification works such as the application of anti-slip treatments to prevent accidents. Temperature was also considered as a predictor, and high ambient temperatures may influence the surface slip resistance characteristics leading to slip and fall hazards. This study helps understand the factors which underscore the need for tailored risk mitigation strategies that consider the unique challenges of tropical hot–humid climates towards public pedestrian safety.

In the scenario analysis conducted as part of this study, the robustness of the classification model was tested for various real-world conditions that could impact slip and fall risks in large campus facilities. The scenarios included changes in environmental conditions (i.e., rain and extreme temperatures) and variations in foot traffic (e.g., peak/off-peak hours). The analysis showed that certain environmental factors, such as wet or slippery surfaces during rainy weather, significantly increase the predicted risk scores in specific facility areas like entrances and hallways. High foot traffic periods are likely to show elevated risk predictions in commonly used walkways and near staircases, indicating a strong correlation between congestion and incident risk. Conversely, scenarios involving drier weather and low traffic volumes demonstrated reduced risk scores, reflecting the model's sensitivity to dynamic input variables. These results help validate the framework's ability to adapt to different conditions and provide insights into specific high-risk scenarios, guiding targeted preventive measures and enhancing safety strategies in large campus facilities.

4. Data-Driven Risk Assessment and Benchmarking Framework

The relationship between slip resistance and pedestrian safety is well documented in the literature. Lower friction coefficients (analogous to lower BPN values) significantly increase slip risk [26]. The random forests provide insights into the importance of different features (e.g., specific conditions or environmental factors) in predicting the BPN value and thus the slip potential of a surface. This capability is crucial in a risk assessment context, as it helps prioritise which factors need the most attention in mitigating slip risks. Risk assessment in this context involves identifying surfaces with low BPN values, which correspond to a higher potential for slips and falls. This is crucial as slips, trips, and falls represent significant causes of injuries in public spaces, contributing to both direct (medical costs, legal liabilities) and indirect (lost productivity, reputation damage) costs. Understanding the importance of various predictors allows for more targeted interventions in surface maintenance and safety planning. A fully trained model with high prediction accuracy can be used to classify each pedestrian surface of a large campus facility into one of the five slip risk categories, providing a granular risk profile for different areas within the campus.

Similarly, the classification results can be used to set baseline safety standards for different surface types and use cases. They serve as a reference for future risk assessments and safety improvements. Based on the risk categories, safety interventions (e.g., increased inspections, surface treatments, signage, and maintenance schedules) can be prioritised for areas with high and very high slip potential, based on the risk categories. Inspection and ongoing monitoring plans can be used to update the risk assessment with new observations. With the availability of new data, the random forest can be retrained periodically to incorporate the latest conditions throughout the facility. This helps update the performance standards to ensure they remain relevant and effective.

This data-driven risk assessment framework can thus be used to create benchmarks for surface maintenance and improvements based on the performance standards. Benchmarking as a concept in safety management is supported by the idea that standards and thresholds should be grounded in empirical data. The authors in [27] argue that benchmarking provides a critical reference point for continuous improvement in safety performance, especially in dynamic environments, such as healthcare or large campus facilities. This dataset provides the empirical basis needed to establish such benchmarks, ensuring that the performance standards are not only theoretically sound but also practically applicable.

5. Discussion

This study on pedestrian surface safety using the BPN contributes significantly to the fields of facility management and safety management by providing a comprehensive evaluation of slip risks across various surface types and conditions. Through comparative analysis, the research identifies the performance of different pedestrian surfaces under varying environmental conditions, such as wet and dry states, offering valuable insights into which surfaces are safer and under what circumstances. This analysis not only aids in identifying safer pedestrian pathways but also evaluates the effectiveness of surface treatments and modifications, thereby contributing to best practices for enhancing pedestrian safety.

One of the critical contributions of this study is the establishment of baseline BPN values for various surface types within a large campus environment. These baselines serve as benchmarks for future safety assessments and performance standards, allowing for more accurate and localised safety guidelines tailored to the specific conditions of the campus. This study also delves into how different surface conditions impact slip resistance, providing a deeper understanding of the dynamics at play. This knowledge has practical implications for surface maintenance and cleanliness, informing more effective maintenance schedules and procedures to enhance safety.

BPN is a widely recognized measure often used to assess the potential slip risk of pedestrian surfaces. Higher BPN values generally indicate better slip resistance and, consequently, lower slip potential. A dataset was developed by manual data collection from various locations on a campus, comprising BPN values and other contextual data. A random forest model was developed to be used to predict which conditions or locations are most likely to result in BPN values below a critical threshold, indicating high slip potential. This predictive modelling helps in proactive risk management by identifying and mitigating hazards before accidents occur. A data-driven risk assessment and benchmarking framework is proposed, where baseline BPN values against which future BPN measurements can be compared. For example, if a surface's BPN value falls significantly below its established baseline, it would signal that the surface has degraded or that maintenance is needed.

Based on this framework, surfaces across the campus can be categorised. Surfaces falling into the low slip resistance category would require attention. This framework, therefore, can help pinpoint specific locations on campus with higher slip risks due to lower BPN values. This information is crucial for campus safety management to target high-risk areas with interventions such as resurfacing, improved cleaning protocols, or the installation of slip-resistant materials. It contributes to informed decision making. By understanding the conditions that lead to low BPN values, facility managers can make informed decisions about where to allocate resources most effectively to enhance pedestrian safety. This framework is robust and adaptable to be continually improved with ongoing monitoring data. Periodic updates to the dataset can retrain the model to ensure the benchmarks and safety interventions remain relevant, contributing to a continuous improvement process in campus safety management.

The proposed approach leverages empirical data to assess and manage slip risks, making the process more objective and evidence-based. This is a significant improvement over relying solely on expert judgment or anecdotal evidence. The findings from this study can be further integrated to update performance standards and guidelines for different floor covering materials, ensuring that these guidelines reflect the most current and relevant data. Moreover, this approach helps clearly communicate recommendations for maintaining and improving surface performance, including specific actions to take when BPN values fall below acceptable levels. And, by extension, to ensure the pedestrians using the campus facilities are safe from slips and falls by helping to effectively allocate resources to safety awareness activities.

At the same time, it ensures an evidence-based approach to pedestrian safety awareness programmes. For example, from the three benchmark locations A to C, when tested with a film of sprayed water (ASTM E303), although all show a reduction in BPN, the final BPNs for all the cases are ranked from "moderate" to "low risk." However, when tested on other locations, the results show that with a film of sprayed water, the frictional resistance of the wet surfaces for all cases was reduced 2 to 3 times compared to that of the corresponding dry surfaces. Similar results were obtained for features including ceramic tiles, pebbles, tactile indicators, and metal coverings for manholes and drainage. This study reinforces the need for awareness of pedestrians when walking over features installed on rough concrete pavements. Those features may appear as slip-resistant as the adjacent rough concrete pavement when dry but may be up to three times more slippery when wet. The perceived affordance to the general public that a feature such as a tactile indicator would give a higher grip or traction requires urgent attention.

The situation can be further exacerbated when a pedestrian is using a slope, in which case the frictional resistance required can be computed based on the forward force and the weight of the pedestrian. In these cases, a higher "Pendulum Test Value" (PTV) to prevent slips on slopes is required. The Health and Safety Executive (HSE) recommends that for a horizontal floor where a Pendulum Test Value of 36 PTV on a wet or contaminated floor is required to ensure a "Low Slip Potential", for every one degree of slope, the PTV value shall be increased by 1.75 PTV. It is suggested to use approximately 2 PTV per degree to allow for tolerancing and floor wear [10].

These considerations and features are to be applied to the classifier in future work. Further future work may include spatial mapping of the classified risk categories onto a campus layout to visualise areas of varying slip potential. This mapping helps identify high-risk zones (Y and Z categories) that require immediate attention.

The integration of advanced statistical models, including random forest classifiers, marks a significant advancement in the predictive modelling of slip risks. Unlike traditional threshold-based assessments, the random forest approach considers a broader set of features, allowing for more nuanced and accurate predictions of slip potential. This innovation is particularly valuable in complex pedestrian environments where safety is a priority. This study's classification framework, which categorises surfaces into specific risk levels, provides actionable insights for targeted safety interventions. This targeted approach ensures that resources are allocated efficiently, focusing on the highest-risk areas to enhance overall pedestrian safety.

Furthermore, this research contributes to the development of benchmarking standards for slip resistance, offering a consistent framework for evaluating and improving pedestrian safety across different environments. These standards can be adopted by other facility typologies, contributing to a broader impact on pedestrian safety management.

From an academic perspective, this work bridges the gap between infrastructure management, safety engineering, and machine learning, demonstrating the applicability of data-driven approaches in solving practical safety challenges. The findings not only contribute to the existing body of knowledge but also pave the way for future research and development in pedestrian surface safety, offering a robust foundation for ongoing improvements in facility asset and safety management.

6. Conclusions

Pendulum slip resistance tests were conducted on 23 sites covering ceramic tiles, pebbles, and features such as tactile indicators and metal coverings for manholes and drainage. The results show that the reduction in frictional resistance can be reduced when tested wet for all cases. Similar observations were derived from laboratory tests under controlled conditions. Pedestrians must pay special attention when stepping over features including tactile indicators, manhole covers, coatings, etc., when wet. The reduction in frictional resistance is further exacerbated if the features are installed on a slope. The perceived affordance of certain features such as tactile indicators providing a better grip or traction requires urgent attention.

By integrating statistical analyses with machine learning models, this study offers a robust framework for assessing slip risks, benchmarking surface performance, and guiding targeted safety interventions within large and complex environments, such as a university campus. This data-driven approach not only enhances the accuracy of slip risk assessments but also establishes empirically grounded benchmarks for surface safety, ensuring that interventions are both effective and resource-efficient.

This study makes a significant contribution to the field of pedestrian safety and risk management by demonstrating how advanced analytical methods can improve the understanding and management of slip risks. The proposed framework and the insights derived from the BPN dataset offer a replicable model that can be adapted by other institutions, providing a strong foundation for future benchmarking and risk management efforts in diverse environments.

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Appendix A

Figure A1. Tactile indicators.

Figure A2. Metal coverings on ramps and manholes.

Figure A3. Drainage metal grills.

Appendix B

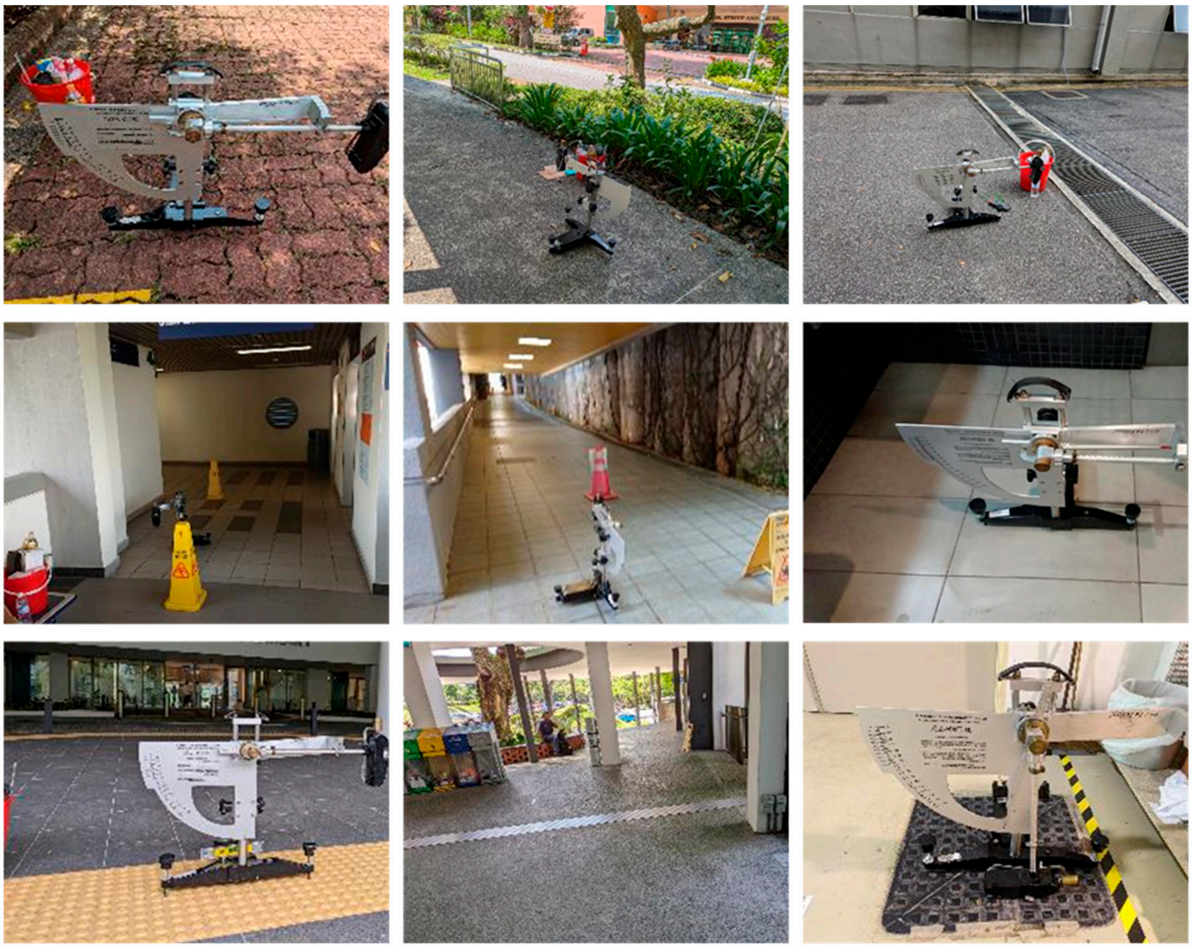

Figure A4. *Cont.*

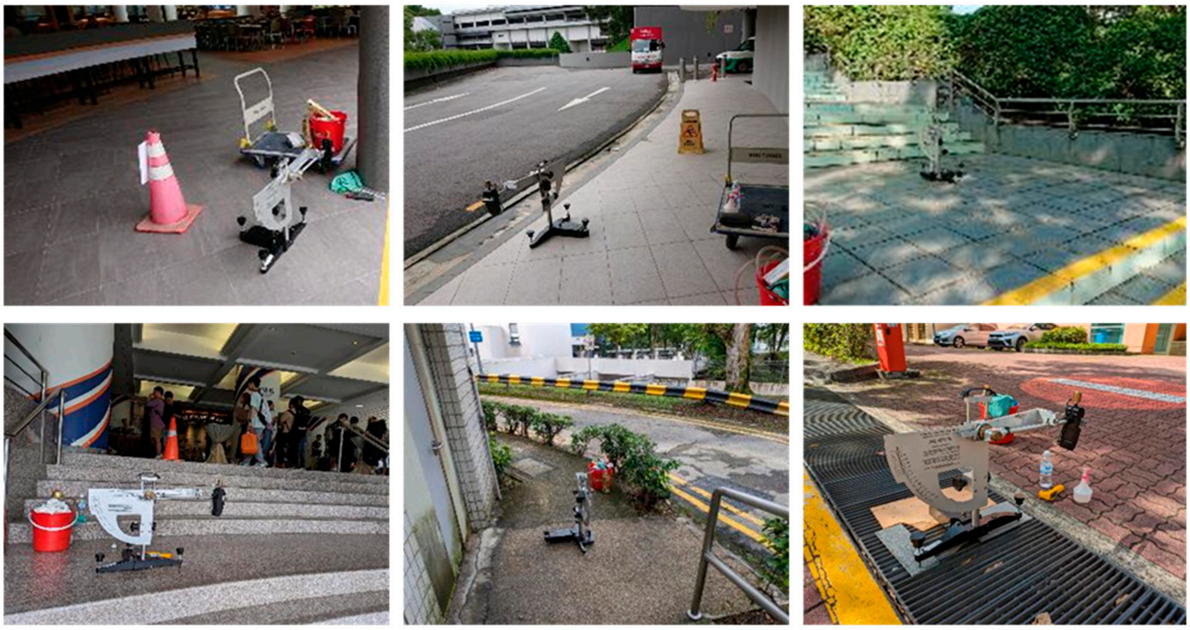

Figure A4. Example portable skid resistance test locations.

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