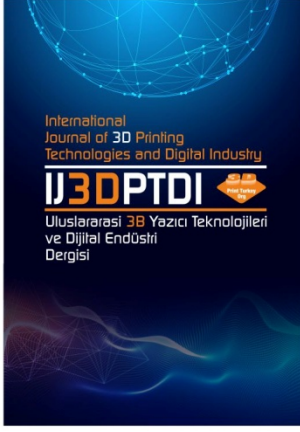




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AN INTEGRATED SLIP RISK ASSESSMENT FRAMEWORK FOR HOSPITAL ENVIRONMENTS USING IN SITU FRICTION MEASUREMENTS AND MACHINE LEARNING

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ABSTRACT

Slip-related accidents remain a critical safety challenge in hospital environments due to high pedestrian traffic, frequent contamination, and heterogeneous flooring conditions. This study proposes a novel and integrative framework for slip risk assessment based on in situ friction measurements, statistical analysis, machine learning, and explainable artificial intelligence. Dynamic Coefficient of Friction (DCOF) measurements were collected from two public hospitals across five functional zones (corridors, patient rooms, toilets, showers, and examination rooms), under both dry and wet conditions, resulting in a dataset of 540 observations. A composite Slip Risk Index (SRI) was developed by integrating frictional performance with environmental, spatial, and material-related factors through a weighted aggregation scheme. Paired-sample statistical analyses confirmed a very strong inverse relationship between DCOF and SRI, while correlation and feature importance analyses revealed that environmental condition and flooring material act as significant secondary contributors. Ensemble-based machine learning models, including Random Forest, Gradient Boosting, Bagging, CatBoost, XGBoost, and LightGBM, were employed to predict SRI values. Among these, Gradient Boosting demonstrated the most robust and balanced performance, achieving near-perfect goodness-of-fit and minimal prediction error. Explainable machine learning analysis using SHAP further validated the dominance of frictional performance in slip risk formation and ensured model transparency. The proposed framework bridges the gap between traditional tribological assessment and data-driven predictive safety management by providing an interpretable, accurate, and scalable decision-support tool. The findings offer actionable insights for hospital designers, facility managers, and safety engineers, supporting evidence-based flooring selection, environmental control, and preventive maintenance strategies aimed at reducing slip-and-fall accidents in healthcare environments.

Keywords: Slip Risk Index, Dynamic Coefficient of Friction, Hospital Floor Safety, Machine Learning.

1. INTRODUCTION

Slip and fall accidents constitute a major public health and occupational safety concern worldwide and remain among the leading causes of unintentional injuries. Globally, such incidents are ranked as the second most frequent cause of accidental injuries, following traffic-related accidents. According to the U.S. Bureau of Labor Statistics, more than 805 fatalities and 211,640 nonfatal injuries were attributed to workplace slips and falls in 2020 [1]. Similarly, in Türkiye, official statistics reported 58,979 slip-and-fall-related occupational accidents in 2019, resulting in 205 fatalities [2]. The

prevalence and severity of these incidents underscore the urgent need for effective risk mitigation strategies aimed at enhancing pedestrian safety in both occupational and public environments.

One of the most critical determinants of pedestrian safety is the slip resistance of flooring surfaces, which is governed by the complex interaction between footwear and floor materials under varying environmental and operational conditions. Prior research has demonstrated that this interaction is highly sensitive to multiple factors, including the

presence of contaminants (e.g., water, oil, dust), surface wear induced by repetitive foot traffic, surface roughness characteristics, lighting conditions, and pedestrian behavior [3–6]. Among the available indicators, the dynamic coefficient of friction (DCOF) is widely adopted as a reliable and standardized metric for evaluating floor safety under both dry and wet conditions [7-8].

Maintaining adequate slip resistance over time remains a persistent challenge, particularly in high-traffic public buildings. Waluś et al. (2022) reported that intensive use in public utility facilities leads to pronounced surface wear in areas such as staircases and elevator entrances, significantly increasing slip risk [9]. In healthcare environments, this risk is further exacerbated by frequent pedestrian movement, routine cleaning practices, and the presence of diverse contaminants. Beschoner and Randolph (2023) demonstrated that common hospital contaminants, including hand sanitizer and canola oil, substantially reduce friction levels on resilient flooring materials [10]. Likewise, Çoşkun and Bendak (2023) revealed that a considerable proportion of hospital floor surfaces in Türkiye failed to satisfy established slip-resistance criteria, particularly under wet conditions, highlighting the vulnerability of healthcare facilities to slip-related hazards [11]. From a tribological and material science perspective, flooring material type (e.g., ceramic tile, PVC, laminate) and surface roughness play a decisive role in determining slip resistance. Textured or roughened surfaces may enhance traction by facilitating contaminant drainage and mitigating squeeze-film effects [12]. However, the effectiveness of such features deteriorates over time due to wear and is strongly influenced by maintenance practices and environmental exposure. These interdependencies necessitate a multidimensional assessment framework that extends beyond isolated friction measurements to incorporate contextual, environmental, and functional characteristics of floor usage.

In recent years, machine learning (ML) techniques have gained increasing attention for modeling the nonlinear and complex relationships inherent in slip risk analysis. Ensemble learning approaches, such as Random Forest, Gradient Boosting, and XGBoost, have demonstrated superior predictive capabilities in

friction and safety-related applications. Midtfjord et al. (2022), for instance, employed an XGBoost–SHAP framework for real-time runway friction estimation, achieving a high predictive performance (ROC AUC = 0.95) while offering transparent model interpretability [13]. Similarly, Sarıışık and Çoşkun (2025) applied ML-based classification models to assess slip risk in public service buildings and identified environmental conditions as the most influential determinant of DCOF, emphasizing the value of explainable artificial intelligence for facility-level safety interventions [14].

Despite these methodological advancements, research focusing specifically on hospital environments remains limited. Even fewer studies have adopted an integrated framework that combines statistical inference, ensemble machine learning, and explainable AI techniques. Moreover, a substantial portion of the existing literature relies on laboratory-based experiments or simulated contamination scenarios, which may not adequately capture the complexity and variability of real-world hospital conditions.

Recent post-2023 research indexed in Web of Science demonstrates a clear shift toward artificial intelligence–driven and explainable modeling approaches for slip resistance and safety assessment. Lau et al. (2024, 2025) showed that machine learning models, including support vector classifiers and deep convolutional neural networks, can successfully classify slip-resistant footwear based on outsole material, geometry, and frictional performance, highlighting the potential of data-driven methods to capture complex tribological patterns that are not easily addressed by conventional threshold-based evaluations [15-16]. Similarly, Wieczorek et al. (2025) investigated slip risk on 3D-printed surfaces and demonstrated that material type and wet–dry interaction effects dominate slip performance, reinforcing the need for multidimensional assessment beyond surface roughness alone[17]. In healthcare-specific contexts, recent studies have emphasized the critical role of environmental conditions and contamination in shaping friction performance and safety outcomes[18]. Moreover, explainable machine learning frameworks using SHAP and LIME have recently been adopted in

medical environments to transparently identify dominant environmental risk drivers and support facility-level decision making[19]. Despite these advances, existing studies predominantly focus on either footwear, material manufacturing, or environmental comfort in isolation, and rarely integrate in situ hospital floor measurements with ensemble learning and explainable AI within a unified slip risk metric. Consequently, a clear gap remains for hospital-focused studies that operationalize friction data, environmental conditions, and functional space characteristics into an interpretable and predictive SRI, which the present study aims to address. Recent studies have highlighted the growing role of artificial intelligence-driven decision-support frameworks in complex operational environments, particularly where safety, efficiency, and sustainability objectives intersect. For instance, agentic and explainable AI approaches have been successfully applied to optimize resource-intensive systems and improve risk-aware decision making under dynamic conditions, demonstrating the value of adaptive and transparent models beyond traditional rule-based evaluations [20–23]. These advancements reinforce the relevance of data-driven, interpretable, and sustainability-oriented AI frameworks, supporting the methodological foundation of the present study in hospital slip risk assessment.

Main contributions of this study can be summarized as follows: (i) a novel and composite Slip Risk Index (SRI) is developed by systematically integrating frictional performance (DCOF), environmental conditions, flooring material characteristics, and functional space attributes using in situ hospital measurements; (ii) the study combines classical statistical inference with ensemble machine learning models and SHAP-based explainable artificial intelligence to ensure both high predictive accuracy and transparent interpretation of slip risk drivers; and (iii) unlike prior laboratory-based or single-factor studies, the proposed framework provides a scalable, data-driven, and decision-oriented methodology that supports practical risk mitigation strategies for real hospital environments under both dry and wet conditions.

In this context, the present study introduces a novel and integrative framework that advances the current slip safety literature in several key aspects. Unlike existing studies that predominantly focus on isolated friction measurements or single-model predictions, this research proposes a composite SRI that systematically integrates frictional performance (DCOF), environmental conditions, flooring material properties, and functional space characteristics within real hospital environments. By jointly employing paired statistical analyses, correlation-based importance ranking, ensemble machine learning models, and SHAP-based explainable artificial intelligence, the study bridges the gap between traditional tribological assessment and data-driven predictive safety management. Furthermore, the use of in situ measurements across multiple hospital zones under both dry and wet conditions addresses a critical limitation of prior laboratory-based or simulation-driven studies. Through this multidimensional and interpretable approach, the study not only enhances predictive accuracy but also delivers actionable and transparent insights for facility managers and safety engineers, thereby filling an important methodological and practical gap in hospital slip risk assessment and offering a scalable decision-support framework for safer healthcare environments.

2. METHODOLOGY

This study employed an integrative methodological framework combining in situ friction measurements with data-driven predictive modeling to assess slip risks in hospital environments. The approach comprised four core components: (1) systematic field measurement of floor slipperiness, (2) statistical analysis to identify significant risk factors, (3) machine learning-based predictive modeling and interpretability, and (4) data encoding and composite SRI computation to support holistic risk assessment.

2.1. Field Measurement Protocol

DCOF measurements were conducted in two public hospitals located in Türkiye—one in Istanbul and the other in Sivas. These institutions were selected for their differing geographical and infrastructural characteristics. To ensure comprehensive environmental coverage, friction data were collected from five

distinct functional zones: patient rooms, toilets, showers, corridors, and examination rooms.

Each zone was evaluated under both dry and wet conditions to reflect realistic usage scenarios. Measurements were taken at three intra-room positions (side, center, and opposite side) using a standardized tribological instrument compliant with DIN 51131 [24]. The DCOF values were adopted as a quantitative indicator of slip resistance following widely accepted interpretation thresholds:

- $\mu \leq 0.20$: Unsafe
- $0.20 < \mu \leq 0.40$: Provisionally safe
- $0.40 < \mu \leq 0.60$: Safe
- $\mu > 0.60$: Very safe

The final dataset consisted of 540 friction readings obtained across both hospitals. Floor materials varied by functional zone, with PVC vinyl predominantly used in dry areas (e.g., corridors and patient rooms) and ceramic tile primarily installed in wet environments (e.g., toilets and showers).

2.2. Statistical Analysis

Descriptive statistics were initially computed to summarize the distribution of DCOF values across hospitals, environmental conditions, floor materials, functional zones, and measurement locations. One-sample *t*-tests were conducted to evaluate whether observed mean DCOF values significantly deviated from a neutral reference baseline. Subsequently, a three-way analysis of variance (ANOVA) was performed to examine the main and interaction effects of environmental condition (dry vs. wet), floor material (PVC vs. ceramic), and functional zone on DCOF. Pearson correlation coefficients were also calculated to explore interdependencies among the studied variables.

2.3. Predictive Modeling and Feature Importance Analysis

Machine learning (ML), a subfield of artificial intelligence, enables algorithms to learn patterns from data and generate predictions without explicit programming. In recent years, ML techniques have been increasingly applied in safety-critical domains including built environment analysis and healthcare infrastructure owing to their capacity to capture nonlinear relationships and enhance predictive accuracy. These advantages are particularly

relevant in hospital environments, where varying surface conditions significantly influence pedestrian slip risk.

In this study, six ensemble-based ML algorithms—Random Forest, Gradient Boosting, Bagging, CatBoost, XGBoost, and LightGBM—were employed to predict DCOF values based on environmental and spatial descriptors, including surface condition, floor material, functional zone, and measurement location. These models were selected due to their robustness, resistance to overfitting, and proven effectiveness in tribological and friction-related applications. To ensure the robustness, generalizability, and reliability of the predictive models, a stratified *k*-fold cross-validation strategy was adopted for all machine learning algorithms. Specifically, the dataset was partitioned into $k = 10$ folds, where in each iteration nine folds were used for training and the remaining fold for validation. This procedure was repeated until each fold had served as the validation set once, and the reported performance metrics represent the mean values across all folds. Stratification was applied with respect to environmental condition (dry vs. wet) to preserve the original class distribution within each fold. The choice of 10-fold cross-validation was motivated by its widespread acceptance in predictive modeling studies as an effective balance between bias and variance, particularly for datasets of moderate size. This approach reduces the dependency of model performance on a single random train–test split and enhances model stability against sampling variability. Potential limitations of this validation strategy include increased computational cost and the assumption of independence among observations; however, given the controlled measurement protocol and the absence of temporal dependence, these limitations are not expected to bias the reported results. To improve model transparency and interpretability, SHapley Additive exPlanations (SHAP) analysis was applied, primarily focusing on the Gradient Boosting model. SHAP results indicated that surface condition (wet vs. dry) and floor type (PVC vs. ceramic) were the most influential predictors of DCOF, consistent with statistical findings. Wet areas such as toilets and showers exhibited negative contributions to slip resistance, particularly under moisture exposure. In parallel, feature importance analysis using XGBoost revealed

that environmental condition accounted for more than 50% of the model's predictive contribution, followed by floor type and functional zone. The consistency between SHAP and model-internal importance metrics

validated the robustness of the findings. A summary of the machine learning models used in the study, including their theoretical foundations and mathematical formulations, is provided in Table 1.

Table 1. Summary of Machine Learning Models Used for DCOF Prediction

Model	Description	Core Principle	Representative Mathematical Formulation	Key References
Random Forest	Ensemble of decision trees trained on bootstrapped datasets; reduces variance and improves generalization.	Bootstrap aggregating (Bagging)	$h(x) = \frac{1}{B} \left(\sum_{b=1}^B h_b(x) \right)$	[25-26]
Gradient Boosting	Sequential ensemble that iteratively minimizes prediction error by fitting weak learners to residuals.	Additive stage-wise optimization	$\text{Residual}_i(m) = \left[\frac{\partial L(y_i, F_{m-1}(x_i))}{\partial F_{m-1}(x_i)} \right]$	[27-28]
Bagging	Parallel aggregation of multiple base learners trained on resampled datasets to reduce overfitting.	Bootstrap resampling and averaging	$\hat{f}(x) = \frac{1}{B} \sum_{b=1}^B f^b(x)$	[29-30]
CatBoost	Gradient boosting algorithm optimized for categorical features; mitigates target leakage using ordered boosting.	Ordered boosting with symmetric trees	$L = \sum_{i=1}^N (y_i - f((x_i)))^2 + \lambda \sum_{j=1}^M w_j^2$	[31-32]
XGBoost	Regularized gradient boosting framework using second-order Taylor approximation for efficient optimization.	Boosted trees with regularization	$w_j = - \frac{\sum_{i \in I_j} g_i}{\sum_{i \in I_j} gh_i + \lambda}$	[33-35]
LightGBM	Histogram-based, leaf-wise gradient boosting algorithm with high scalability and efficiency.	Gradient-based one-side sampling (GOSS)	$\Omega(x) = \gamma T + \frac{1}{2} \lambda \sum_{j=1}^T w_j^2$	[36-37]

2.4. Data Encoding and SRI Computation

To enable quantitative analysis and integration of heterogeneous variables, all categorical descriptors in the dataset—including hospital identity, environmental condition, functional area, floor material, and measurement location—were numerically encoded using an automatic categorical indexing procedure. This approach is consistent with established practices in flooring tribology and slip-resistance analytics, where contextual variables are incorporated into predictive frameworks through reproducible integer mappings[10,38]. The encoding strategy does not impose artificial ordinal meaning but ensures systematic representation of spatial and environmental attributes.

Surface friction, quantified by the Dynamic Coefficient of Friction (DCOF), was retained as the principal continuous variable due to its

dominant role in slip initiation. Experimental studies consistently demonstrate that slip probability increases markedly as DCOF decreases, particularly under liquid contamination and variable surface textures [39]. To operationalize this inverse relationship, a normalized friction-based risk component was defined as:

$$RD = (1 - D) \times 100 \quad (1)$$

where D represents the experimentally measured DCOF value. This transformation scales friction-related risk to a 0–100 hazard range, consistent with slip-risk assessment practices and international standards such as ANSI A326.3 and NFSI B101.3[40,41].

To obtain an integrated and interpretable slip-risk metric, a weighted linear aggregation model was constructed by combining encoded

contextual variables with the DCOF-derived risk component. The resulting SRI is expressed as:

$$SRI = 0.05H + 0.15C + 0.10P + 0.20F + 0.05L + 0.45R_D \quad (2)$$

where H denotes hospital code (1: Hospital 1, 2: Hospital 2), C represents environmental condition (dry/wet), P indicates functional area (corridors, patient rooms, toilets, showers, examination rooms), F corresponds to floor type (PVC vinyl or ceramic tile), L denotes measurement location (side, center, opposite side), and R_D is the normalized DCOF-based risk term.

The weighting coefficients were determined through a hybrid, literature-informed and empirically validated rationale. First, the dominant weight assigned to the friction-related component ($R_D = 0.45$) reflects the well-established primacy of surface friction in slip biomechanics and fall initiation, consistently reported across tribological, ergonomic, and healthcare safety studies [6,11,39]. Environmental condition ($C = 0.15$) and floor material ($F = 0.20$) were assigned intermediate weights based on extensive empirical evidence demonstrating their strong moderating influence on friction degradation under wet or contaminated conditions [28,39]. Functional area ($P = 0.10$) was included to capture usage-related exposure differences inherent to hospital spaces, while hospital identity ($H = 0.05$) and intra-room measurement location ($L = 0.05$) were deliberately assigned lower weights due to their limited and inconsistent influence on slip risk reported in prior studies and confirmed by preliminary correlation analyses conducted in this work.

To assess the robustness of the proposed weighting structure, alternative weighting schemes were examined through sensitivity analyses, including (i) equal-weight allocation across all variables and (ii) friction-dominant variants with redistributed minor weights among contextual factors. These alternative

configurations yielded highly consistent ranking patterns and predictive performance, with no material change in the identification of high-risk surfaces or zones. Given this stability, the presented weighting scheme was retained as the most physically interpretable and empirically grounded formulation.

The resulting SRI is a continuous, dimensionless indicator in which higher values correspond to elevated slip hazard. This formulation facilitates structured comparison across hospitals, flooring materials, environmental conditions, and functional zones, and additionally provides a robust engineered feature for subsequent machine learning-based predictive analyses.

3. RESULTS

3.1. Paired Sample Analysis between SRI and Floor Safety Parameters

The relationship between the proposed SRI and the primary environmental, spatial, and friction-related variables was examined using paired-sample analyses. This approach enables a direct comparison between SRI and each contributing parameter across the full dataset ($N = 540$). The descriptive paired statistics are summarized in Table 2, followed by the correlation results (Table 3) and paired-sample t-test outcomes (Table 4).

As presented in Table 2, the mean Dynamic Coefficient of Friction (DCOF) across all observations was 0.3334 ($SD = 0.1358$), while the corresponding mean SRI was 30.9967 ($SD = 6.5010$). The relatively low standard error values indicate stable estimates and a consistent distribution of both variables across measurement conditions. Similarly, the paired descriptive statistics for categorical variables (Hospital, Conditions, Place, Floor Type, and Location) demonstrate uniform representation across the dataset, with mean values closely aligned with their respective coding schemes. Notably, the SRI exhibited identical mean and dispersion characteristics across all pairings, confirming that it is a composite metric consistently derived from the same observational structure.

Table 2. Paired Samples Statistics between SRI and Key Variables (N = 540)

Variables	Mean	N	STD	SEM
DCOF/SRI	0.3334 / 30.9967	540	0.1358 /6.5010	0.0058 /0.2798
H/SRI	1.5000 / 30.9967	540	0.5005 /6.5010	0.0215 /0.2798
C/SRI	1.5000 / 30.9967	540	0.5005 /6.5010	0.0215 /0.2798
P/SRI	2.8000 / 30.9967	540	1.2232 /6.5010	0.0526 /0.2798
FT/SRI	1.5333 / 30.9967	540	0.4994 /6.5010	0.0215 /0.2798
L/SRI	2.0000 / 30.9967	540	0.8173 /6.5010	0.0352 /0.2798

Note: H: Hospital C. Conditions, P:Place, FT:Floor Type, L:Location, STD: Standard Deviation, SEM:Std. Error Mean

The strength and direction of the linear association between SRI and each explanatory variable were evaluated using paired-sample correlation analysis. The results are presented in Table 3.

A very strong negative correlation was observed between DCOF and SRI ($r = -0.909$, $p < 0.001$), confirming that lower friction values are associated with substantially higher slip risk levels. This finding empirically validates the conceptual structure of the SRI and aligns with established tribological theory, which identifies surface friction as the dominant determinant of pedestrian slip risk.

Among the categorical variables, *Conditions* exhibited a strong positive correlation with SRI ($r = 0.719$, $p < 0.001$), indicating that wet environments significantly elevate slip risk. *Floor Type* ($r = 0.483$, $p < 0.001$) and *Place* ($r = 0.397$, $p < 0.001$) also demonstrated moderate positive correlations, suggesting that both material properties and functional zones contribute meaningfully to overall risk levels. In contrast, *Hospital* and *Location* showed weak and statistically insignificant correlations with SRI ($p > 0.05$), implying that institutional differences and intra-room measurement positions have a comparatively minor influence.

Table 3. Paired Samples Correlations between SRI and Key Variables (N = 540)

Variables	Correlation (r)	Sig.
DCOF/SRI	-0.909	<0.001
H/SRI	0.071	0.100
C/SRI	0.719	<0.001
P/SRI	0.397	<0.001
FT/SRI	0.483	<0.001
L/SRI	0.035	0.412

To statistically assess whether the mean differences between SRI and each paired variable were significant, paired-sample *t*-tests were conducted. The results are summarized in Table 4.

All paired comparisons yielded highly significant results ($p < 0.001$), with large absolute *t*-values, indicating that SRI differs substantially from each individual variable. The largest mean difference was observed for the DCOF–SRI pairing (mean difference = -30.66 , $t = -107.56$), further reinforcing the dominant influence of frictional performance on slip risk magnitude.

The consistently narrow 95% confidence intervals across all pairs indicate high statistical reliability and robustness of the estimated differences. Collectively, these findings confirm that SRI is not a trivial transformation of any single input variable but rather a comprehensive risk metric that integrates frictional, environmental, and spatial characteristics into a statistically distinct construct.

The paired sample analyses provide strong statistical evidence supporting the validity and sensitivity of the proposed SRI. The exceptionally strong inverse relationship between DCOF and SRI confirms the central role of surface friction in slip risk formation, while the significant contributions of environmental condition, floor type, and functional zone underscore the multifactorial nature of slip hazards in hospital environments. These findings demonstrate that the SRI offers a robust, interpretable, and statistically sound framework for integrated floor safety assessment and subsequent predictive modeling.

Table 4. Paired Samples *t*-Test Results between SRI and Key Variables (N = 540)

Variables	Mean Difference	<i>t</i>	df	Sig. (2-tailed)
DCOF/SRI	−30.66	−107.56	539	<0.001
H/SRI	−29.50	−105.70	539	<0.001
C/SRI	−29.50	−111.43	539	<0.001
P/SRI	−28.20	−107.08	539	<0.001
FT/SRI	−29.46	−109.11	539	<0.001
L/SRI	−29.00	−103.29	539	<0.001

3.2. Correlation Structure between SRI and Floor-Related Parameters

The interrelationships among the studied variables and their individual contributions to slip risk formation were examined by constructing a correlation matrix based on coefficients of determination (R^2). The results are illustrated in Figure 1, which presents the pairwise associations between hospital-related parameters, environmental conditions, spatial characteristics, frictional performance (DCOF), and the SRI.

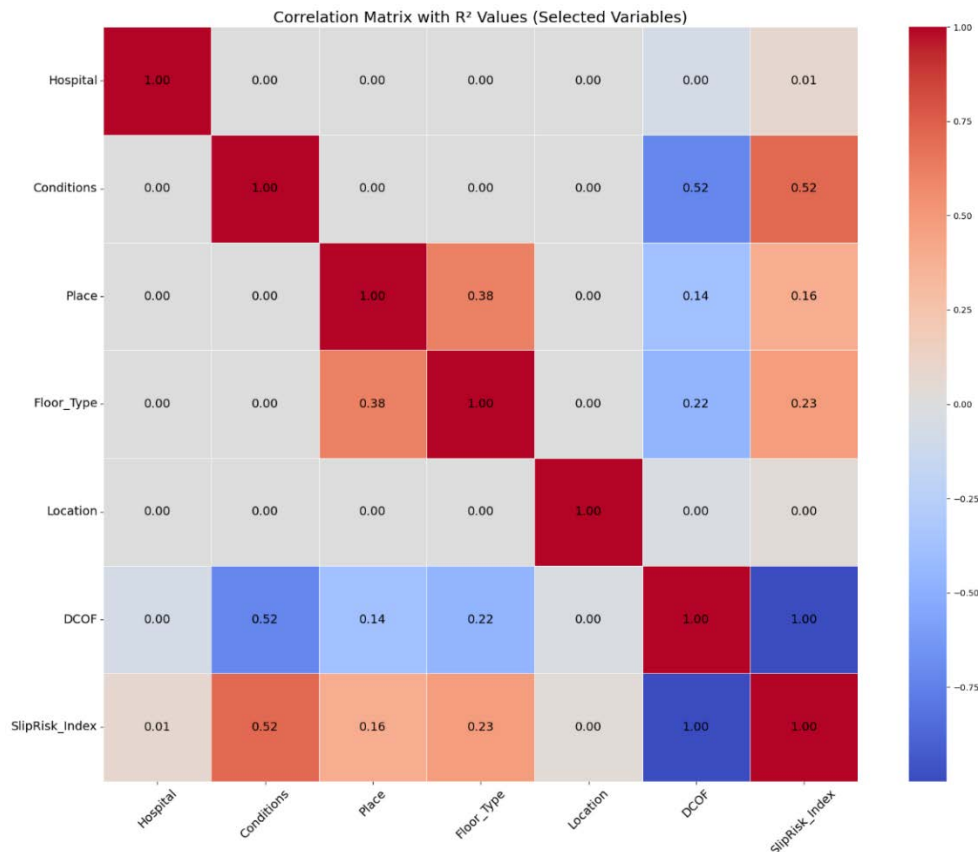


Figure 1. Correlation matrix with R^2 values illustrating the relationships between SRI and key environmental, spatial, and friction-related variables.

As shown in **Figure 1**, the SRI exhibits its strongest association with the Dynamic Coefficient of Friction. The relationship between DCOF and SRI demonstrates an almost perfect inverse dependency, with an R^2 value approaching 1.00. This finding confirms that variations in slip risk are predominantly governed by surface friction performance, thereby empirically validating the theoretical foundation of the proposed SRI formulation. Lower DCOF values are consistently associated with higher slip risk levels, highlighting friction as the primary controlling factor in pedestrian safety assessments.

Environmental surface condition (dry versus wet) also shows a substantial relationship with both DCOF and SRI, with R^2 values of approximately 0.52. This indicates that more than half of the variance in slip risk can be attributed to changes in surface condition alone. The result underscores the critical role of moisture presence in hospital environments, where wet conditions significantly reduce frictional resistance and consequently elevate slip hazard potential.

Moderate associations are observed between SRI and spatial–material variables such as *Floor Type* ($R^2 \approx 0.23$) and *Place* ($R^2 \approx 0.16$). These findings suggest that flooring material selection and functional area usage contribute meaningfully—but secondarily—to slip risk levels. In particular, ceramic tile surfaces and high-exposure functional zones (e.g., toilets and showers) tend to amplify slip risk when combined with unfavorable frictional and environmental conditions.

In contrast, the *Hospital* variable exhibits a negligible relationship with SRI ($R^2 \approx 0.01$), indicating that institutional differences between the two hospitals included in the study do not substantially influence slip risk outcomes. Similarly, the *Location* variable (measurement position within the room) shows an almost null association with SRI ($R^2 \approx 0.00$), suggesting that intra-room spatial variation has a minimal effect compared to frictional and environmental determinants.

Overall, the correlation structure presented in Figure 1 reveals a clear hierarchical influence

among the evaluated parameters. Frictional performance (DCOF) and environmental condition emerge as dominant predictors of slip risk, while material type and functional space act as moderating factors. Institutional identity and local measurement position, however, appear to exert negligible influence. These results reinforce the robustness of the SRI as an integrative metric that captures the multifactorial nature of slip hazards in hospital settings.

3.3. Feature Importance and Explainable Machine Learning Analysis of SRI

Classical statistical analyses were complemented with feature importance and explainable machine learning techniques to provide deeper insight into the relative contribution of floor safety parameters. In this context, both correlation-based importance ranking and SHAP (SHapley Additive exPlanations) analysis were employed to evaluate the drivers of the SRI. The results are illustrated in Figures 2 and 3, respectively.

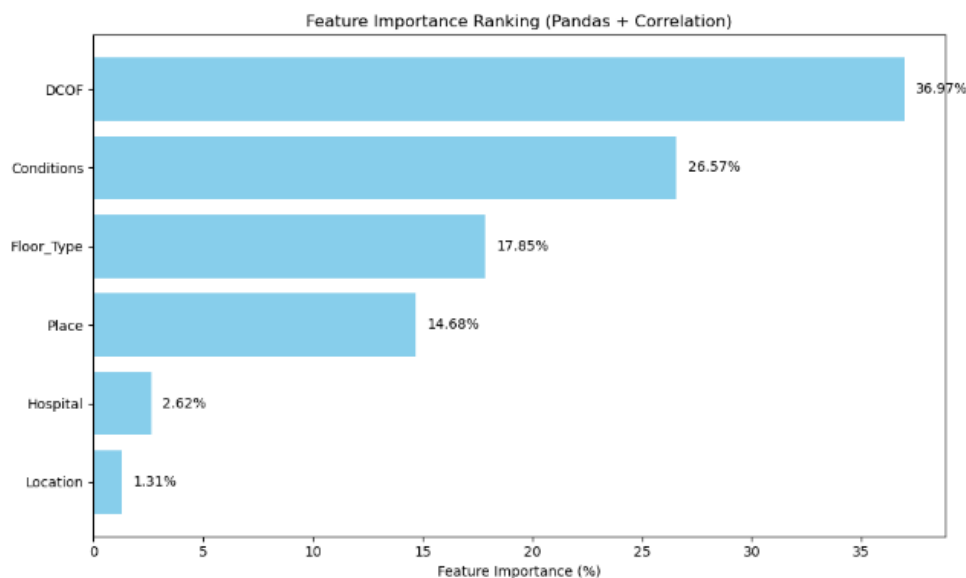


Figure 2. Correlation-based feature importance ranking illustrating the relative contribution of floor safety parameters to the SRI.

Figure 2 presents the feature importance ranking derived from normalized correlation contributions between the explanatory variables and SRI. The Dynamic Coefficient of Friction (DCOF) emerges as the most influential parameter, accounting for approximately 36.97% of the total explained importance. This dominant contribution is consistent with the

exceptionally strong inverse correlation identified in the paired-sample analysis and confirms that frictional performance is the primary determinant of slip risk magnitude. Environmental surface condition constitutes the second most influential factor, contributing 26.57% to the overall importance. This finding highlights the substantial impact of wet versus

dry conditions on slip risk formation and corroborates the observed correlation structure, where surface condition explained more than half of the variance in SRI when combined with DCOF. Floor Type (17.85%) and Place (14.68%) exhibit moderate importance levels, indicating that flooring material characteristics and functional space usage play meaningful, yet secondary, roles in shaping slip risk. In contrast, Hospital (2.62%) and Location (1.31%) demonstrate minimal contributions, reinforcing the conclusion that institutional identity and intra-room measurement position have negligible influence on slip risk outcomes. To

further enhance model interpretability and to examine the directionality and magnitude of feature effects at the individual observation level, SHAP analysis was conducted. Figure 3 illustrates the mean absolute SHAP values, reflecting the average impact of each variable on the model output. Consistent with the correlation-based ranking, DCOF overwhelmingly dominates the model, with SHAP values several orders of magnitude greater than those of the remaining variables. This result confirms that variations in SRI predictions are predominantly driven by changes in frictional performance.

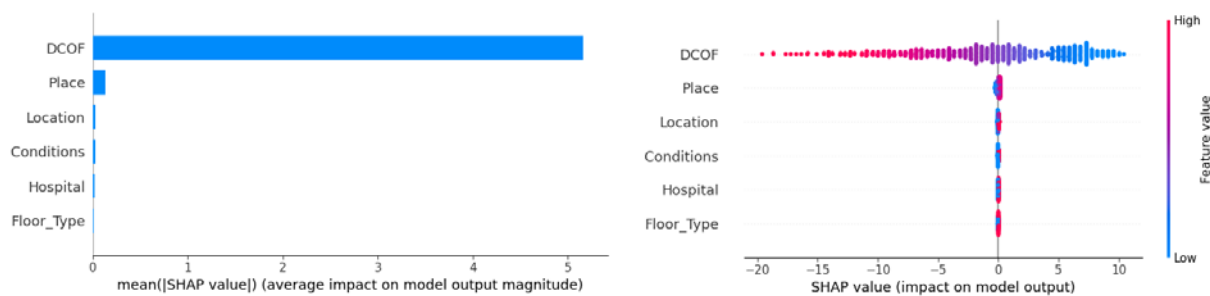


Figure 3. SHAP-based feature importance and summary analysis illustrating the magnitude and directional impact of input variables on SRI predictions.

The SHAP summary (beeswarm) plot in Figure 3 provides additional insight into the directional effects of each variable. Lower DCOF values (shown in blue) are associated with positive SHAP values, indicating a strong increase in predicted slip risk, whereas higher DCOF values (shown in red) contribute to risk reduction. This monotonic and physically interpretable behavior aligns closely with tribological theory and validates the conceptual construction of the SRI. Other variables, including Conditions, Floor Type, Place, Hospital, and Location, exhibit SHAP values clustered near zero, suggesting limited marginal influence on model predictions relative to DCOF.

Overall, the combined evidence from correlation-based importance ranking and SHAP explainability analysis confirms a clear hierarchical structure among the slip risk determinants. Frictional performance (DCOF) and environmental condition constitute the core drivers of slip risk, while flooring material and functional space act as moderating factors. Institutional differences and local spatial positioning exert only marginal effects. These findings not only reinforce the statistical

robustness of the proposed SRI but also demonstrate its compatibility with modern explainable machine learning frameworks, thereby enhancing its applicability for predictive modeling and decision-support systems in hospital floor safety management.

3.4. Predictive Performance Comparison of Machine Learning Models

The predictive capability of the proposed SRI framework was evaluated by developing and systematically comparing six ensemble-based machine models Random Forest, Gradient Boosting, CatBoost, LightGBM, Bagging, and XGBoost. Model performance was assessed using multiple error and goodness-of-fit metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Nash–Sutcliffe Efficiency (NSE), and the coefficient of determination (R^2). These complementary metrics were selected to ensure a balanced evaluation of both accuracy and generalization performance. The predictive accuracy and generalization ability of the models are visually illustrated in Figure 4, while the quantitative performance metrics are summarized in Table 5.

Table 5. Comparative performance metrics of machine learning models for SRI prediction on training and testing datasets.

Model	MAE (Train)	MAE (Test)	RMSE (Train)	RMSE (Test)	MAPE (Train)	MAPE (Test)	NSE (Train)	NSE (Test)
Random Forest	0.0293	0.0959	0.0524	0.1644	0.1178	0.4315	0.9999	0.9995
Gradient Boosting	0.0230	0.0751	0.0318	0.1569	0.0818	0.3636	0.9999	0.9995
CatBoost	0.0942	0.1487	0.1229	0.2441	0.3348	0.6216	0.9996	0.9989
LightGBM (LGBM)	0.1594	0.2854	0.5105	0.7440	0.8002	1.4516	0.9934	0.9895
Bagging	0.0301	0.0959	0.0543	0.1717	0.1223	0.4303	0.9999	0.9994
XGBoost	0.0200	0.1325	0.0284	0.2893	0.0691	0.5652	0.9999	0.9984

Figure 4 presents the scatter plots of predicted versus actual SRI values for both training and testing datasets. Across most models, predictions closely align with the 45-degree reference line, indicating excellent agreement between observed and estimated slip risk values. Random Forest, Gradient Boosting, Bagging, CatBoost, and XGBoost demonstrate

near-perfect predictive performance, with training and testing R^2 values approaching unity. This close alignment indicates that the underlying nonlinear relationships between floor safety parameters and the SRI are effectively captured by ensemble-based learning approaches.

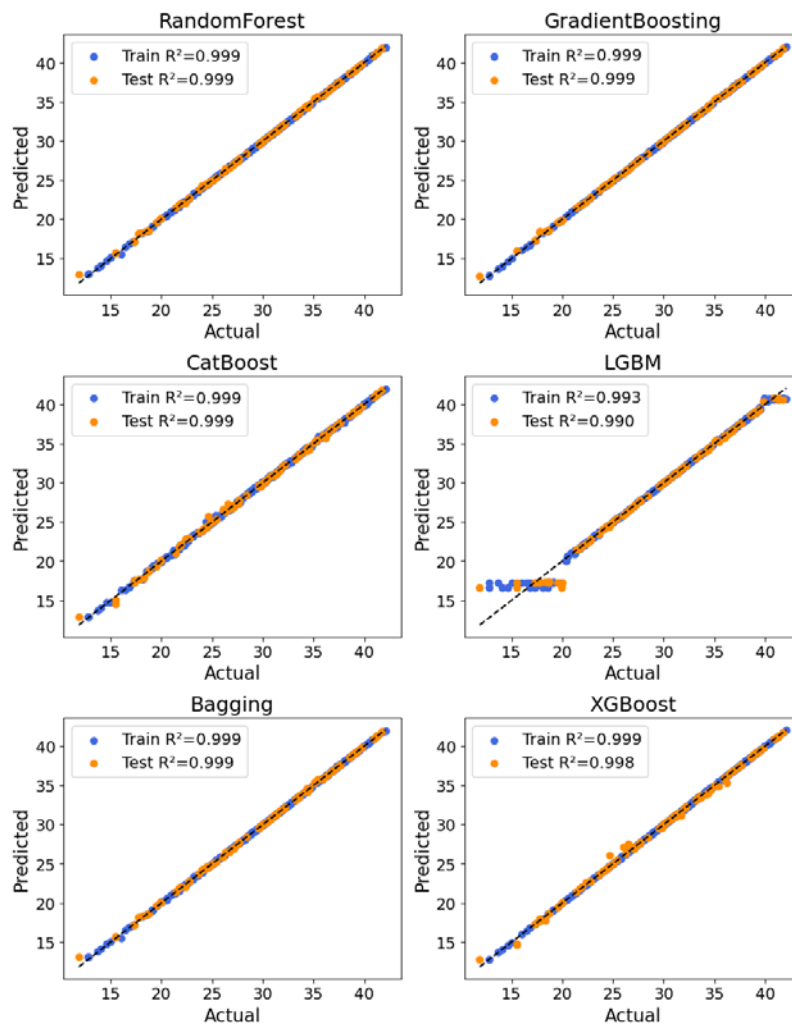


Figure 4. Actual versus predicted SRI values for training and testing datasets obtained using ensemble-based machine learning models.

Among the evaluated models, Gradient Boosting exhibits the most balanced and robust performance, achieving R^2 values of 0.999 for both training and testing datasets, with minimal dispersion around the ideal prediction line. Random Forest and Bagging models also show outstanding generalization ability, with test R^2 values of 0.999, indicating negligible overfitting despite their perfect or near-perfect training performance. CatBoost performs similarly, although slightly greater prediction dispersion is observed at intermediate SRI levels, suggesting a marginal sensitivity to specific feature interactions.

In contrast, the LightGBM model, while still demonstrating strong predictive capability, shows comparatively higher deviation in the lower SRI range, as reflected by a reduced test R^2 value (0.990) and visibly larger scatter in Figure 4. This behavior can be attributed to LightGBM's leaf-wise tree growth strategy and histogram-based feature discretization, which, although highly efficient for large-scale and high-dimensional datasets, may lead to suboptimal partitioning when applied to relatively compact datasets with limited feature diversity. Moreover, the predominance of categorical and ordinal predictors—such as functional space and environmental condition—may favor algorithms like CatBoost and Gradient Boosting, which incorporate more robust mechanisms for handling categorical structures and sequential residual correction.

The detailed numerical comparison provided in Table 5 further supports these observations. Gradient Boosting achieves the lowest testing MAE (0.0751) and RMSE (0.1569), indicating superior accuracy and stability. Random Forest and Bagging follow closely, with comparable error magnitudes and consistently high NSE values (>0.999), confirming their excellent predictive reliability. XGBoost demonstrates competitive training performance; however, its test errors are marginally higher than those of Gradient Boosting and Random Forest, suggesting a slightly reduced generalization capability under unseen conditions. LightGBM records the highest MAE, RMSE, and MAPE values among all models, although its NSE values remain above 0.98, indicating that its overall predictive skill remains acceptable despite reduced precision.

Overall, the model-specific performance differences highlight the importance of aligning algorithmic design characteristics with dataset properties. The superior performance of Gradient Boosting, Random Forest, and Bagging underscores the suitability of depth-controlled, variance-reducing ensemble strategies for slip risk prediction problems characterized by nonlinear interactions, moderate sample size, and categorical-dominant feature spaces.

Collectively, the results presented in Figure 4 and Table 5 demonstrate that ensemble-based machine learning models can predict the SRI with exceptionally high accuracy. In particular, Gradient Boosting emerges as the most effective model, offering an optimal trade-off between accuracy, robustness, and generalization performance, thereby providing a strong foundation for integrating the proposed SRI into real-time decision-support and floor safety management systems.

3.5. Comprehensive Evaluation of Slip Safety Classification and Practical Implications

An integrated and application-oriented assessment of slip safety in hospital environments was conducted by analyzing the distribution of slip safety classes—derived from the Dynamic Coefficient of Friction (DCOF, μ)—across environmental, spatial, and material-related factors. The results are comprehensively illustrated in Figure 5, which presents slip safety distributions by hospital, environmental condition, functional space (place), floor type, and intra-room measurement location, together with the overall safety class distribution.

As shown in Figure 5a, both Hospital 1 and Hospital 2 exhibit broadly similar slip safety profiles, with the majority of measurements concentrated in the *provisionally safe* and *safe* categories. However, a non-negligible proportion of *unsafe* observations is evident in both hospitals, indicating that institutional differences alone do not sufficiently mitigate slip risk. This finding is consistent with the statistical and machine learning results presented earlier, which identified the hospital variable as having a minimal influence on slip risk formation.

Figure 5b highlights the pronounced effect of environmental surface condition on slip safety. Under dry conditions (Condition = 1), measurements are predominantly classified as *safe* or *very safe*. In contrast, wet conditions (Condition = 2) result in a marked shift toward *unsafe* and *provisionally safe* classes. This distributional change underscores the critical role of moisture presence in reducing surface friction and confirms that wetness is one of the most decisive contributors to elevated slip risk in hospital settings.

The influence of functional space is clearly illustrated in Figure 5c. Corridors (Place = 1) and patient rooms (Place = 2) show relatively balanced distributions, with fewer *unsafe* observations. Conversely, toilets (Place = 3) and showers (Place = 4) exhibit substantially higher counts of *unsafe* and *provisionally safe* measurements, reflecting their frequent exposure to water and contaminants. Examination rooms (Place = 5) display comparatively lower measurement counts and a predominantly safer classification, suggesting more controlled environmental conditions. These findings emphasize that functional usage patterns significantly modulate slip risk levels.

Figure 5d demonstrates the strong impact of flooring material on slip safety classification. PVC vinyl floors (Floor Type = 1) are largely

associated with *safe* and *very safe* classes, whereas ceramic tile surfaces (Floor Type = 2) show a pronounced concentration of *unsafe* and *provisionally safe* measurements. This result confirms that material selection is a critical design factor for slip prevention, particularly in wet-prone hospital areas.

The effect of intra-room measurement position is presented in Figure 5e. Although minor variations are observed among side (Location = 1), center (Location = 2), and opposite side (Location = 3) positions, the overall slip safety distributions remain broadly similar. This suggests that localized spatial positioning within a room has a limited effect on slip risk compared to environmental conditions and flooring characteristics. Finally, the overall distribution of slip safety classes shown in Figure 5f reveals that the majority of measurements fall within the *provisionally safe* category, followed by *safe* and *unsafe* classes, with a relatively small proportion classified as *very safe*. This distribution highlights the prevalence of marginal safety conditions in hospital environments and underscores the necessity of proactive risk management strategies aimed at improving frictional performance, particularly under wet conditions and in high-risk functional zones.

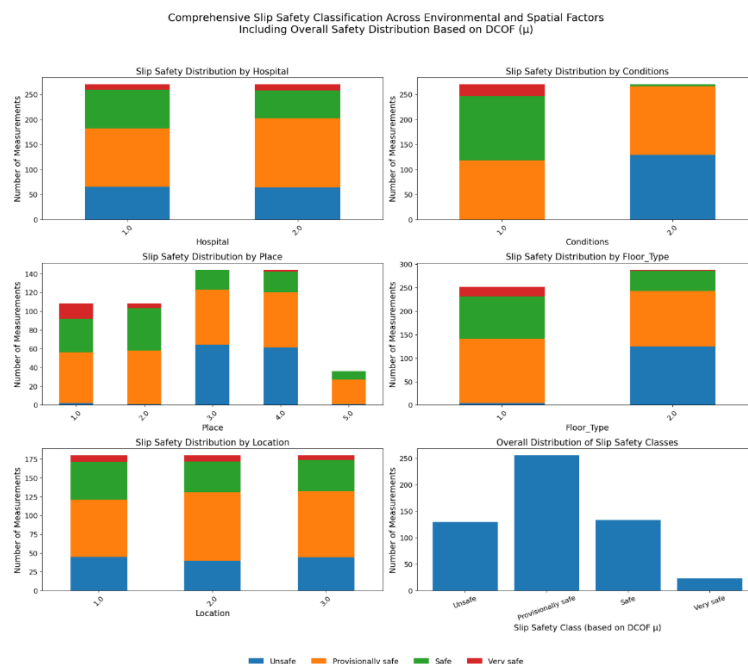


Figure 5. Comprehensive slip safety classification across hospitals, environmental conditions (dry/wet), functional spaces, floor types, and measurement locations, including the overall distribution of slip safety classes based on the Dynamic Coefficient of Friction (DCOF, μ).

In summary, the comprehensive classification results presented in Figure 5 confirm that slip risk in hospitals is governed by a hierarchical set of factors. Environmental condition and flooring material emerge as dominant determinants, functional space acts as a critical moderating factor, while institutional identity and intra-room location exert comparatively minor influence. These findings reinforce the practical relevance of the proposed SRI and provide actionable insights for hospital designers, facility managers, and safety engineers seeking to enhance pedestrian safety through targeted material selection, environmental control, and preventive maintenance strategies

4. DISCUSSION

The present study provides a comprehensive and integrative evaluation of slip risk in hospital environments by combining classical statistical analyses, correlation-based assessments, explainable machine learning techniques, and predictive modeling. By integrating these complementary methodologies, the study enables a multidimensional interpretation of slip risk formation. The findings collectively demonstrate that slip risk formation is governed by a clear hierarchy of determinants, with frictional performance, environmental condition, and flooring characteristics emerging as the dominant contributors. These results not only validate the conceptual foundation of the proposed SRI but also align strongly with and extend the existing body of slip safety literature. Importantly, this integrative approach allows slip risk to be examined not merely as a statistical outcome, but a physically interpretable and operationally meaningful phenomenon shaped by interacting material, environmental, and usage-related mechanisms.

The exceptionally strong inverse relationship observed between the Dynamic Coefficient of Friction (DCOF) and SRI confirms that surface friction is the primary determinant of pedestrian slip risk. The near-perfect correlation ($r = -0.909$) and R^2 values approaching unity are consistent with established tribological theory and prior empirical studies conducted in public utility buildings and healthcare facilities [6,11]. Similar to the findings reported by Waluś et al. [9], who demonstrated substantial increases in slip probability due to surface wear and friction degradation, the present study quantitatively

confirms that even small reductions in DCOF can lead to disproportionate increases in slip risk. From a biomechanical perspective, this nonlinear amplification arises because slip initiation occurs when available friction falls below the required friction threshold during gait transitions, particularly at heel strike. Consequently, minor friction losses often overlooked in routine maintenance can trigger abrupt transitions from stable to unstable walking conditions, underscoring the critical importance of friction-centered safety monitoring.

Environmental surface condition emerged as the second most influential factor affecting slip risk. Both correlation analysis and feature importance rankings consistently showed that wet conditions significantly elevate SRI values. This finding corroborates earlier studies indicating that moisture presence dramatically reduces frictional resistance and increases slip hazard potential [6]. Beschoner and Randolph [10] demonstrated that contaminant conditions, including liquids commonly encountered in healthcare settings, exert a stronger influence on friction performance than flooring material alone. The present study extends this knowledge by demonstrating that environmental condition plays a central role not only in friction reduction but also in integrated, index-based risk metrics such as the SRI, thereby highlighting the necessity of strict moisture control and surface maintenance protocols in hospital environments.

Flooring material type and functional space were found to have moderate yet statistically significant contributions to slip risk formation. Ceramic tile floors and water-exposed functional areas such as toilets and showers consistently exhibited higher SRI values and a greater concentration of unsafe and provisionally safe classifications. These findings are in agreement with prior hospital-focused investigations reporting that certain floor coverings fail to meet slip resistance standards under wet conditions [6,11]. The observed material- and space-specific risk patterns also align with recent machine learning-based studies that emphasize the interaction between surface properties and usage context in determining slip resistance [14]. Importantly, the observed material- and space-specific risk patterns reinforce the

concept that slip risk is an emergent property of material–environment interaction rather than an intrinsic property of flooring materials alone. This reinforces the theoretical notion that slip risk is an emergent property of material–environment interaction rather than an intrinsic characteristic of flooring materials alone. In contrast, institutional identity (Hospital) and intra-room measurement position (Location) exhibited negligible influence on slip risk. Both correlation and SHAP analyses showed minimal contributions from these variables, suggesting that slip risk is largely independent of the specific hospital studied and localized spatial positioning within rooms. This finding supports earlier observations that slip hazards are primarily governed by physical surface and environmental conditions rather than organizational or spatial labeling [1,6]. From a practical perspective, this implies that slip prevention strategies can be standardized across hospitals with similar environmental and material characteristics, without requiring extensive customization at the institutional level. Such transferability enhances the scalability and applicability of the proposed SRI framework across different healthcare settings.

The integration of explainable machine learning techniques further strengthens the interpretability and robustness of the proposed framework. SHAP analysis confirmed that DCOF overwhelmingly dominates model predictions, while other variables exert secondary or marginal effects. This hierarchical structure mirrors findings from recent explainable AI applications in safety-critical domains, such as runway friction assessment and footwear slip resistance prediction [13,42-43]. In particular, the clear monotonic relationship between DCOF and predicted slip risk observed in SHAP plots enhances confidence in the physical plausibility and transparency of the predictive models. This interpretability is essential for real-world adoption, as safety engineers and facility managers require not only accurate predictions but also clear causal explanations to support evidence-based decision-making.

The predictive modeling results demonstrate that ensemble-based machine learning algorithms can estimate the SRI with exceptionally high accuracy. Gradient Boosting, Random Forest, and Bagging models

achieved near-perfect goodness-of-fit and minimal prediction error, outperforming more sensitive models such as LightGBM. These findings are consistent with prior studies showing the strong capability of ensemble learning methods to capture complex, nonlinear relationships in friction-related safety data [13-14]. The robustness of these models suggests that the underlying slip risk structure is stable and learnable, reinforcing confidence in the generalizability of the SRI across similar datasets. The successful combination of statistical validation, explainable modeling, and predictive performance positions the SRI as a robust and practically applicable tool for real-time decision support in hospital floor safety management.

The findings of this study are strongly supported and contextualized by recent WoS-indexed literature employing machine learning and explainable analytics in slip resistance research. Lau et al. (2024, 2025) demonstrated that outsole material and tread characteristics are decisive factors governing slip resistance, which is consistent with the present study's observation that frictional performance (DCOF) overwhelmingly dominates slip risk formation [24-25]. Likewise, Wiecek et al. (2025) reported that material type and wet–dry interaction effects significantly influence slip risk, while geometric or spatial factors play a secondary role—an outcome that closely aligns with the negligible contribution of measurement location and institutional identity observed in the present SHAP analysis [36]. In healthcare environments, Beschorner and Randolph (2023) emphasized that contaminant and environmental conditions exert a stronger influence on friction than flooring product alone, a finding that is quantitatively confirmed here through the high importance of environmental condition in the SRI [37]. Furthermore, recent applications of SHAP- and LIME-based explainability in medical environments have highlighted the value of transparent model outputs for actionable facility management [38]. By synthesizing these strands of literature within a single, interpretable risk index, the present study advances the field from isolated factor analysis toward integrated, decision-oriented slip risk assessment.

Overall, the findings of this study confirm and extend existing knowledge by demonstrating that slip risk in hospital environments is a multifactorial phenomenon dominated by frictional performance and environmental conditions, moderated by flooring material and functional space, and minimally influenced by institutional or localized spatial factors. By integrating traditional statistical methods with modern machine learning and explainable AI approaches, this study provides a comprehensive and scientifically grounded framework for slip risk assessment. The principal theoretical contribution lies in formalizing the hierarchy of slip risk determinants within a transparent quantitative index, while the principal practical contribution is the translation of complex frictional dynamics into an operational decision-support tool. The proposed SRI offers a valuable decision-support tool for designers, facility managers, and safety engineers seeking to reduce slip-related accidents through evidence-based material selection, environmental control, and preventive maintenance strategies.

5. CONCLUSION

This study presented a comprehensive and integrative framework for assessing slip risk in hospital environments by combining in situ friction measurements, statistical inference, ensemble machine learning, and explainable artificial intelligence. The proposed SRI was developed to systematically integrate frictional performance with environmental, material, and spatial characteristics, enabling a holistic and interpretable evaluation of slip hazards.

The results clearly demonstrated that frictional performance, quantified by the Dynamic Coefficient of Friction, is the dominant determinant of slip risk. Environmental surface condition emerged as the second most influential factor, with wet conditions substantially increasing slip hazard across all functional zones. Flooring material and functional space exhibited moderate but meaningful effects, particularly in moisture-prone areas such as toilets and showers, while institutional identity and intra-room measurement location had negligible influence. These findings confirm a hierarchical structure of slip risk determinants in hospital settings.

The predictive modeling results further showed that ensemble-based machine learning algorithms can estimate the SRI with exceptionally high accuracy. Gradient Boosting, Random Forest, and Bagging models achieved near-perfect predictive performance, while explainable AI analysis using SHAP ensured transparency and physical interpretability of the model outputs. The strong agreement between statistical analysis, feature importance ranking, and SHAP results reinforces the robustness and reliability of the proposed framework.

From a practical perspective, the findings highlight the necessity of prioritizing frictional performance maintenance, effective moisture management, and context-sensitive flooring material selection in hospitals. The proposed SRI provides a scalable and data-driven decision-support tool that can assist facility managers and safety engineers in identifying high-risk zones, optimizing maintenance strategies, and implementing targeted interventions to reduce slip-related accidents.

Future research may extend this framework by incorporating temporal wear effects, pedestrian biomechanics, footwear characteristics, and real-time sensor data to support dynamic slip risk monitoring. Nevertheless, the present study contributes a scientifically grounded, interpretable, and practically applicable methodology that advances slip safety assessment in healthcare environments and offers broader applicability to other high-risk public buildings.

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