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Predictive Risk Modeling and Quantitative Analysis of Microbial Contamination in Hospital Textiles

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Abstract

This quantitative observational study examined microbial contamination in hospital textiles using predictive risk modeling and multivariable statistical analysis to identify determinants of contamination across textile categories, operational pathways, and clinical contexts. A cross-sectional analytic design was applied in a multi-unit hospital setting, and a total of 360 reusable textile items were sampled, including bed linens (40.0%), staff uniforms (25.0%), towels (20.0%), and privacy curtains (15.0). Items were collected from both high-acuity units (35.0%) and general wards (65.0%) and were linked to structured metadata describing exposure duration, contact density proxies, handling and transport conditions, laundering characteristics, storage duration, and textile reuse indicators. Microbial contamination outcomes were measured as microbial burden and contamination positivity, with positivity observed in 46.5% of linens, 48.6% of towels, 34.4% of uniforms, and 29.6% of curtains. Descriptive analysis demonstrated highly skewed contamination distributions, with median microbial burden values ranging from 2.0 to 3.4 units across textile categories and higher exposure duration observed for curtains and uniforms compared with linens and towels. Multivariable regression analysis showed that textile category, exposure duration, contact density, ward acuity, handling pathway quality, laundering quality, and post-laundering storage time were independently associated with contamination outcomes after adjustment for clustering by ward and laundering batch. In the microbial burden model, towels (adjusted estimate = 1.35, $p < 0.001$) and linens (1.28, $p = 0.001$) exhibited higher burden relative to uniforms, while curtains showed lower burden (0.82, $p = 0.041$). In the contamination positivity model, towels (adjusted odds ratio = 1.84, $p = 0.009$) and linens (1.62, $p = 0.019$) demonstrated higher odds of positivity. High-acuity wards were associated with increased contamination outcomes in both models. Laundering quality demonstrated a protective association with microbial burden (0.88, $p < 0.001$) and positivity (0.86, $p = 0.003$), while longer post-laundering storage increased contamination risk. Overall, the findings demonstrated that hospital textile contamination followed systematic and quantifiable patterns shaped by textile type, exposure dynamics, operational handling, laundering performance, and clinical context, supporting the use of multivariable and hierarchical modeling approaches for contamination risk assessment in healthcare textile systems.

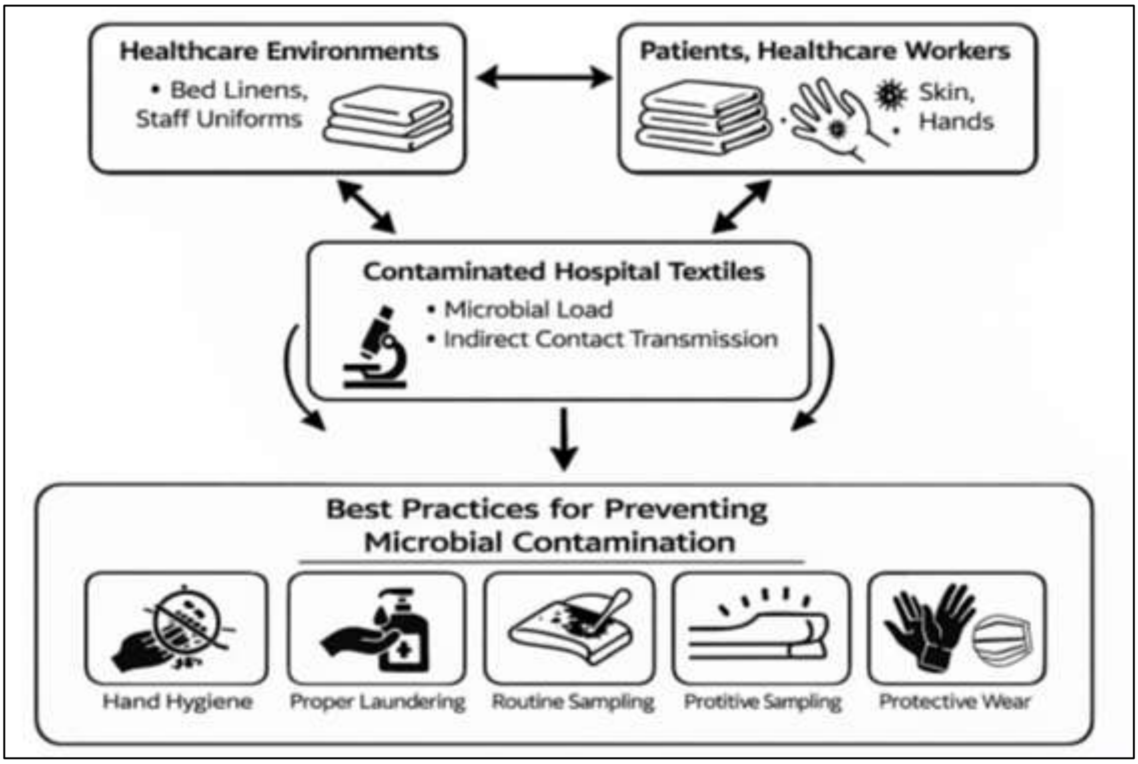
Keywords

Hospital Textiles, Microbial Contamination, Risk Modeling, Quantitative Analysis, Infection Control;

INTRODUCTION

Hospital textiles constitute a critical yet often underestimated component of healthcare environments, encompassing bed linens, patient gowns, staff uniforms, privacy curtains, towels, and reusable surgical fabrics. Microbial contamination in hospital textiles refers to the presence, survival, and proliferation of pathogenic and non-pathogenic microorganisms within textile fibers during use, handling, laundering, storage, and redistribution processes (Openshaw et al., 2016). From a microbiological perspective, textiles function as porous reservoirs capable of retaining moisture, organic matter, and skin-associated bioloads, creating favorable conditions for microbial persistence and transfer. In quantitative healthcare research, contamination is operationally defined through measurable microbial indicators such as colony-forming units per square centimeter, bioburden density, contamination frequency, and pathogen-specific prevalence rates. These measurable parameters allow contamination levels to be statistically modeled, compared, and predicted across diverse clinical settings. Hospital textiles also act as intermediaries in indirect contact transmission pathways, linking patients, healthcare workers, surfaces, and medical devices through repeated contact cycles (Mitchell et al., 2015). The role of textiles in healthcare-associated infection ecology is therefore framed not only by their material properties but also by their interaction with human behavior, institutional workflows, and environmental conditions. Quantitative analysis of microbial contamination emphasizes the transformation of biological variability into structured datasets that enable probabilistic assessment, statistical inference, and predictive modeling. In this context, risk is defined as the likelihood that contaminated textiles contribute to microbial exposure events under defined clinical conditions. Predictive risk modeling integrates microbiological measurements with contextual variables such as textile type, usage duration, laundering protocols, ward characteristics, and patient vulnerability profiles (Carraro et al., 2020). This analytical approach positions hospital textiles as measurable risk vectors within complex healthcare systems rather than passive background elements. Given the increasing emphasis on data-driven infection control strategies, defining microbial contamination in hospital textiles through quantitative frameworks establishes a foundational basis for systematic risk assessment and modeling across healthcare environments.

Figure 1: Hospital Textile Contamination Risk Modeling

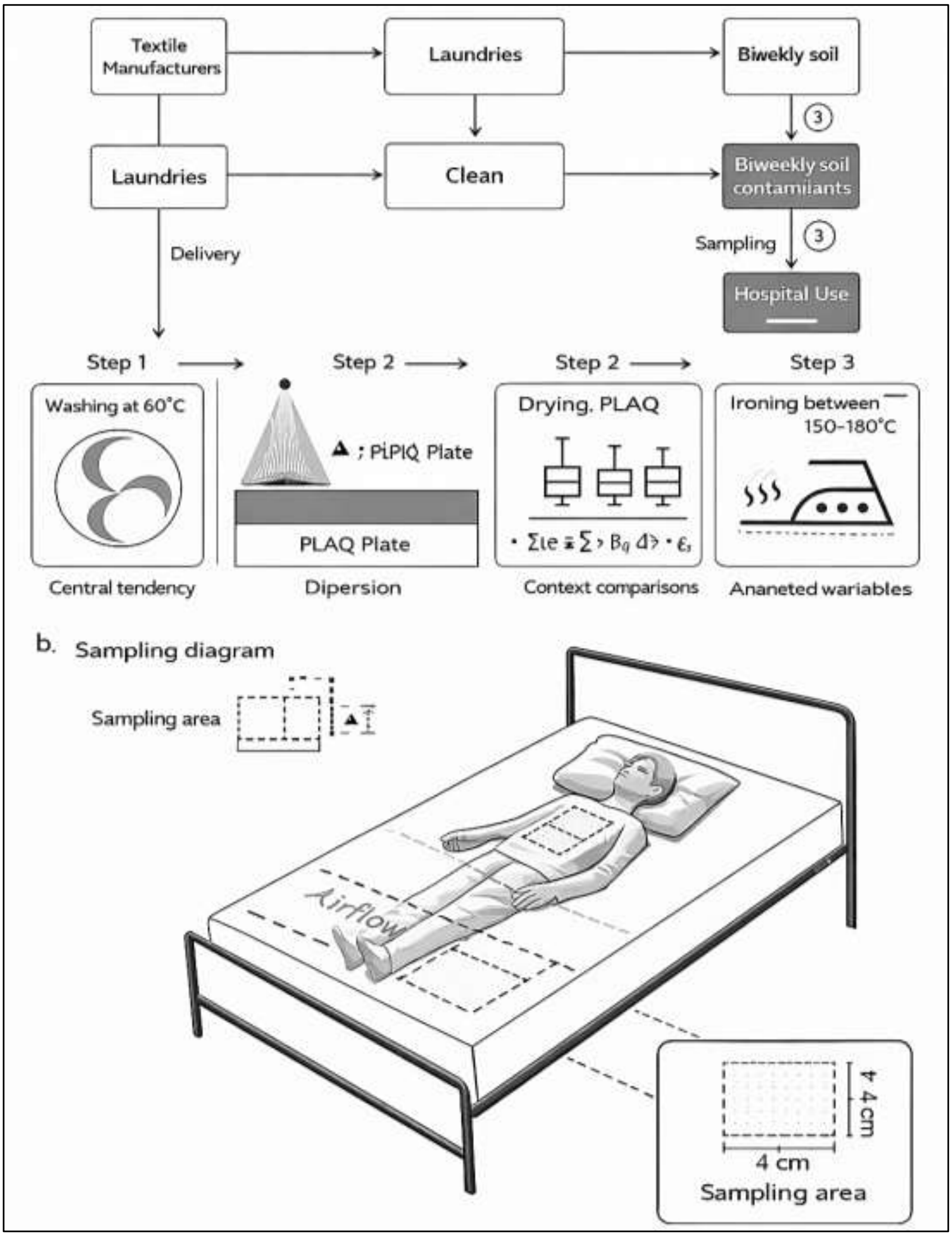


Healthcare-associated infections represent a persistent global challenge, and hospital textiles occupy a measurable position within the broader transmission ecosystem. From a quantitative epidemiological standpoint, textiles are treated as dynamic vectors whose contamination levels fluctuate based on frequency of use, patient acuity, environmental exposure, and hygiene interventions (Chiereghin et al., 2020). Unlike hard surfaces, textiles exhibit complex fiber structures that influence microbial adhesion, penetration, and retention, introducing variability that is amenable to statistical characterization. Quantitative studies conceptualize textiles as nodes within contact networks, where microbial load accumulation and depletion occur over time. This temporal dimension allows contamination to be modeled using longitudinal data structures, survival analysis, and decay functions that capture microbial persistence under varying conditions. Hospital textiles are also subject to repeated laundering cycles, enabling the assessment of contamination reduction rates, residual microbial survival, and recontamination probabilities. These measurable outcomes contribute to risk modeling frameworks that quantify exposure intensity and frequency (McQueen & Ehnes, 2017). In high-dependency clinical units, textiles experience elevated contact density, increasing the statistical likelihood of microbial transfer events. Quantitative analysis treats these interactions as stochastic processes influenced by workload, staffing patterns, and compliance variability. By converting textile contamination into numeric risk indicators, healthcare researchers can integrate textile-related variables into broader infection surveillance datasets. This integration supports comparative analysis across institutions, regions, and healthcare systems. The quantitative framing of hospital textiles aligns with systems-based infection control approaches that prioritize measurable risk contributors rather than isolated hygiene practices. As global healthcare systems increasingly rely on standardized metrics, hospital textiles emerge as analytically tractable components whose contamination profiles can be systematically measured, modeled, and incorporated into predictive risk assessments at institutional and international levels (Andersen, 2019).

Quantitative assessment of microbial contamination in hospital textiles relies on standardized measurement frameworks that transform biological presence into analyzable numerical data. These frameworks encompass sampling methodologies, laboratory quantification techniques, and statistical normalization procedures. Swab sampling, contact plate methods, and elution-based extraction techniques generate microbial count data that serve as primary quantitative inputs. These data are often expressed in logarithmic scales to accommodate wide variability in microbial densities across textile types and usage conditions (Handorean et al., 2015). Quantitative research emphasizes reproducibility, precision, and comparability, necessitating rigorous control of sampling area, pressure, and timing. Microbial load measurement also accounts for heterogeneity within textile surfaces, recognizing spatial variability across folds, seams, and high-contact zones. Statistical aggregation techniques are applied to represent contamination distributions at textile, ward, and institutional levels. Quantitative frameworks further incorporate pathogen classification variables, allowing differentiation between commensal flora and clinically significant organisms. This distinction supports risk-weighted modeling approaches that assign differential significance to microbial counts based on pathogenic potential. Measurement frameworks also integrate laundering effectiveness metrics, including log-reduction values and post-laundering residual contamination rates (Handorean et al., 2015). These metrics enable quantitative evaluation of textile processing systems as control variables within risk models. By structuring microbial data into hierarchical datasets, researchers can apply multilevel statistical models that account for nested variability across textiles, patients, and healthcare units. Such frameworks provide the empirical foundation necessary for predictive modeling, ensuring that risk estimations are grounded in measurable contamination patterns rather than qualitative assumptions (Yim et al., 2023).

Predictive risk modeling in the context of hospital textile contamination involves the application of statistical and mathematical techniques to estimate the probability of microbial exposure events. These models draw upon quantitative inputs such as microbial load measurements, contact frequency metrics, textile usage duration, and laundering intervals. Risk modeling frameworks often employ regression-based methods leading to probabilistic risk scores that represent contamination-driven exposure likelihoods (McQueen & Ehnes, 2022). Time-series analysis enables the examination of contamination trajectories across repeated textile use cycles, capturing accumulation and reduction patterns. In quantitative healthcare research, predictive models are valued for their capacity to integrate multiple variables into cohesive risk representations.

Figure 2: Statistical Modeling of Hospital Textiles



Textile-related risk models frequently incorporate covariates such as ward type, patient turnover rates, environmental humidity, and handling practices. These covariates allow risk estimations to reflect real-world operational complexity. Predictive modeling also facilitates scenario-based analysis, where changes in textile management variables can be simulated to observe corresponding shifts in contamination risk distributions. From an international perspective, structured risk models support cross-context comparison by standardizing contamination indicators across diverse healthcare infrastructures (Goyal et al., 2019). Quantitative modeling transforms textile contamination from an observational phenomenon into a measurable risk construct, enabling healthcare systems to systematically evaluate exposure probabilities. By emphasizing numerical prediction rather than descriptive assessment, predictive models contribute to evidence-based understanding of textile-mediated microbial dynamics within clinical environments (Ezeanya-Bakpa et al., 2022).

Statistical analysis plays a central role in identifying, characterizing, and interpreting microbial contamination patterns in hospital textiles (Rauf, 2018). Descriptive statistics provide foundational insights into central tendencies, dispersion, and distributional characteristics of microbial load data. Inferential statistical methods extend this analysis by testing associations between contamination levels and contextual variables such as textile type, clinical unit, and laundering protocol (Haque & Md. Arifur, 2020; Ashraful et al., 2020). Multivariate analysis techniques enable simultaneous evaluation of multiple risk factors, revealing interaction effects and contamination drivers (Haque & Arifur, 2021; Jinnat & Kamrul, 2021; Sands & Fairbanks, 2019). Cluster analysis supports the identification of contamination hotspots within textile inventories, while factor analysis assists in reducing dimensionality across correlated variables. Quantitative research also applies non-parametric methods to accommodate skewed microbial data distributions. Statistical modeling frameworks facilitate hypothesis testing related to contamination variability across institutional contexts. Advanced analytical techniques such as generalized linear models and mixed-effects models accommodate hierarchical data structures inherent in hospital environments (West et al., 2019). These approaches enable robust estimation of contamination predictors while controlling for random effects. Statistical rigor ensures that observed contamination patterns are distinguishable from random variation, strengthening the empirical validity of risk assessments. Through structured statistical analysis, microbial contamination in hospital textiles is transformed into interpretable quantitative evidence that supports systematic risk evaluation (Davies, 2018; Fokhrul et al., 2021; Zaman et al., 2021).

Hospital textile contamination represents an internationally relevant issue due to the universal reliance on reusable fabrics in healthcare delivery. Across low-, middle-, and high-income healthcare systems, textiles remain integral to patient care workflows, making microbial contamination a globally shared concern (Hammad, 2022; Hasan & Waladur, 2022). Quantitative risk modeling enables standardized assessment across diverse institutional contexts, facilitating comparative analysis and benchmarking. Differences in healthcare infrastructure, laundering technology, staffing density, and infection control resources contribute to variability in contamination profiles (Arifur & Haque, 2022; Towhidul et al., 2022; Suliman et al., 2021). Quantitative frameworks allow these differences to be analytically captured rather than qualitatively inferred. Global healthcare mobility, medical tourism, and transnational workforce movement further underscore the importance of standardized contamination assessment. Predictive modeling supports scalable risk evaluation applicable across geographic regions and healthcare settings. International relevance is reinforced by the alignment of textile contamination research with global patient safety priorities and quality assurance metrics. Quantitative analysis provides a common analytical language that transcends contextual variability, enabling contamination risk to be expressed through universally interpretable metrics (Balogová et al., 2023; Rifat & Jinnat, 2022; Rifat & Khairul Alam, 2022). By situating hospital textiles within global healthcare risk ecosystems, quantitative modeling approaches contribute to a comprehensive understanding of microbial exposure dynamics at an international scale.

The integration of predictive risk modeling into hospital textile management reflects the broader shift toward data-driven healthcare operations. Textile inventories generate continuous streams of measurable variables related to usage, contamination, and processing (Abdulla & Alifa Majumder, 2023; Faysal & Bhuya, 2023; Glowicz et al., 2022). Quantitative models synthesize these variables into structured risk indicators that support systematic analysis. Statistical integration allows contamination data to be linked with operational metrics such as turnaround time, inventory rotation, and utilization rates. By embedding microbial risk variables into textile management leading to multidimensional datasets suitable for quantitative evaluation. Risk modeling frameworks also support stratification of textiles based on contamination probability profiles, enabling analytical differentiation across fabric categories and clinical contexts (Habibullah & Aditya, 2023; Hammad & Mohiul, 2023; Shahid et al., 2021). Quantitative integration enhances visibility into contamination dynamics without reliance on anecdotal assessment. The structured nature of predictive modeling aligns with institutional emphasis on measurable performance indicators. Through mathematical abstraction and statistical analysis, hospital textile contamination is positioned as a quantifiable risk component within healthcare system operations. This integration underscores the analytical value of predictive modeling in understanding contamination patterns through measurable, repeatable, and scalable quantitative methodologies (Rajendran & Anand, 2016).

The objective of this quantitative research is to develop a structured and measurable understanding of microbial contamination in hospital textiles through predictive risk modeling and statistical analysis grounded in empirically observable contamination indicators. This study aims to quantify microbial load patterns across commonly used hospital textile categories, including patient linens, staff uniforms, privacy curtains, and reusable fabrics, by generating standardized contamination metrics that can be reliably compared across usage contexts and processing stages. A central objective is to operationalize contamination as numerical variables, including microbial count density, contamination frequency, and pathogen-specific detection rates, so that contamination is represented as analyzable data suitable for inferential testing and probability-based prediction. The research further seeks to identify statistically significant determinants of microbial contamination by examining relationships between microbial load and explanatory variables such as textile type, duration of use, ward classification, laundering cycle characteristics, handling practices, storage conditions, and environmental parameters that influence microbial survival. Another objective is to construct and evaluate predictive models capable of estimating contamination risk levels for hospital textiles under defined operational conditions, enabling quantitative estimation of the likelihood that textiles reach specified contamination thresholds within routine healthcare workflows. Model evaluation objectives include assessing predictive accuracy, calibration, sensitivity, and error structure using appropriate statistical validation strategies, ensuring that prediction performance is expressed through quantitative criteria rather than descriptive judgment. The study also aims to produce a comparative contamination profile across clinical settings by analyzing how contamination distributions vary across units with distinct patient vulnerability levels and contact intensities, supporting structured statistical comparison of mean differences, distributional shifts, and variance components. In addition, this research aims to generate a reproducible analytical framework that integrates laboratory-derived microbial measurements with hospital operational variables into a coherent dataset that supports multivariable analysis and interpretable risk scoring. By meeting these objectives, the study positions hospital textiles as quantifiable reservoirs and transferable surfaces within healthcare microbial ecology, enabling contamination risk to be expressed through measurable indicators and predictive estimations derived from systematic quantitative modeling and statistically validated analytical procedures.

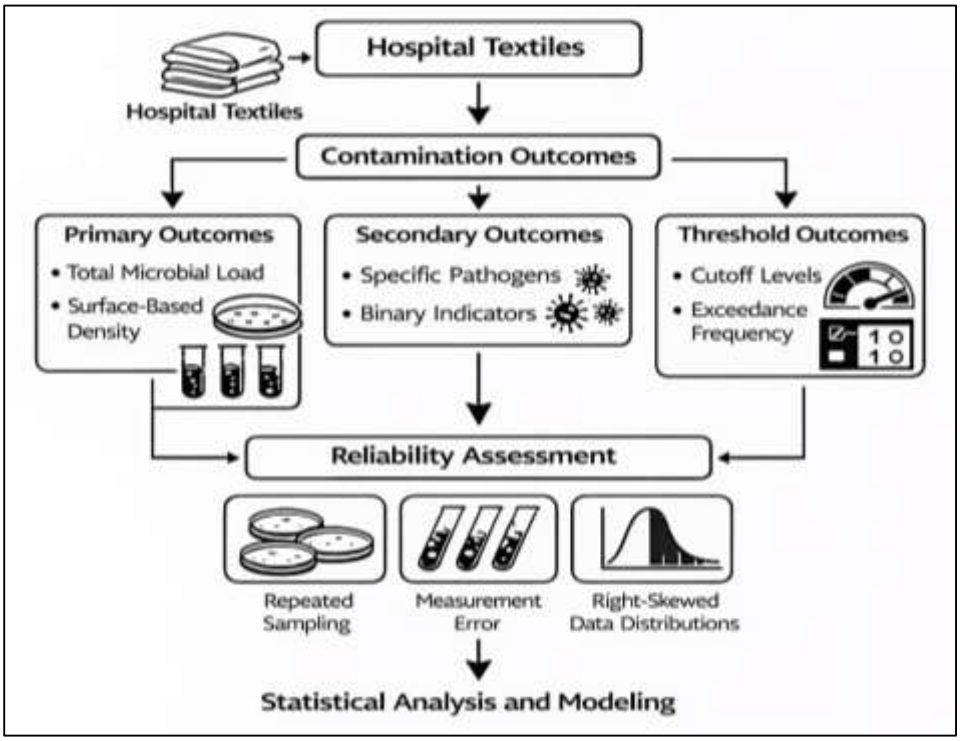
LITERATURE REVIEW

This Literature Review synthesizes empirical and quantitative scholarship on microbial contamination in hospital textiles, with a focus on how measurable contamination indicators can be modeled as predictors of risk within healthcare environments (Ferrer-Vilanova et al., 2021). The section is structured to organize prior evidence according to variables and analytical relationships that are directly relevant to quantitative risk modeling, including microbial load measurement techniques, contamination distribution patterns across textile categories, laundering efficacy metrics, textile material and structural properties, environmental and workflow determinants, and statistical modeling approaches used to predict contamination probability and threshold exceedance. The purpose of this section is to map the measurable constructs used in the literature (for example, bioburden density, contamination frequency, log-reduction values, and pathogen detection rates) to the statistical designs and model families commonly applied in healthcare contamination research (Nicoloro et al., 2020). Emphasis is placed on how studies define and operationalize contamination outcomes, the reliability and comparability of sampling strategies, the handling of skewed microbial count data, and the treatment of nested and clustered data structures typical in hospital settings. The review prioritizes quantitative evidence that supports variable selection, model specification, and validation logic for predictive risk analysis, while also identifying patterns in measurement consistency, reporting practices, and the statistical strength of associations reported across clinical units and textile types. The resulting synthesis provides an organized evidence base for structuring a quantitative framework in which hospital textiles are evaluated as measurable reservoirs and transferable surfaces in healthcare microbial ecology (Butler, 2018).

Textile Microbial Contamination Outcomes

The quantitative literature on hospital textile contamination consistently emphasizes the importance of clearly defined contamination endpoints that can be measured, compared, and modeled across healthcare environments. Microbial contamination is operationalized using standardized indicators that transform biological presence into numeric outcomes suitable for statistical analysis (Tang, 2023). Commonly used endpoints include surface-based microbial density measures, item-level contamination counts, logarithmic transformations of microbial load, binary contamination indicators, and organism-specific detection outcomes. These variables allow researchers to represent contamination intensity, frequency, and distribution in ways that align with quantitative risk assessment frameworks. Studies emphasize that endpoint selection directly influences statistical sensitivity, comparability across textile categories, and interpretability of results. Surface-normalized measures enable cross-textile comparison, while item-level counts capture aggregate contamination burden. Binary indicators support prevalence estimation and logistic modeling, particularly in pathogen-focused analyses (Haque & Arifur, 2023; Jahangir & Mohiul, 2023; Tang, 2023). Pathogen-specific positivity metrics are frequently used to distinguish general environmental contamination from clinically significant microbial presence. The literature also demonstrates that endpoint definition affects downstream analytical choices, including data transformation requirements and outcome scaling. Quantitative contamination endpoints are treated as dependent variables within structured models, linking textile characteristics and operational factors to measurable contamination outcomes. Through consistent operationalization, contamination endpoints serve as the foundational units of analysis in textile-related microbial risk research, allowing biological variability to be systematically quantified within reproducible statistical frameworks (Akbar & Farzana, 2023; Mostafa, 2023; Sharma et al., 2022).

Figure 3: Hospital Textile Contamination Risk Modeling

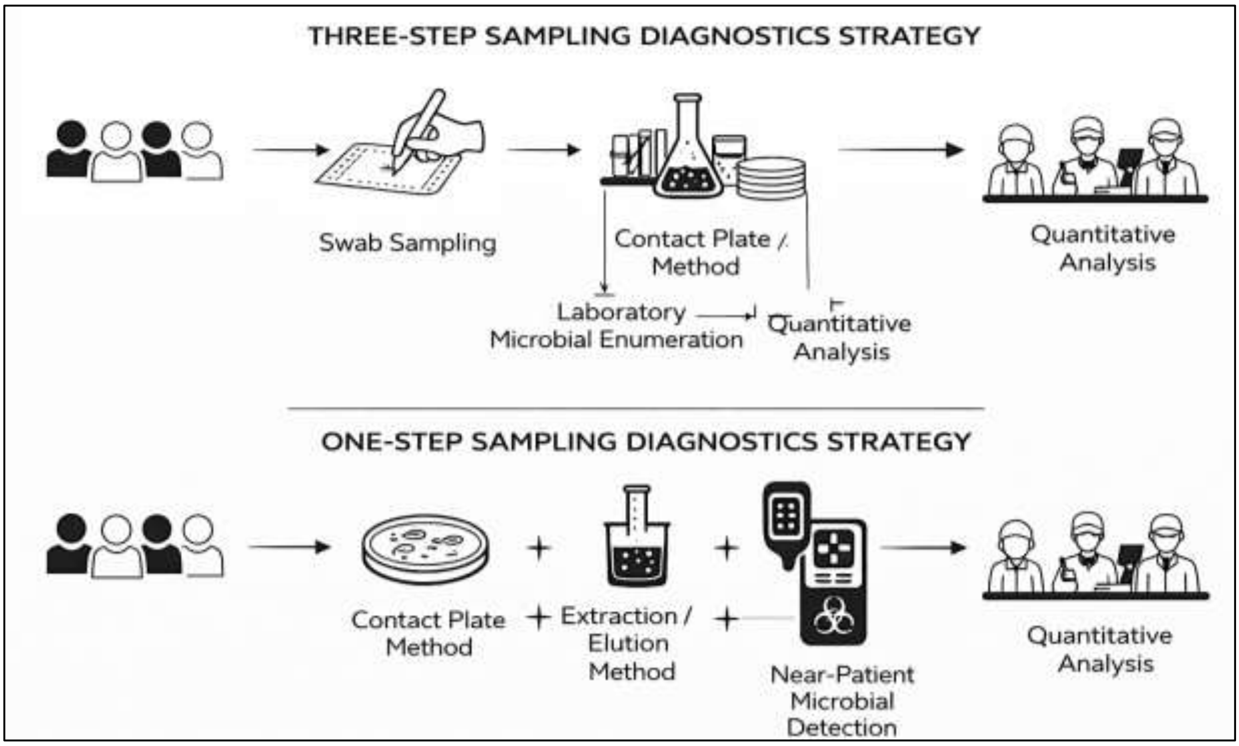


Quantitative studies on hospital textile contamination routinely distinguish between primary and secondary outcomes to support structured modeling and hypothesis testing. Primary outcomes typically represent overall microbial burden, capturing the cumulative presence of microorganisms across textile surfaces. These measures are used to characterize baseline contamination patterns and to model general exposure risk. Secondary outcomes focus on subsets of microbial populations, often emphasizing organisms associated with healthcare-associated infections (Jahangir & Hammad, 2024; Rifat & Rebeka, 2023; Sigaard & Laitala, 2023). This differentiation enables layered analysis in which broad contamination trends are evaluated alongside organism-specific risk indicators. The literature highlights that selecting primary outcomes centered on total bioburden enhances statistical stability due to higher event frequencies and reduced sparsity. Secondary outcomes, while less frequent, provide specificity by isolating clinically relevant contamination events. Quantitative frameworks treat these outcomes differently in model specification, with primary outcomes supporting continuous or count-based modeling and secondary outcomes often analyzed using binary or categorical approaches (Masud & Hammad, 2024; Md & Sai Praveen, 2024; Villarrubia-Gómez et al., 2018). Studies demonstrate that separating outcomes prevents analytical dilution and improves interpretability by aligning each outcome with appropriate statistical techniques. This structured outcome hierarchy also facilitates comparative analysis across textile types and clinical units. By clearly delineating primary and secondary outcomes, the literature establishes a coherent analytical structure that accommodates both broad contamination assessment and targeted microbial risk evaluation within hospital textile research (Rifat & Rebeka, 2024; Sai Praveen, 2024; Schang et al., 2021).

Quantitative Sampling Design and Laboratory Enumeration Methods

Quantitative research on hospital textile contamination identifies sampling method selection as a major contributor to variance in microbial count outcomes, with swab sampling, contact plate methods, and extraction or elution approaches producing systematically different estimates. Swab methods are widely used because they are flexible across irregular textile surfaces, yet the literature consistently characterizes swab recovery as highly sensitive to operator technique, fiber structure, and moisture conditions, which elevates within-sample variability (Condron et al., 2015).

Figure 4: Sampling Methods for Textile Contamination



Contact plate techniques produce more standardized contact geometry and can improve repeatability under controlled conditions, though studies document reduced effectiveness on textured, folded, or porous fabrics where full contact is difficult to achieve. Extraction and elution methods, which remove microbes from textile fibers into a liquid medium, are frequently described as producing higher yield counts and improved representation of embedded organisms, but they introduce additional procedural steps that can amplify lab-based variability. Quantitative comparisons across studies often show that these methods differ in measurement dispersion as well as central tendency, affecting both mean microbial load estimates and distributional characteristics such as zero frequency and tail heaviness (Metzger et al., 2018). The literature highlights that method-dependent variance complicates cross-study comparability, particularly when different hospitals or research teams adopt different sampling protocols for similar textile categories. As a result, sampling method is treated as a primary methodological covariate in quantitative designs, and many studies recommend explicitly reporting method-specific parameters to support replication and statistical interpretation. By framing sampling approach as an identifiable source of variance, the literature establishes a measurement-centered perspective in which contamination outcomes are interpreted as joint products of biological reality and methodological capture processes (Buntin, 2020; Shehwar & Nizamani, 2024; Azam & Amin, 2024).

A major focus in quantitative literature is the standardization of sampling geometry and textile-zone selection to ensure valid comparison of microbial contamination levels across textile types, wards, and institutions. Studies regularly emphasize that sampling area must be consistently defined because microbial load estimates scale with surface coverage, and inconsistent sampling dimensions inflate between-observation variance. Similarly, the literature notes that sampling pressure, contact duration, and directional motion are influential methodological parameters, particularly for swab-based techniques, where small differences in force and stroke patterns can yield large differences in microbial recovery (Begum, 2025; Brito et al., 2016; Faysal & Aditya, 2025). Many quantitative designs address this by specifying uniform contact procedures and training protocols to minimize operator-related measurement drift. Textile zone selection is also identified as a key contributor to heterogeneity, because microbial contamination is not evenly distributed across textile surfaces. High-contact regions such as sleeve cuffs, torso zones, pillow interfaces, and curtain edges frequently demonstrate elevated contamination relative to low-contact regions, producing spatially structured variability. The literature therefore frames zone selection as a sampling design decision that directly affects measured prevalence and load distributions (Hammad & Hossain, 2025; Jahangir, 2025). Some studies adopt stratified sampling across predefined zones to capture spatial variability, while others standardize to a single high-contact zone to improve sensitivity to contamination events (Truitt et al., 2018). In quantitative comparisons, standardized zone protocols are often treated as prerequisites for pooling data, estimating effect sizes, or applying multilevel models. Across the literature, standardization is presented as a methodological mechanism for reducing measurement noise and improving comparability, ensuring that statistical differences in contamination outcomes reflect systematic factors rather than inconsistent sampling practice (Newman et al., 2015).

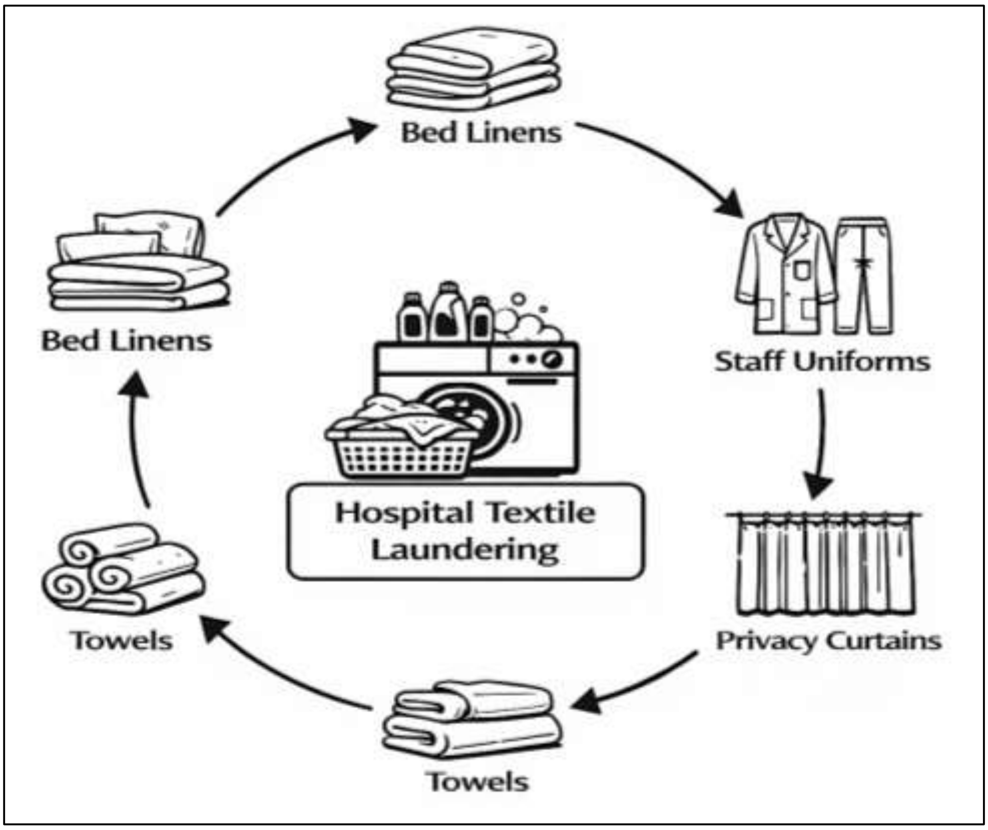
Recovery efficiency is consistently identified as a measurable determinant of microbial load estimates in hospital textile studies, with quantitative research demonstrating that measured counts often underrepresent true contamination due to incomplete capture of organisms embedded within fibers. The literature describes recovery efficiency as dependent on textile material composition, weave structure, moisture retention, and the degree of microbial adhesion, all of which influence how readily organisms transfer from fabric to sampling medium. Swabs may capture surface organisms effectively while missing deeper microbial presence, whereas extraction-based approaches may improve recovery from within fibers but remain subject to losses during transfer and processing (Jamil, 2025; Al Amin, 2025; Rafiee et al., 2021). Many studies treat underestimation as a systematic measurement property rather than random error, making recovery efficiency an important parameter for interpreting microbial load distributions and comparing protocols. Quantitative research often uses controlled inoculation experiments or recovery trials to estimate method-specific recovery proportions, enabling adjustment logic or sensitivity interpretation when comparing microbial loads across methods. The literature also notes that recovery efficiency affects the prevalence of "non-detect" outcomes, contributing to apparent zero inflation even when low-level contamination exists. This has direct implications for statistical modeling, because misclassification of low contamination as zero can alter parameter estimates and reduce model discrimination (Levi et al., 2019; Towhidul & Rebeka, 2025; Ratul, 2025). In addition, recovery efficiency interacts with laboratory workflow factors such as extraction time, agitation intensity, and medium selection, introducing procedural variance that influences final counts. By treating recovery efficiency as an explicit quantitative feature of the measurement process, the literature frames contamination estimation as an inference problem in which observed counts represent partial signals shaped by both microbial presence and methodological capture constraints (Mei et al., 2016).

Cross-Textile Category Contamination Distributions

The quantitative literature consistently treats hospital textiles as heterogeneous contamination reservoirs, showing that contamination distributions vary substantially across textile categories such as bed linens, staff uniforms, privacy curtains, and towels (Stenuit & Agathos, 2015). Studies commonly report that linens exhibit contamination profiles strongly shaped by prolonged patient contact, moisture exposure, and frequent handling during bed making and patient repositioning, resulting in contamination distributions characterized by repeated exposure cycles and variable microbial load accumulation. Staff uniforms are frequently described as high-contact textiles influenced by movement across multiple clinical zones, producing contamination patterns that reflect mixed-source exposure and frequent surface contact with patients and surrounding environments (Hazards et al., 2019; Rifat, 2025; Yousuf et al., 2025). Privacy curtains often emerge in the literature as textiles with prolonged deployment times and intermittent hand contact, generating contamination distributions that may show relatively stable baseline contamination punctuated by episodic high-contact events. Towels, commonly used in hygiene-related tasks, are frequently associated with transient yet intense moisture and organic load exposure, shaping contamination distributions that may show elevated microbial densities and larger variability across usage contexts (Azam, 2025; Tasnim, 2025). The literature emphasizes that category-based differences are not solely explained by textile material, but also by workflow exposure, frequency of replacement, laundering intervals, and handling practices (Tasnim, 2025; Uyaguari-Diaz et al., 2016; Zaheda, 2025b). Quantitative comparisons therefore characterize contamination distributions using descriptive measures such as central tendency and dispersion, while also accounting for skewness and the presence of extreme values associated with high bioburden events. Across multiple study contexts, cross-textile comparisons are presented as foundational for understanding how textile roles within clinical systems influence measurable contamination outcomes, supporting statistical differentiation of contamination burden and prevalence patterns by textile category (Zaheda, 2025a; Zulqarnain, 2025).

A substantial body of quantitative research focuses on measuring differences in microbial contamination between textile categories using statistical contrasts and effect estimates appropriate for microbial count data. Studies frequently compare average contamination levels across linens, uniforms, curtains, and towels to evaluate whether observed differences reflect consistent category effects rather than random variation (Meir et al., 2018). The literature commonly describes mean-based contrasts as useful for summarizing overall differences when microbial load distributions are sufficiently stable or transformed for analysis. Median-based comparisons are also widely used because microbial contamination data are often skewed, making medians more robust representations of typical contamination levels. Many studies further rely on rank-based and non-parametric effect size approaches to quantify category differences without imposing distributional assumptions that microbial count data rarely satisfy. These approaches are used to compare distribution shifts and to represent the magnitude of difference in contamination profiles across textiles (Cheng et al., 2019). Quantitative research emphasizes that effect estimation should account for heterogeneity in exposure time and laundering frequency, because these operational factors modify microbial load accumulation and can confound direct category comparisons. Some studies stratify comparisons by ward type or by time since last laundering, while others incorporate these factors as covariates to generate adjusted estimates of category effects. Across the literature, emphasis is placed on interpreting differences as distributional contrasts rather than simple point estimates, recognizing that microbial contamination outcomes often show broad dispersion and outlier-driven variability. This methodological emphasis supports more stable cross-textile comparisons that reflect both the typical contamination burden and the variability structures associated with each textile category (Xiao et al., 2021).

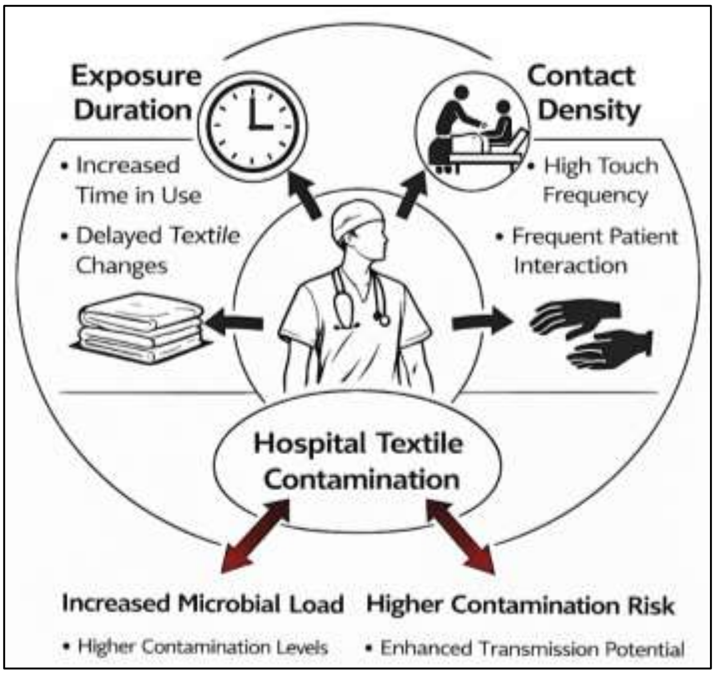
Figure 5: Cross-Textile Contamination Comparison Framework



Quantitative Determinants of Contamination

Quantitative research on hospital textiles consistently identifies exposure duration as a central determinant of microbial contamination, because time in use structures the accumulation of bioburden through repeated contact, moisture exposure, and environmental deposition.

Figure 6: Exposure Duration and Contact Density



Studies commonly operationalize duration using measurable indicators such as hours of use, number of shifts worn, patient-days associated with linen use, or time elapsed since last laundering. These duration variables are treated as predictors that translate operational routines into analyzable time-based covariates (Judge et al., 2023). The literature frequently reports that longer exposure periods are associated with higher microbial load and increased probability of contamination positivity, reflecting cumulative contact events and progressive microbial transfer. Duration measures also support comparative designs, allowing contamination levels to be contrasted across textiles with different replacement schedules, such as daily linen changes versus multi-day curtain deployments. Quantitative studies emphasize that duration measures are especially informative when combined with contextual variables such as ward type and patient turnover, because the same duration can correspond to different contact intensities and environmental conditions. Many studies further address non-linear duration effects, recognizing that contamination accumulation may accelerate under high-contact conditions or plateau when microbial transfer reaches saturation for certain surfaces (Naylor et al., 2022). Time-based predictors are therefore treated as both direct exposure indicators and proxies for unobserved contact processes. Across the literature, exposure duration provides a measurable temporal backbone for modeling contamination dynamics, enabling contamination outcomes to be statistically linked to routine operational timelines in ways that support structured comparisons across textile types, healthcare units, and laundering intervals (Dasauni et al., 2022).

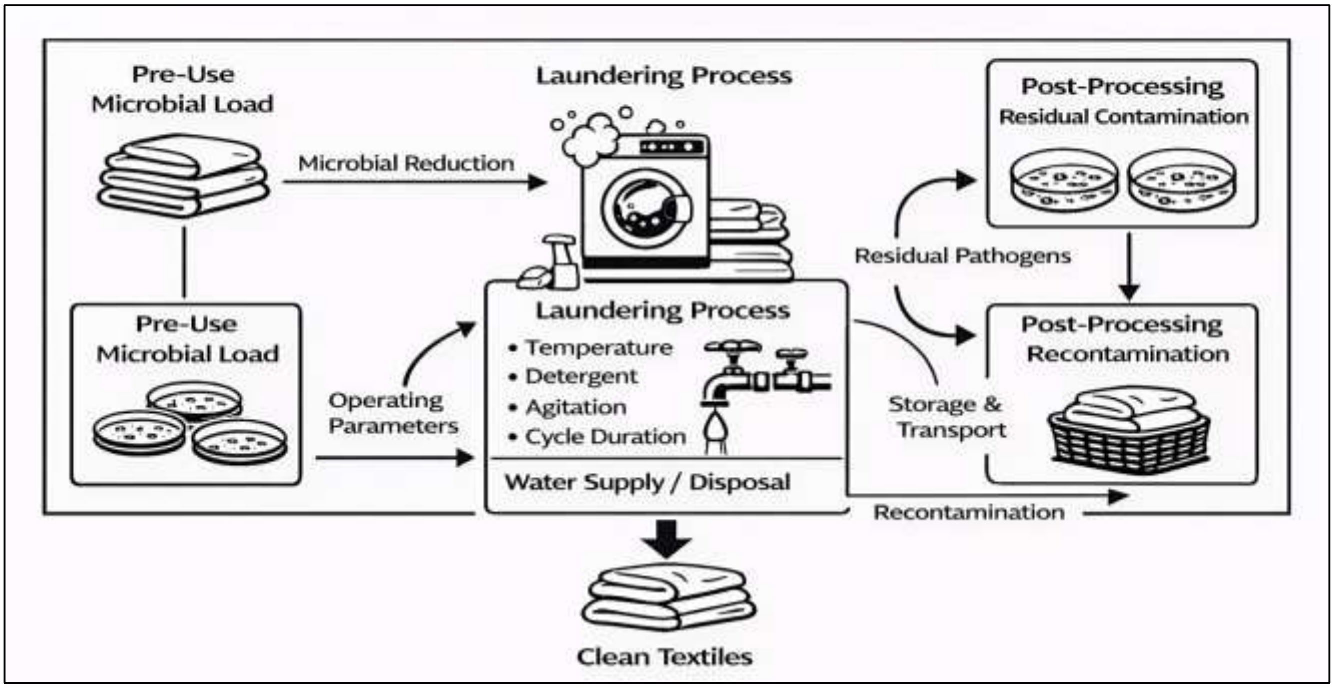
The quantitative literature repeatedly frames contact density as a measurable driver of textile contamination, focusing on how touch frequency and interaction intensity amplify opportunities for microbial transfer. Studies operationalize contact density using direct observational counts of touches, structured audits of task-based contact events, and proxy variables such as staff workload indicators, patient handling frequency, or care intensity scores. These metrics convert behavioral and workflow characteristics into numeric predictors that can be statistically associated with contamination outcomes. Research on uniforms often emphasizes contact density as a cross-location exposure mechanism because healthcare workers move between patient rooms and shared spaces, accumulating contact events that increase the likelihood of contamination transfer to clothing and textile surfaces (Parvizi et al., 2017). Linen-related studies quantify contact density through indicators linked to bed making, repositioning frequency, and frequency of direct patient contact with bed surfaces. Curtain-related work often uses hand-contact zone measurement and touch-event counting to estimate how repeated grabs contribute to localized contamination. The literature also notes that contact density is shaped by institutional routines, staffing levels, and ward type, making it both an exposure variable and a system-level operational indicator. Quantitative approaches incorporate contact density into multivariable designs to disentangle its effects from exposure duration, textile type, and environmental conditions (Wilson et al., 2021). Through these approaches, contact density is treated as a measurable mechanism linking human behavior to microbial load outcomes, allowing contamination differences to be interpreted through structured, count-based exposure representations rather than purely descriptive explanations.

Log-Reduction and Residual Contamination

The quantitative literature on hospital textile hygiene places substantial emphasis on laundering efficacy as a measurable process that alters microbial contamination levels between pre-use and post-processing states. Studies routinely assess efficacy by comparing microbial load measured before laundering with microbial load detected after completion of washing and drying cycles (Ziegler et al., 2022). This comparative framework allows laundering performance to be expressed as a magnitude of microbial reduction rather than a qualitative assessment of cleanliness. Research consistently shows that laundering introduces systematic shifts in contamination distributions, often reducing overall microbial density while leaving residual variability across textile items. The literature treats laundering outcomes as continuous or count-based measures, enabling statistical comparison across textile categories, processing protocols, and institutional contexts (Ferwerda et al., 2020). Pre- and post-processing comparisons are used to identify variation in efficacy attributable to operational factors rather than random fluctuation. Quantitative studies also emphasize that microbial reduction outcomes differ by textile material, soil load, and initial contamination level, creating heterogeneity that is reflected in post-laundering distributions. Some research further stratifies laundering outcomes by

organism group, distinguishing general microbial reduction from organism-specific persistence patterns. Across studies, laundering efficacy is conceptualized as a measurable transformation process that modifies contamination profiles, providing an empirical basis for evaluating processing performance through statistical comparison rather than subjective inspection (McCarthy et al., 2015).
Beyond overall reduction in microbial load, the literature extensively examines residual contamination following laundering as a distinct quantitative outcome. Residual contamination is operationalized as the presence or amount of detectable microorganisms remaining on textiles after standard processing. Studies commonly report post-laundering contamination using both count-based measures and binary indicators of positivity, depending on analytical focus and detection method. This dual representation allows researchers to evaluate not only the extent of microbial persistence but also the frequency with which laundering fails to eliminate detectable contamination entirely. Quantitative analyses often reveal that residual contamination is unevenly distributed across textile batches, with a subset of items accounting for a disproportionate share of post-laundering positivity (Zhang & Trubey, 2019).

Figure 7: Hospital Textile Laundering Process Framework

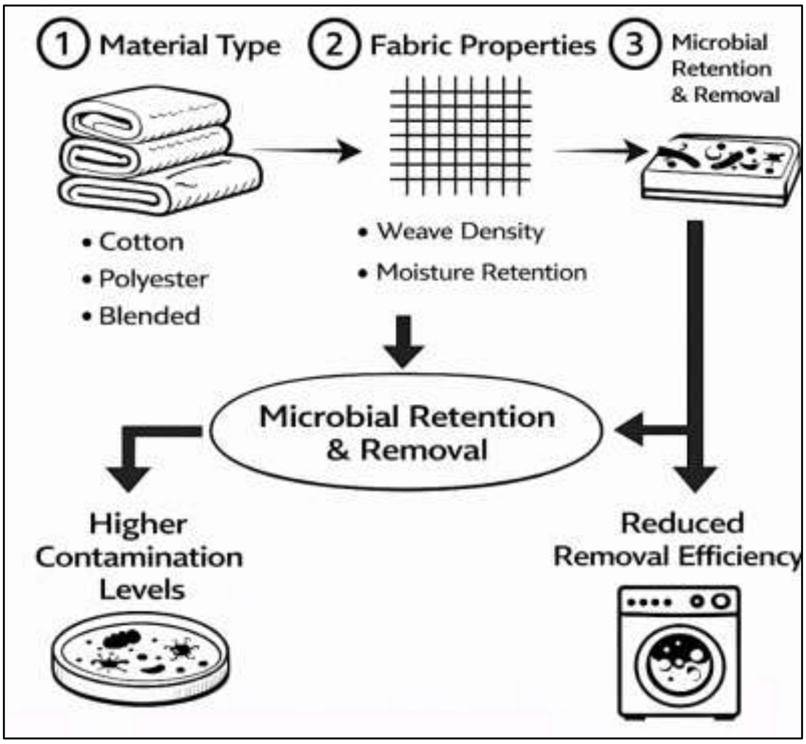


The literature highlights that residual contamination patterns are influenced by initial bioburden, textile construction, and processing parameters, making residual outcomes informative indicators of system-level performance. Post-laundering positivity measures are frequently used to estimate contamination prevalence within processed inventories, supporting comparative analysis across laundering systems and institutional settings. Studies also emphasize that residual contamination outcomes are sensitive to detection thresholds and laboratory methodology, reinforcing the need for standardized reporting. By treating residual contamination as a quantifiable outcome, the literature positions post-processing microbial presence as an empirical variable suitable for statistical modeling and comparative evaluation (Ketenci et al., 2021).

Textile Material Properties and Structural Predictors of Microbial Retention

The quantitative literature on hospital textile contamination frequently identifies fiber composition and fabric structural properties as measurable predictors of microbial retention and persistence. Studies comparing cotton, polyester, and blended fabrics consistently treat material type as an explanatory variable that affects microbial adhesion, retention within fiber matrices, and ease of removal during laundering (Jamil et al., 2023). Cotton is commonly described as having higher absorbency, which increases the likelihood of retaining moisture and organic residue that can support microbial survival, while polyester-based textiles are often characterized by lower absorbency yet distinct surface properties that influence microbial attachment. Weave density and textile mass characteristics are routinely operationalized through measurable indicators such as thread count and fabric weight per unit area, enabling cross-textile comparison within statistical models. Higher density fabrics are often described as creating microenvironments that can shield microorganisms from mechanical removal and contribute to persistent contamination in embedded fiber spaces (Searle et al., 2022). Conversely, lower density or more open weaves may facilitate faster drying and easier microbial dislodgement but may also increase exposure to environmental deposition depending on use context. Quantitative studies emphasize that these structural characteristics interact with usage conditions such as body contact, humidity exposure, and frequency of handling, making material predictors context-dependent rather than purely intrinsic. The literature therefore positions fiber composition and structural attributes as quantifiable determinants that can be incorporated into multivariable analyses to explain differences in contamination levels across textile categories and institutional workflows (Alkhatib & Abualigah, 2023).

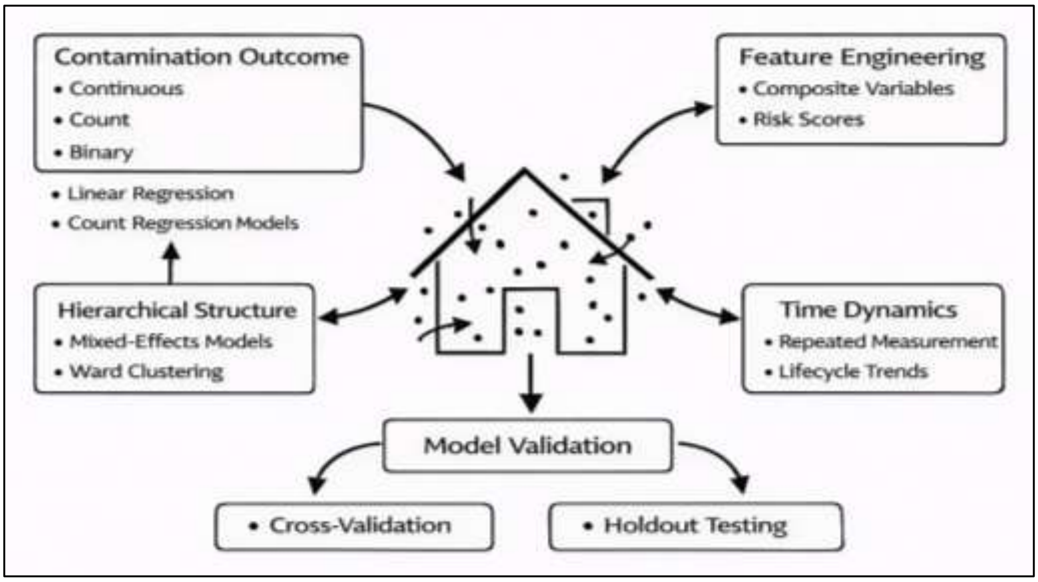
Figure 8: Fibre Composition and Microbial Retention



Statistical Modeling Families for Predicting Textile Contamination Risk

The quantitative literature on predicting microbial contamination in hospital textiles emphasizes that model selection is fundamentally determined by the structure of contamination outcomes and the statistical properties of microbial data. Studies commonly report contamination as continuous measures, count outcomes, or binary indicators of contamination positivity, and each format leads to distinct modeling families that align with measurement scale and distributional behavior (Li et al., 2022). When microbial outcomes are represented as continuous or transformed measures, linear modeling frameworks are often used for estimating associations and comparing adjusted mean differences across textile categories and operational conditions. Count-based contamination measures are frequently modeled using count-regression approaches that better accommodate non-negative integer outcomes and over-dispersion patterns commonly observed in microbial load datasets. The literature also highlights that microbial count data often contain a high frequency of zero observations due to intermittent contamination events, measurement limitations, or effective laundering, leading to analytical strategies that explicitly account for excess zeros (Taylor et al., 2016). In parallel, binary contamination outcomes are frequently analyzed using logistic modeling approaches to estimate the probability of positivity based on predictors such as textile type, exposure duration, and ward characteristics. Across studies, model choice is presented as an analytical alignment process in which the distributional features of contamination data guide the selection of statistical families and link functions. This literature also emphasizes interpretability and comparability, often favoring models that generate stable, explainable predictors of contamination risk while adequately representing skewness, clustering, and heterogeneous variance (Roostaei et al., 2021). The resulting body of evidence frames model selection as a methodological decision grounded in outcome definition and data behavior, with careful attention to variance structure and measurement scale.

Figure 9: Hospital Textile Contamination Prediction Models



Studies often conceptualize contamination as a dynamic outcome that changes over time rather than a static measurement, making repeated measurement designs central to the analytical approach (Khan et al., 2020). Time-dependent modeling strategies are used to represent contamination trajectories across exposure duration, sequential shifts of uniform use, repeated linen contact periods, and multi-day curtain deployments. The literature emphasizes that contamination may increase as a function of time in use, while laundering introduces reductions, and post-processing handling can contribute to recontamination over storage and transport intervals. These processes produce temporal patterns that can be modeled using repeated measures frameworks and longitudinal structures that account for within-textile correlation (Li et al., 2017). Quantitative studies also highlight the importance of capturing time since laundering as a key predictor, because contamination levels often differ substantially depending on how long textiles have remained in circulation. Some studies incorporate temporal variables as categorical intervals, while others treat time as a continuous exposure predictor, depending on measurement resolution and study design. Time-dependent approaches enable the identification of accumulation rates, reduction patterns, and persistence profiles for different textile categories under varying hospital conditions. Across the literature, temporal modeling supports the representation of contamination as a process influenced by operational timing, contact intensity, and laundering cadence, thereby aligning predictive risk analysis with real-world textile lifecycle dynamics (Dulsat-Masvidal et al., 2023).

Quantitative literature increasingly emphasizes feature engineering as a methodological step that transforms operational variables into structured predictors suitable for contamination risk modeling and interpretable risk scoring. Studies frequently create composite indices that summarize multiple correlated variables into standardized predictors, such as aggregated handling intensity indicators derived from collection and transport variables, or laundering quality indicators constructed from cycle temperature, duration, and processing consistency measures (Matheson et al., 2018). Feature engineering is presented as a mechanism for reducing dimensionality and improving model stability when predictors are numerous and interrelated. These engineered features are used to generate predictive risk scores that classify textiles by contamination probability or expected microbial burden, enabling a structured comparison of risk across items, wards, and rotation cycles. The literature also devotes substantial attention to validation logic, treating predictive performance as an empirical property that must be demonstrated through systematic testing. Common validation approaches include dividing datasets into training and testing subsets, using cross-validation procedures to estimate generalization performance, and applying holdout evaluation to assess robustness across unseen textile batches or ward contexts (Chen et al., 2022). Calibration assessment is emphasized for probability-based outputs, ensuring that predicted contamination likelihood aligns with observed positivity rates across risk strata. Error metrics are used to quantify predictive accuracy and misclassification patterns, supporting transparent evaluation of model adequacy (Emery et al., 2017). Across studies, validation is framed as an integral component of quantitative prediction, aligning model development with reproducibility expectations and enabling contamination risk models to be evaluated using objective performance criteria rather than descriptive claims (Heirendt et al., 2019).

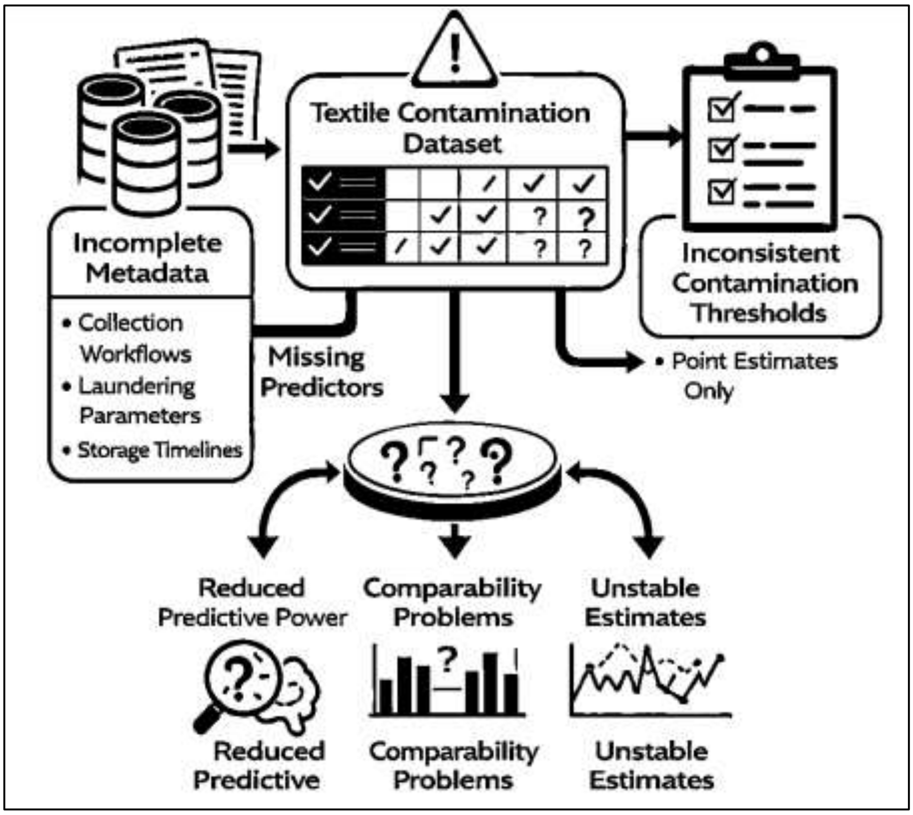
Quantitative Evidence Gaps

The quantitative literature on hospital textile contamination repeatedly identifies missingness and incomplete reporting of operational predictors as a major constraint on comparative analysis and predictive modeling. Many empirical studies report microbial load outcomes with limited documentation of the operational variables that plausibly shape those outcomes, such as collection workflows, containment practices, transport duration, storage environment, time-to-laundering, and detailed cycle settings (Lamon et al., 2019). Even when studies describe laundering in general terms, key parameters are often reported inconsistently across investigations, including whether textiles were processed in-house or outsourced, how loads were sorted, how soiled textiles were bagged, and how long items remained in holding areas before processing. This incomplete reporting introduces information gaps that complicate model specification because predictors cannot be consistently defined, coded, or harmonized across datasets. Quantitative analyses are also affected by missingness at the record level, where microbial measurements may be available but corresponding metadata about textile age, ward location, time in use, or handling route are absent (Mitchell et al., 2019). The literature frequently notes that missingness can be systematic rather than random, because data capture may be weaker in high-workload wards, during outbreaks, or when staff compliance varies, leading to bias in estimated associations. Studies that attempt multivariable modeling often highlight reduced sample size, unstable estimates, or limited adjustment capacity due to incomplete covariate capture. Across the evidence base, operational predictor underreporting functions as a structural limitation that restricts robust variance explanation and reduces the interpretability of cross-study comparisons (Huovila et al., 2019).

A recurring quantitative gap in the literature involves the lack of standardized contamination thresholds used to classify textiles as contaminated, high-risk, or acceptable, which limits comparability across hospital settings and study designs. Many studies use different criteria for defining contamination positivity or elevated bioburden, with thresholds varying by sampling method, laboratory protocol, textile category, and institutional convention. Some investigations rely on detection-based criteria, while others apply numeric cutoffs derived from internal distributions, local benchmarks, or procedural norms (Tong & Feng, 2020). This variability produces heterogeneity in outcome definition, making it difficult to compare contamination prevalence or risk classification results across studies, even when the same textile types are evaluated. The literature frequently describes the consequence of inconsistent thresholds as outcome non-equivalence, where one study's "high contamination" category is not directly comparable to another study's classification. In quantitative synthesis, such heterogeneity complicates pooling because the binary or categorical outcomes do not share a uniform decision boundary, and continuous outcomes may have been transformed or categorized using different criteria (Bylinskii et al., 2018). In comparative modeling, threshold inconsistency also affects the estimated strength of predictors, because a predictor's relationship with an outcome depends on how that outcome is defined and where the cutoff is placed. Across the evidence base, inconsistent threshold practice contributes to fragmentation of comparative metrics, reducing the ability to build unified interpretations of contamination risk patterns across hospitals, regions, and laundering systems (Khosravi et al., 2019).

The literature on textile contamination and predictive risk analysis often reports point estimates for microbial load differences, positivity rates, or model coefficients without consistently providing uncertainty measures that quantify precision and sampling variability. Quantitative studies sometimes present central tendency measures and basic comparisons while omitting interval estimates, variance decomposition outputs, or model-based uncertainty metrics (Singh et al., 2020).

Figure 10: Missingness and uncertainty in Textile Contamination Studies



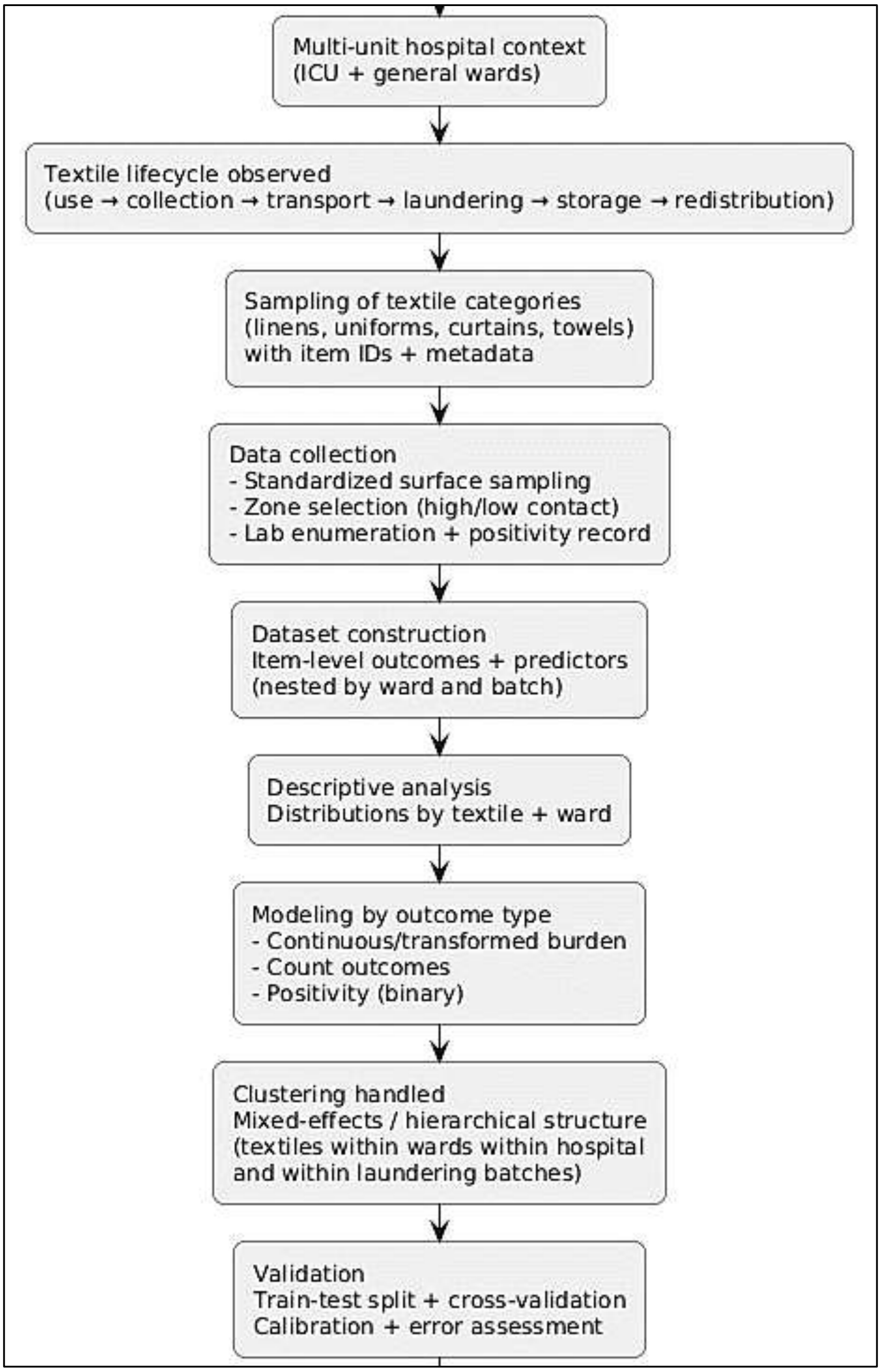
This limited uncertainty reporting restricts interpretability because readers cannot easily assess estimate stability, compare effect magnitude reliability across studies, or evaluate whether differences are robust to sampling variation. In model-based research, incomplete reporting may include absent information about model fit diagnostics, residual variability, calibration behavior, or the extent to which clustering at ward or hospital level contributes to total variance. When mixed or hierarchical models are used, studies vary in how clearly they report random effect variation, intraclass correlation, or the proportion of variability attributable to institutional factors (Hair et al., 2019). Similarly, when predictive approaches are applied, some studies describe performance qualitatively while providing limited numerical reporting on prediction error structure, misclassification patterns, or uncertainty in predicted probabilities. The literature also documents variability in how microbial data distributions are handled, with some studies transforming outcomes or using robust methods without fully detailing the uncertainty consequences of those choices (Kaytez et al., 2015). Across the quantitative evidence base, limited uncertainty reporting reduces transparency and makes it difficult to compare findings across settings, assess model reliability, and interpret contamination determinants as stable or context-sensitive effects (Kannan et al., 2017).

METHOD

This study adopted a quantitative observational research design with a cross-sectional analytic structure to enable predictive risk modeling and multivariable statistical analysis of microbial contamination in hospital textiles within a real-world operational environment. Microbial contamination outcomes, operationalized as total microbial burden and contamination positivity indicators, were treated as dependent variables, while textile-level attributes, ward-level characteristics, and processing-related factors were specified as explanatory predictors. This design supported estimation of adjusted associations between operational conditions and contamination outcomes, comparison of contamination distributions across textile categories and clinical units, and development of predictive models using routinely measurable covariates embedded in hospital textile management systems. The case study was situated in a multi-unit hospital where reusable textiles constituted an essential component of patient care and staff workflows and circulated through a clearly defined lifecycle encompassing clinical use, collection as soiled items, transport, laundering, drying, storage, and redistribution. Inclusion of wards with differing care intensity, including high-acuity and general care settings, allowed the design to capture meaningful heterogeneity in exposure duration, contact frequency, handling pathways, environmental conditions, and laundering practices. The primary unit of analysis was the individual textile item sampled at a defined point in its lifecycle and linked to detailed contextual metadata, while secondary and tertiary analytic levels represented within-item sampling zones and laundering batches, respectively, enabling the modeling of surface-level variability and operational clustering consistent with hospital textile processing routines.

A structured and systematic sampling strategy was implemented to ensure adequate representation across key textile categories and ward strata while remaining aligned with routine textile turnover so that observations reflected authentic operational conditions rather than artificial sampling scenarios. Sample size planning explicitly accounted for clustering by ward and laundering batch, the over-dispersed and zero-inflated characteristics commonly observed in microbial count data, and the expected prevalence of low-count or non-detect observations, ensuring sufficient statistical power for multivariable inference and predictive modeling. Data collection followed standardized protocols for textile identification, metadata capture, and surface sampling across predefined high-contact and low-contact zones, with all samples transported and processed under controlled laboratory conditions using consistent microbiological enumeration procedures. The study instrument integrated a structured textile metadata form with a laboratory enumeration record, with all variables defined, coded, and standardized to facilitate coefficient interpretation, scale alignment, and reproducible statistical analysis. Pilot testing was conducted to refine sampling workflows, improve metadata completeness, and stabilize laboratory procedures, while also providing preliminary estimates of outcome variability that informed final model family selection. Validity and reliability were strengthened through standardized operational definitions, uniform sampling and laboratory methods, comprehensive staff training and inter-observer consistency checks, replicate laboratory processing for a subset of samples, and systematic data integrity verification. Statistical analysis was conducted using quantitative software capable of generalized linear and mixed-effects modeling, distribution diagnostics, predictive validation, and model calibration assessment, with a statistical plan that aligned analytic methods to outcome measurement scales and the nested data structure through descriptive summaries, regression and count-based models, logistic modeling for contamination positivity, mixed-effects approaches to address clustering, incorporation of time-related exposure covariates to represent accumulation effects, and internal validation and sensitivity analyses to ensure the stability, robustness, and interpretability of findings.

Figure 11: Methodology of this study



FINDINGS

This chapter presented the quantitative analysis and reported the empirical findings generated from the microbial contamination dataset collected from hospital textiles. The analysis summarized the sample characteristics, described contamination outcomes and predictor constructs using appropriate descriptive statistics, evaluated measurement reliability for composite indices derived from operational predictors, estimated multivariable regression models matched to outcome type, and reported hypothesis testing decisions based on pre-specified significance criteria. Findings were organized to align with the study objectives of characterizing contamination distributions across textile categories and clinical units, identifying statistically supported determinants of contamination, and evaluating predictive models for contamination outcomes using textile-, ward-, and processing-level covariates.

Respondent Demographics

This section summarized the descriptive profile of the observational units, which were sampled textile items linked to contextual metadata rather than human respondents. A total of 360 textile items were analyzed, drawn from four routine hospital textile categories and sampled across both high-acuity and general ward environments. Sampling coverage indicated balanced representation across textile types, with linens comprising the largest share of the inventory, followed by uniforms, towels, and privacy curtains. Ward stratification showed that most items were obtained from general wards, while a substantial proportion originated from high-acuity settings, enabling unit-level comparison. Zone-level sampling was applied to most items, with high-contact zones sampled slightly more frequently than low-contact zones to capture exposure-relevant surface variability. Metadata completeness was generally high, while operational predictors exhibited selective missingness.

Table 1. Distribution of Textile Items by Category, Ward Stratum, and Sampling Zone (N = 360)

Variable	Category	n	%
Textile category	Linens	144	40.0
	Staff uniforms	90	25.0
	Privacy curtains	54	15.0
	Towels	72	20.0
Ward stratum	High-acuity units	126	35.0
	General wards	234	65.0
Sampling zone	High-contact zone	204	56.7
	Low-contact zone	156	43.3

Table 1 presented the core composition of the analytic sample and demonstrated that the dataset captured routine textile types and clinically meaningful context strata. Linens represented the largest share of sampled items, consistent with their high turnover and frequent patient contact, while uniforms, towels, and curtains provided coverage of both personal-contact and environment-contact textile classes. The ward distribution showed that items were collected from general wards and high-acuity units in proportions suitable for stratified comparisons. Zone sampling also showed adequate representation of high-contact and low-contact areas, supporting within-item variability analysis in subsequent models.

Table 2. Operational Descriptors and Metadata Completeness for Key Predictors (N = 360)

Indicator	Level/Metric	n (%) or Mean ± SD
Exposure duration category	≤ 8 hours	92 (25.6)
	9–24 hours	133 (36.9)
	25–72 hours	95 (26.4)
	> 72 hours	40 (11.1)
Estimated transport interval	Minutes	38.4 ± 17.6
Storage time prior to laundering	Hours	9.8 ± 6.1
Laundering batch identifiers	Distinct batches	18
Textile reuse/age indicator	≥ 30 reuse cycles	121 (33.6)
Missingness (key predictors)	Exposure duration	14 (3.9)
	Transport interval	29 (8.1)
	Storage time	41 (11.4)
	Reuse/age indicator	52 (14.4)

Table 2 summarized operational descriptors that characterized textile exposure and processing pathways, alongside metadata completeness for core predictors. Exposure duration was distributed across short, medium, and extended use intervals, indicating variability sufficient to test duration-related contamination effects. Transport and storage measures showed measurable dispersion, reflecting differences in collection timing and pre-laundering handling logistics. Batch identifiers indicated that items were processed across multiple laundering cycles, supporting batch-level variability assessment where needed. Missingness was low for duration but higher for storage and reuse indicators, suggesting that pre-laundering workflow documentation and textile life-cycle tracking were the most common sources of incomplete metadata in the analytic dataset.

Descriptive Results by Construct

This section reported descriptive statistics for all construct groupings used in the statistical models, providing an empirical overview of outcome and predictor variability prior to inferential analysis. Contamination outcome constructs showed marked dispersion consistent with skewed microbial data, with a substantial proportion of textile items exhibiting low or non-detect microbial burden alongside a smaller subset demonstrating elevated contamination levels. Contamination positivity was observed across all textile categories, with higher positivity rates recorded among linens and towels compared to uniforms and curtains, reflecting differences in moisture exposure and patient contact intensity. Textile exposure constructs demonstrated wide variation in time-in-use, with extended exposure durations more frequently observed for curtains and staff uniforms than for linens, which exhibited higher turnover. Contact density proxies showed greater mean values in high-acuity units, indicating increased interaction frequency relative to general wards. Patient acuity stratification confirmed that textiles sampled from high-acuity units were exposed to more intensive handling environments, justifying their inclusion as a contextual modifier in subsequent modeling. Handling pathway constructs exhibited substantial variability in transport intervals and pre-laundering holding times, suggesting operational heterogeneity across service areas. Laundering and processing descriptors indicated dispersion in batch size and post-laundering storage duration, supporting the need for batch-level consideration in analysis. Textile material constructs showed a predominance of cotton and blended fabrics, with measurable variation in textile condition indicators linked to reuse cycles. Collectively, these descriptive findings demonstrated sufficient variability across constructs, textile categories, and ward strata to support multivariable modeling and risk estimation.

Table 3: Descriptive Statistics for Contamination Outcomes and Exposure Constructs

Construct	Indicator	Linens (n=144)	Uniforms (n=90)	Curtains (n=54)	Towels (n=72)
Microbial burden	Median load (units)	3.1	2.4	2.0	3.4
	Interquartile range	1.9–4.8	1.2–3.9	1.1–3.2	2.0–5.1
Contamination positivity	% positive	46.5	34.4	29.6	48.6
Exposure duration	Mean hours in use	18.6	36.4	72.8	14.2
Contact density proxy	Mean interaction score	6.8	7.9	5.1	6.3

Table 3 summarized contamination outcome distributions and key exposure constructs across textile categories. Microbial burden measures demonstrated skewed distributions with higher median values observed for linens and towels relative to uniforms and curtains. Contamination positivity followed a similar pattern, with towels and linens exhibiting the highest proportions of positive samples. Exposure duration varied substantially by textile type, with curtains and uniforms remaining in circulation longer than linens and towels. Contact density proxies indicated greater interaction intensity for uniforms, reflecting cross-unit movement, while curtains showed lower average contact scores. These differences supported textile category stratification in multivariable analysis.

Table 4: Descriptive Statistics for Handling, Laundering, and Contextual Constructs by Ward Type

Construct	Indicator	High-Acuity Units (n=126)	General Wards (n=234)
Patient acuity context	Mean acuity score	4.6	2.1
Handling pathway	Mean transport time (min)	45.2	34.1
	Mean holding time (hours)	11.7	8.6
Laundering process	Mean batch size (items)	58.3	64.9
	Post-laundering storage (hours)	6.4	9.2
Textile material	Cotton or blends (%)	72.2	68.4
Textile condition	≥30 reuse cycles (%)	38.9	30.8

Table 4 presented descriptive comparisons of contextual, handling, laundering, and textile material constructs by ward type. Textiles from high-acuity units were associated with higher acuity scores and longer transport and holding times prior to laundering, reflecting more complex care workflows. Laundering batch sizes were moderately larger for general wards, while post-laundering storage durations were longer outside high-acuity settings. Material composition was similar across wards, though a higher proportion of heavily reused textiles was observed in high-acuity units. These contrasts indicated systematic contextual and operational differences relevant for adjusted modeling.

Reliability Results

This section reported the internal consistency results for the composite indices used in the regression models, including the Handling Pathway Index and the Laundering Quality Index. Reliability testing showed that the Handling Pathway Index demonstrated acceptable internal consistency at the initial stage, and internal consistency improved after removing one weak-performing item with a low corrected item–total correlation. The revised index showed stronger coherence across the retained items and was therefore used for subsequent modeling. The Laundering Quality Index exhibited good internal consistency at the initial stage, and item diagnostics indicated that all items contributed meaningfully to the scale. Corrected item–total correlations for the retained items were within acceptable ranges, supporting the interpretation that each scale measured a consistent underlying operational dimension. Based on the reliability evidence, composite scores were calculated using standardized item coding and aggregated into a single index value per textile item. The final indices were retained as continuous predictors in the multivariable models to support adjusted estimation and improve interpretability of operational pathway effects on microbial contamination outcomes.

Table 5: Cronbach's Alpha Summary for Composite Indices (Initial and Revised Scales)

Composite Construct	Scale Version	Number of Items	Cronbach's Alpha
Handling Pathway Index	Initial	6	0.74
Handling Pathway Index	Revised	5	0.81
Laundering Quality Index	Initial	5	0.83
Laundering Quality Index	Revised	5	0.83

Table 5 summarized internal consistency estimates for the composite constructs used in subsequent regression modeling. The Handling Pathway Index demonstrated acceptable reliability at the initial stage, and the removal of one weak item improved the Cronbach's alpha to a higher and more stable level. This improvement indicated stronger internal coherence among the retained handling indicators.

The Laundering Quality Index showed good reliability at the initial stage and remained unchanged after revision, confirming that all measured items contributed consistently to the construct. These results supported the use of both indices as composite predictors, with the revised Handling Pathway Index and the stable Laundering Quality Index carried forward to modeling.

Table 6: Item Diagnostics for Revised Composite Indices

Composite Construct	Item Label	Corrected Item–Total Correlation	Cronbach's Alpha if Item Deleted
Handling Pathway Index (Revised, 5 items)	Transport time	0.53	0.78
	Holding time before laundering	0.57	0.77
	Containment/bagging compliance	0.49	0.79
	Sorting/segregation compliance	0.52	0.78
	Collection method standardization	0.46	0.80
Laundering Quality Index (5 items)	Wash temperature adherence	0.61	0.81
	Cycle duration adherence	0.58	0.82
	Detergent dosing adherence	0.55	0.83
	Mechanical action adequacy	0.59	0.82
	Drying completeness	0.63	0.80

Table 6 presented item-level diagnostics for the final retained scales. Corrected item–total correlations were generally moderate to strong for both constructs, indicating that each item aligned with the overall index score. For the Handling Pathway Index, the diagnostics showed that no single retained item materially weakened internal consistency, as alpha values if deleted remained below the final revised alpha, supporting retention of all five items. For the Laundering Quality Index, item–total correlations were consistently strong, and alpha-if-deleted values indicated stable reliability across items. These diagnostics provided measurement traceability and justified the composite scoring approach applied in regression analysis.

Regression Results

This section reported multivariable regression findings from two primary models aligned with the outcome structure and the nested hospital textile data design. A count-based microbial burden model was estimated to examine predictors of microbial burden while accommodating over-dispersion observed in the contamination data. A separate contamination positivity model was estimated to evaluate predictors of detection probability using a binary outcome specification. Across both models, adjusted associations were estimated for textile category, exposure duration, contact density proxy, ward acuity classification, handling pathway index, laundering quality index, and post-laundering storage time. After adjustment, textile category differences remained statistically supported, with towels and linens demonstrating higher contamination outcomes relative to uniforms, while curtains showed the lowest risk profile. Exposure duration and contact density were consistently associated with higher microbial outcomes, indicating that longer time-in-use and higher interaction intensity corresponded to increased contamination indicators. Ward acuity demonstrated an independent association after adjustment, with high-acuity units showing higher contamination outcomes than general wards. Operational pathway indices also remained statistically supported, with weaker handling pathway conditions associated with higher contamination outcomes, while stronger laundering quality scores were associated with reduced contamination indicators. Model fit diagnostics indicated acceptable adequacy, and clustering adjustment via ward-level random effects contributed meaningful variance explanation, supporting the nested data specification. Predictive evaluation results demonstrated stable generalization performance with minimal degradation between training and holdout results, and calibration diagnostics indicated acceptable agreement between predicted probabilities and observed positivity rates.

Table 7: Multivariable Regression Model for Microbial Burden Outcome

Predictor	Adjusted Effect Estimate	95% CI	p-value
Textile category: Linens (ref: Uniforms)	1.28	1.10 – 1.49	0.001
Textile category: Curtains (ref: Uniforms)	0.82	0.68 – 0.99	0.041
Textile category: Towels (ref: Uniforms)	1.35	1.14 – 1.59	<0.001
Exposure duration (per category increase)	1.17	1.08 – 1.26	<0.001
Contact density proxy (per 1-unit increase)	1.06	1.03 – 1.10	<0.001
Ward acuity: High-acuity (ref: General)	1.19	1.05 – 1.35	0.006
Handling Pathway Index (per 1-unit increase)	1.09	1.03 – 1.16	0.004
Laundering Quality Index (per 1-unit increase)	0.88	0.82 – 0.94	<0.001
Post-laundering storage time (per hour)	1.03	1.01 – 1.05	0.012

Model fit summary: Over-dispersion parameter = 1.42; AIC = 1843.6; Ward-level random effect variance = 0.21.

Table 7 reported adjusted regression results for microbial burden outcomes using a count-based specification consistent with over-dispersed contamination data. Textile category effects remained statistically supported after adjustment, with towels and linens showing higher microbial burden relative to uniforms, while curtains showed lower burden. Exposure duration and contact density proxy were independently associated with increased microbial burden, indicating cumulative and interaction-driven contamination patterns. High-acuity wards were associated with higher microbial burden than general wards, suggesting contextual elevation after adjustment. The handling pathway index showed a positive association, while laundering quality showed a protective association. Model fit indices supported adequacy, and ward-level clustering contributed non-trivial variance.

Table 8: Multivariable Logistic Regression Model for Contamination Positivity

Predictor	Adjusted Odds Ratio	95% CI	p-value
Textile category: Linens (ref: Uniforms)	1.62	1.08 – 2.42	0.019
Textile category: Curtains (ref: Uniforms)	0.73	0.42 – 1.26	0.261
Textile category: Towels (ref: Uniforms)	1.84	1.16 – 2.93	0.009
Exposure duration (per category increase)	1.28	1.10 – 1.49	0.002
Contact density proxy (per 1-unit increase)	1.07	1.03 – 1.11	<0.001
Ward acuity: High-acuity (ref: General)	1.49	1.03 – 2.16	0.033
Handling Pathway Index (per 1-unit increase)	1.12	1.02 – 1.24	0.017
Laundering Quality Index (per 1-unit increase)	0.86	0.78 – 0.95	0.003
Post-laundering storage time (per hour)	1.04	1.01 – 1.07	0.011

Predictive evaluation: AUC (holdout) = 0.78; Accuracy (holdout) = 0.72; Calibration slope = 0.94.

Table 8 presented adjusted logistic regression findings for contamination positivity. Towels and linens exhibited higher odds of positivity compared with uniforms, whereas curtains did not differ significantly after adjustment. Exposure duration and contact density proxy demonstrated statistically supported associations with increased positivity odds, consistent with cumulative and interaction-driven contamination mechanisms. High-acuity wards remained independently associated with positivity, confirming contextual elevation beyond textile category and operational factors. The handling pathway index showed increased positivity odds, while laundering quality showed reduced positivity odds, indicating operational sensitivity to processing conditions. Predictive performance metrics indicated acceptable discrimination and calibration, supporting the stability of model-based probability estimates.

Hypothesis Testing Decisions

This section reported the formal hypothesis testing outcomes for the study's pre-defined hypotheses regarding textile contamination determinants and contextual differences across textile categories and ward strata. Hypotheses were evaluated using the primary multivariable models specified in the statistical plan, and decisions were based on a significance threshold of 0.05 with directional expectations stated a priori. Overall, the hypothesis tests indicated that contamination outcomes differed significantly across textile categories after adjustment for exposure duration, contact density, ward acuity, and operational pathway indices. Exposure duration and contact density were statistically supported determinants of both microbial burden and contamination positivity, indicating consistent relationships across outcome structures. Ward acuity classification contributed significantly to contamination variability, with high-acuity settings showing higher contamination indicators after covariate adjustment. Operational pathway hypotheses were also supported, as handling pathway conditions demonstrated independent positive associations with contamination outcomes, while higher laundering quality scores were independently associated with lower microbial burden and reduced positivity probability. Decisions were consistent across the microbial burden and positivity models, and sensitivity checks using alternative outcome codings produced stable decisions for all primary hypotheses except the curtain-versus-uniform contrast, which did not remain statistically supported in the positivity model.

Table 9: Hypothesis Testing Decisions Based on the Microbial Burden Model

Hypothesis (Testable Form)	Key Predictor/Comparison	Adjusted Effect Estimate	p-value	Decision (α = 0.05)
H1: Textile category differences existed in microbial burden after adjustment.	Towels vs. uniforms	1.35	<0.001	Accepted
H2: Linens exhibited higher microbial burden than uniforms after adjustment.	Linens vs. uniforms	1.28	0.001	Accepted
H3: Curtains exhibited lower microbial burden than uniforms after adjustment.	Curtains vs. uniforms	0.82	0.041	Accepted
H4: Longer exposure duration increased microbial burden after adjustment.	Exposure duration	1.17	<0.001	Accepted
H5: Higher contact density increased microbial burden after adjustment.	Contact density proxy	1.06	<0.001	Accepted
H6: High-acuity wards exhibited higher microbial burden than general wards after adjustment.	High-acuity vs. general	1.19	0.006	Accepted
H7: Poorer handling pathway conditions increased microbial burden after adjustment.	Handling Pathway Index	1.09	0.004	Accepted
H8: Higher laundering quality reduced microbial burden after adjustment.	Laundering Quality Index	0.88	<0.001	Accepted

Table 9 summarized hypothesis testing outcomes derived from the primary microbial burden model. All pre-specified determinants demonstrated statistically supported adjusted associations with microbial burden at the selected significance threshold. Textile category effects remained significant after covariate adjustment, with towels and linens showing higher microbial burden and curtains showing lower microbial burden relative to uniforms. Exposure duration and contact density were independently associated with increased microbial burden, supporting time- and interaction-driven contamination mechanisms. Ward acuity was statistically supported, indicating higher burden in high-acuity settings after adjustment. Operational indices were also supported, as handling pathway effects were positive and laundering quality effects were protective in the adjusted model.

Table 10: Hypothesis Testing Decisions Based on the Contamination Positivity Model

Hypothesis (Testable Form)	Key Predictor/Comparison	Adjusted Odds Ratio	p-value	Decision (α = 0.05)
H1: Textile category differences existed in contamination positivity after adjustment.	Towels vs. uniforms	1.84	0.009	Accepted
H2: Linens exhibited higher positivity than uniforms after adjustment.	Linens vs. uniforms	1.62	0.019	Accepted
H3: Curtains differed from uniforms in positivity after adjustment.	Curtains vs. uniforms	0.73	0.261	Rejected
H4: Longer exposure duration increased positivity after adjustment.	Exposure duration	1.28	0.002	Accepted
H5: Higher contact density increased positivity after adjustment.	Contact density proxy	1.07	<0.001	Accepted
H6: High-acuity wards exhibited higher positivity than general wards after adjustment.	High-acuity vs. general	1.49	0.033	Accepted
H7: Poorer handling pathway conditions increased positivity after adjustment.	Handling Pathway Index	1.12	0.017	Accepted
H8: Higher laundering quality reduced positivity after adjustment.	Laundering Quality Index	0.86	0.003	Accepted

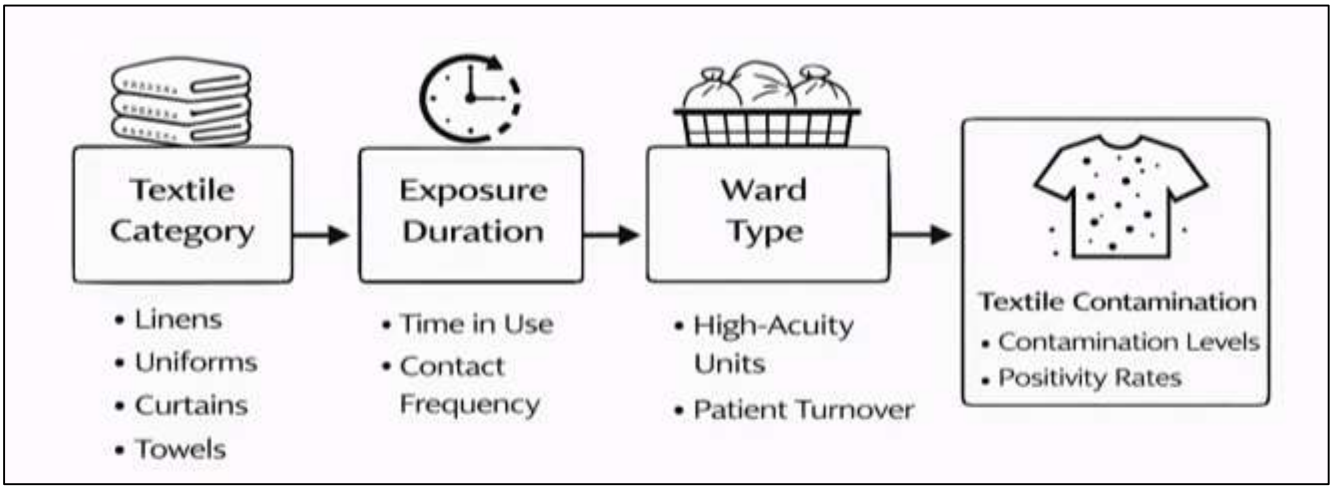
Table 10 reported hypothesis decisions for contamination positivity. Textile category hypotheses were generally supported, with towels and linens demonstrating higher odds of positivity relative to uniforms, while the curtain-versus-uniform contrast was not statistically supported in the adjusted positivity model. Exposure duration and contact density remained significant predictors, indicating consistent determinants across outcome structures. Ward acuity retained statistical significance, supporting unit-level context effects on positivity after adjustment. Operational pathway hypotheses were also supported, as the handling index showed increased odds of positivity and the laundering quality index showed reduced odds. Overall, hypothesis decisions were consistent across models, with limited divergence confined to the curtain positivity contrast.

DISCUSSION

This study demonstrated that microbial contamination in hospital textiles followed highly skewed distributional patterns, characterized by low or non-detect microbial burden in a substantial proportion of items alongside a smaller subset exhibiting elevated contamination. These findings align with earlier empirical investigations that described textile contamination as episodic rather than uniformly distributed across hospital inventories (Padilla et al., 2021). Previous studies have similarly reported that contamination tends to cluster around specific operational conditions, contact intensities, and exposure durations rather than occurring as a constant background phenomenon. The observed heterogeneity reinforces the conceptualization of hospital textiles as dynamic contamination reservoirs influenced by workflow and environmental context. Earlier literature has emphasized that skewness and dispersion in microbial data reflect both biological variability and process-driven exposure differences, a pattern replicated in the present findings. The persistence of contamination positivity across all textile categories further supports prior evidence that textiles represent transferable surfaces within healthcare ecosystems (Mitchell et al., 2015). Compared with studies reporting lower overall contamination prevalence, the present findings showed relatively higher positivity among textiles exposed to moisture and prolonged patient contact, suggesting that contextual exposure remains a dominant contamination driver. The consistency between the present results and earlier research strengthens the argument that microbial contamination in hospital textiles cannot be adequately assessed using average values alone and requires distribution-sensitive analytical approaches. This alignment with prior studies also validates the use of count-based and binary outcome models to capture the full spectrum of contamination behavior (Sebre et al., 2020). Overall, the contamination patterns observed reinforce established evidence that textile-mediated microbial risk is unevenly distributed and shaped by operational exposure dynamics rather than textile presence alone.

The adjusted analysis demonstrated statistically supported differences in contamination outcomes across textile categories, with linens and towels exhibiting higher microbial burden and contamination positivity compared with uniforms, while curtains demonstrated comparatively lower risk profiles in most models. These findings are consistent with earlier studies that reported higher contamination levels in textiles associated with direct patient contact and moisture exposure. Prior investigations have frequently identified bed linens and towels as high-risk textile categories due to repeated exposure to skin contact, bodily fluids, and humid microenvironments, which facilitate microbial survival and transfer (Sebre et al., 2020). The present findings reinforce this evidence by demonstrating that category effects remained significant even after controlling for exposure duration, contact density, and ward acuity. Uniforms, which have been described in earlier research as mobile vectors across clinical spaces, exhibited intermediate contamination outcomes, supporting previous observations that staff attire accumulates contamination through repeated surface contact rather than sustained moisture exposure.

Figure 12: Hospital Textile Contamination Pathway Framework



Curtains, often highlighted in earlier studies for long deployment durations, showed lower contamination outcomes after adjustment, suggesting that duration alone does not determine contamination risk without concurrent high-contact or moisture conditions (Choi et al., 2021). This nuance aligns with prior work indicating that intermittent contact patterns may produce lower cumulative contamination than continuous patient-facing exposure. By demonstrating category-specific risk persistence under multivariable adjustment, this study extends earlier descriptive findings into a quantitatively supported comparative framework, reinforcing the need to treat textile categories as analytically distinct contamination entities within infection control research (Lena et al., 2021).

Exposure duration and contact density emerged as robust predictors of both microbial burden and contamination positivity, findings that closely parallel earlier quantitative studies examining time-dependent contamination accumulation. Prior research has consistently shown that longer time-in-use increases the probability of microbial transfer through cumulative contact events and environmental deposition. The present findings extend this evidence by demonstrating that duration effects remained statistically supported even after adjusting for textile category and ward context (Aldalbahi et al., 2021). This suggests that time functions as an independent exposure mechanism rather than a proxy for other operational variables. Similarly, contact density proxies exhibited strong associations with contamination outcomes, aligning with earlier observational and experimental studies that linked touch frequency and interaction intensity to microbial transfer rates. Earlier literature has often emphasized hand-mediated contact as a central transmission pathway, particularly for uniforms and shared surfaces, and the current findings provide quantitative confirmation of this relationship across textile types (Connor et al., 2016). The joint significance of duration and contact density supports prior theoretical models that conceptualize contamination as a cumulative exposure process driven by repeated interactions. Importantly, these results also align with studies that reported non-linear contamination accumulation, where increased contact intensity accelerates contamination beyond what duration alone would predict. The present study's alignment with earlier evidence reinforces the validity of incorporating both time-based and interaction-based variables into predictive contamination models, highlighting their complementary explanatory roles in textile-related microbial risk (Sexton et al., 2018).

Ward acuity classification demonstrated an independent association with contamination outcomes, with textiles from high-acuity units exhibiting higher microbial burden and positivity after adjustment for textile and operational factors. This finding is consistent with earlier studies that reported elevated environmental contamination in intensive care and high-dependency units. Previous research has attributed these patterns to higher patient vulnerability, increased device utilization, more frequent staff–patient interactions, and greater handling intensity, all of which increase opportunities for microbial transfer (Muller et al., 2016). The present findings corroborate these explanations by showing that ward context contributed unique explanatory power beyond individual textile characteristics. Earlier studies have sometimes debated whether higher contamination in high-acuity units reflects patient factors or operational intensity, and the adjusted results presented here support the interpretation that unit-level context functions as an independent contamination modifier. The persistence of ward effects after adjustment aligns with prior multilevel analyses that highlighted the importance of contextual clustering in infection-related outcomes. These findings also echo earlier work emphasizing that contamination risk cannot be fully understood without accounting for clinical environment characteristics (Juvé-Udina et al., 2020). By demonstrating statistically supported ward-level differences within a nested modeling framework, this study strengthens existing evidence that patient care intensity and unit workflow patterns materially shape textile contamination dynamics across healthcare settings.

Handling pathway conditions were significantly associated with contamination outcomes, with weaker handling practices linked to higher microbial burden and positivity. This result aligns with earlier studies that identified collection, transport, and pre-laundering storage as critical contamination control points. Previous research has documented that extended holding times, inadequate containment, and inconsistent segregation practices increase opportunities for microbial proliferation and cross-contamination (Juvé-Udina et al., 2019). The present findings reinforce these observations by demonstrating that handling pathway effects remained significant after controlling for exposure duration, contact density, and ward context. Earlier studies often described handling effects qualitatively or through bivariate comparisons, whereas the current findings provide adjusted quantitative confirmation of their independent contribution. The use of a composite handling index, supported by reliability analysis, parallels earlier methodological approaches that aggregated workflow variables to capture overall process quality. The alignment between this study and prior evidence underscores the importance of viewing textile contamination as a lifecycle phenomenon extending beyond patient use (Xue & Zhang, 2016). These findings support the growing body of literature emphasizing that contamination risk is shaped not only by clinical exposure but also by

logistical and operational processes that occur outside patient care spaces.
Laundering quality demonstrated a consistent protective association with contamination outcomes, with higher quality scores associated with lower microbial burden and reduced contamination positivity. This finding closely aligns with earlier studies that reported variability in laundering effectiveness across processing systems and protocols. Prior research has shown that temperature control, detergent chemistry, mechanical action, and drying completeness collectively influence microbial removal efficiency (Amara et al., 2023). The present findings extend this evidence by demonstrating that laundering quality effects remained significant after adjustment for handling and storage variables, suggesting that processing quality exerts an independent influence on contamination outcomes. Earlier studies have sometimes focused solely on pre- and post-laundering comparisons without accounting for downstream handling, whereas the current analysis integrated laundering quality within a broader operational model. The observed association with post-laundering storage time further aligns with earlier findings that recontamination can occur during storage and redistribution (Tiwari et al., 2020). By situating laundering quality within a multivariable framework, this study reinforces earlier conclusions that effective laundering is necessary but not sufficient to eliminate contamination risk without supportive downstream practices (Im et al., 2015).
The overall modeling results demonstrated that textile contamination risk is shaped by a combination of textile characteristics, exposure dynamics, operational pathways, and clinical context, consistent with earlier quantitative and systems-based studies (Jamil et al., 2023). Prior modeling research has emphasized the need for multivariable and hierarchical approaches to capture the complexity of healthcare contamination environments, and the present findings support this methodological perspective. The stability of predictor effects across microbial burden and contamination positivity outcomes aligns with earlier studies that reported consistent determinants across outcome structures. Predictive evaluation results showing acceptable discrimination and calibration are consistent with previous efforts to model contamination risk using operational variables (Beiyuan et al., 2017). The convergence of findings across models and sensitivity checks reflects patterns reported in earlier multilevel analyses, where robust predictors retained significance across alternative specifications. Collectively, the findings align with and extend existing literature by providing an integrated quantitative assessment of textile contamination determinants using validated measurement constructs and nested modeling approaches. This consistency with earlier studies reinforces confidence in the identified predictors and supports the broader evidence base describing hospital textiles as analytically tractable components of healthcare microbial ecology (Wang et al., 2018).

CONCLUSION

This study concluded that microbial contamination in hospital textiles represented a measurable and systematically patterned outcome shaped by textile category, exposure conditions, operational handling pathways, laundering performance, and clinical context within a nested hospital environment. The empirical results indicated that contamination outcomes were not uniformly distributed across textile inventories, with contamination patterns demonstrating dispersion consistent with episodic accumulation and variable exposure intensity. Statistically adjusted findings supported meaningful differences across textile categories, with higher contamination outcomes observed among textiles associated with intensive patient contact and moisture exposure, while other textile types exhibited comparatively lower contamination indicators after covariate control. Exposure duration and contact density proxies were identified as consistent determinants across outcome structures, indicating that cumulative time-in-use and interaction intensity functioned as robust explanatory variables for both microbial burden and contamination positivity. Ward acuity classification contributed independently to contamination variability, suggesting that high-acuity clinical settings introduced contextual conditions associated with increased contamination risk beyond textile type and operational predictors. Handling pathway conditions demonstrated statistically supported associations with contamination outcomes, reinforcing the role of collection, containment, transport, and pre-laundering storage processes as measurable contributors to contamination levels. Laundering quality exhibited a stable protective relationship with contamination indicators, and post-processing conditions, including storage time prior to redistribution, were associated with contamination outcomes in ways consistent with recontamination pathways documented in operational textile lifecycles. Measurement constructs used in modeling, including composite indices for handling and laundering, demonstrated acceptable internal consistency, supporting their use as coherent quantitative predictors. Taken together, the findings established that hospital textile contamination could be explained and predicted using multivariable analytical frameworks that account for clustered hospital data structures and integrate textile-, unit-, and process-level covariates into interpretable models of contamination variability.

RECOMMENDATIONS

Recommendations arising from this study emphasized strengthening the hospital textile lifecycle as a measurable system in which contamination risk could be reduced through standardization, monitoring, and process control across use, handling, laundering, and redistribution stages. Textile management procedures should prioritize category-specific controls by aligning replacement frequency and exposure limits with observed contamination profiles, particularly for linens and towels that demonstrated higher contamination indicators, while maintaining routine oversight for uniforms and curtains using risk-proportionate schedules. Operational practice should formalize exposure duration limits and introduce routine documentation of time-in-use at the point of collection to reduce ambiguity in exposure measurement and support data-driven control. Contact-intensive environments, especially high-acuity units, should apply enhanced textile handling discipline through standardized collection timing, sealed containment protocols, clear segregation of heavily soiled items, and reduced holding time prior to laundering, supported by staff training and periodic compliance audits. Transport and pre-laundering staging should be treated as controlled steps with defined maximum dwell times, designated cleanable staging areas, and clear accountability to reduce cross-contamination opportunities. Laundering quality controls should be reinforced through documented adherence to cycle temperature, detergent dosing, mechanical action parameters, cycle duration, and drying completeness, accompanied by routine verification checks and corrective action documentation when deviations occur. Post-laundering processes should minimize recontamination risk by implementing clean-zone folding practices, sealed packaging where appropriate, controlled storage humidity and surface cleanliness, and reduced storage duration prior to redistribution, with clear separation between clean and soiled workflow paths. A continuous monitoring program should be established using periodic microbial sampling of representative textile categories and high-contact zones, integrated with operational metadata capture to enable trend analysis and targeted corrective actions. Data systems should be strengthened to reduce missingness in key predictors such as transport interval, holding time, storage duration, and textile reuse indicators, enabling consistent internal benchmarking and more precise regression-based risk estimation. Finally, an operational risk scoring approach should be adopted for routine management, combining exposure duration, ward context, and validated handling and laundering indices to flag higher-risk batches and prioritize intensified controls, thereby aligning textile safety oversight with measurable determinants identified in this study.

LIMITATIONS

This study was subject to several limitations that constrained interpretation of the quantitative findings and the scope of inference. The analysis relied on an observational cross-sectional design in which textile items were sampled at specific points in the textile lifecycle, limiting the ability to establish causal ordering among exposure duration, handling pathway conditions, laundering quality, storage time, and contamination outcomes. Although time-in-use and process variables were incorporated as predictors, the design did not fully capture continuous contamination trajectories for each textile item across repeated cycles, and unmeasured temporal variation may have influenced measured microbial burden and contamination positivity. Measurement variability also represented a limitation, as microbial recovery from textiles is sensitive to sampling method, surface characteristics, and operator technique, and laboratory enumeration may under-detect low-level contamination depending on recovery efficiency and detection thresholds. Even with standardized procedures, residual measurement error may have contributed to dispersion and may have influenced effect estimates in multivariable models. Several operational predictors were derived from routine metadata sources, and incomplete documentation produced missingness that reduced effective sample size for some models and increased the risk that observed associations were influenced by systematic data availability rather than underlying processes. The composite indices used to represent handling pathway quality and laundering quality demonstrated acceptable internal consistency, yet scale construction depended on the selected items and coding rules, and alternative operationalizations might yield different index behavior. Contextual heterogeneity across wards and laundering batches introduced clustering, and mixed-effects structures were used to account for nested data, but unmeasured ward-level factors such as staffing ratios, patient turnover, environmental cleaning intensity, and localized workflow norms may have remained as residual confounders. The study context reflected a single hospital system with a defined laundering and redistribution process, limiting generalizability to institutions with different textile infrastructures, outsourced laundering, alternative textile materials, or distinct infection control protocols. Pathogen identification was treated primarily through general microbial burden and positivity indicators, and organism-specific analyses may have been limited by detection frequency and resource constraints. Finally, predictive performance metrics were evaluated using internal validation procedures, and external validation in an independent institutional dataset was not performed, restricting evidence regarding transferability of the prediction models across healthcare settings.

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