

Research on the Adaptation Strategies of Ergonomically-Based Textile Soft Furnishings in Health Care Space Design

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ABSTRACT Smart textile systems integrated with intelligent sensing and adaptive optimization technologies have emerged as an important component of next-generation healthcare environments. This study proposes an Adaptive Ergonomic– Smart Textile Optimization Framework (AESTOF) for healthcare space applications by integrating ergonomic biomechanical modeling, smart textile functional characterization, environmental comfort analysis, and multi-objective decision optimization. The framework combines anthropometric mapping, pressure distribution simulation, thermal acoustic performance evaluation, antimicrobial efficiency assessment, and IoT-based sensor feedback to establish a quantitative adaptive textile evaluation system. A hybrid AHP–TOPSIS decision model is further employed to optimize textile configuration and adaptive performance. Simulation results demonstrate that the proposed framework reduces peak interface pressure by 34.6%, improves thermal comfort stability by 27.3%, decreases ergonomic risk by 22.8%, and enhances antimicrobial efficiency by 18.5% compared with conventional furnishing solutions. The results verify the effectiveness of intelligent sensing, adaptive control, and data-driven optimization in healthcare textile systems. This work provides a practical engineering framework for smart textile applications, intelligent sensing environments, and human-centered adaptive healthcare infrastructure.

INDEX TERMS smart textiles, intelligent sensing, adaptive optimization, healthcare infrastructure

I. INTRODUCTION

THE healthcare facilities have been exposing themselves to the need to have evidence-based interior solutions that promote patient recovery, employee efficiency, and infection control performance. Although there are advancements in the field of medical infrastructure, textile soft furnishings, including the bedding systems, the privacy curtains, the upholstery, and the acoustic panels, have not been at all optimized in an ergonomic and adaptive perspective [1]. The traditional approaches to furnishing have been mainly based on what appeals to the eye, the cost-effectiveness, or the single-isolate antimicrobial treatment without much consideration of the biomechanistic engagement between the users and the textile substances [2]. Extended patient immobility has been among the factors in pressure injuries and musculoskeletal discomfort, and healthcare providers have remained under cumulative ergonomic load in the form of poor seating, support surfaces, and environmental stressors [3]. Moreover, thermal instability, acoustic discomfort and microbial survival on the textile surfaces have remained as a challenge to healthcare space performance [4]. The above constraints have underscored the lack of a comprehensive ergonomic-smarter textile opti-

mization framework that has the potential to quantitatively connect the human factors with material science and environmental simulation in healthcare design.

The Existing methods of designing the healthcare furnishing have been more or less based on the three prevailing approaches [5]. To examine posture-associated risks, the methods of ergonomic assessment like Rapid Upper Limb Assessment (RULA) and Rapid Entire Body Assessment (REBA) have been very popular but have typically offered a qualitative or semi-quantitative evaluation approach without incorporating the behavior of textile materials under biomechanical load [6]. Second, tensile strength, air permeability, antimicrobial coating and durability performance have been conducting research extensively in textile engineering research, but these studies have been laboratory-focused with no modeling of the real-time user interaction [7]. Third, in healthcare architecture, environmental comfort modeling, especially thermodynamic comfort prediction based on Predicted Mean Vote (PMV) and acoustic absorption coefficient measurements, is used but these models have seldom been related to adaptive textile furnishing strategies [8]. Despite the recent development of smart textiles, with conductive yarns and moisture sensors, their integration

into interior ergonomics in healthcare institutions, however, has been disjointed and has not been optimized with an algorithm [9]. As a result, previous studies have failed to develop the standard framework that integrates anthropometric variability, biomechanical simulation, textile functional performance, environmental analytics, and multiobjective decision algorithms [10].

This study states that three key technical goals are set based on quantitative modelling, functional optimization and algorithmic decision intelligence of healthcare textile systems.

- To begin with, the research constructs a superior Ergonomic Biomechanical Modeling framework as it combines the anthropometric percentile mapping, joint kinematic evaluation, interface pressure calculations and musculoskeletal load transfer evaluation through finite element simulation. The module is used to produce structured biomechanical descriptors to accurately identify the stress propagation, deformation behavior, and ergonomic risk distribution at body-textile interfaces.
- The study develops a Smart Textile Functional Optimization layer which mathematically assesses antimicrobial kinetics, thermal stability (PMV/PPD modeling), moisture vapor transmission, air permeability, and acoustic absorption. The synthesized multidimensional parameters are combined into single functional performance representation, which makes it possible to produce adaptive textile behavior in the dynamic environmental and hygienic conditions.
- A Multi-Objective Algorithmic Decision Framework is adopted through incorporating AHP based criteria weighting, TOPSIS ranking, and regression based validation to compute the Composite Healthcare Textile Adaptation Index (CHTAI). The framework allows the optimal choice of textile configuration based on the strong performance aggregation and comparative analysis of the data.

The objectives are developed to provide a definite ergonomic improvement, decrease of infection risk, and stabilization of the environment of the healthcare spaces in the design. Current study has thus come up with Adaptive Ergonomic-smart textile optimization Framework (AESTOF) that incorporates biomechanical modeling, textile material science, intelligent sensing systems, and decision-fusion algorithms into a stature of adaptation plan. The framework has been subdivided into three subphases that are technologically sound. Subphase I, have done anthropometry percentiles mapping and simulation of pressure distribution to determine an Ergonomic Distribution Matrix of Load. Subphase II has already implemented textile characterization of functional workings and smart sensor-based performance measurement to calculate a Textile Functional Performance Index. Subphase III has used hybrid AHP-TOPSIS optimization, statistical regression validation in the

process of identifying the optimum furnishing configuration. With this, integrated computational and simulation-based framework, the research has offered a predictive and adaptatory furnishing design methodology instead of a pure description assessment. Ergonomically adaptive textile furnishings have become a critical issue to investigate because healthcare systems have focused on encouraging patient-centered care, employee well-being, and long-lasting infrastructure. This study has bridged the gap between the isolated ergonomic evaluation and textile engineering research that has produced a quantifiable and scalable optimization strategy. The study has not only used new algorithmic techniques in current furnishing concepts but has also addressed the loopholes that existed in earlier literature through the incorporation of the biomechanical simulation, environmental analytics and smart textile responsiveness in one cohesive system. With the persistence of healthcare environments to become smart and responsive in infrastructure, this kind of integration has proved necessary in enhancing operational safety, comfort stability and sustainability in the long-term.

The rest of this paper was organized in the following way. Section II provides the review of all available literature on ergonomic evaluation, textile functional performance, and integration of smart material in healthcare design. Section III explains the AESTOF proposed Adaptive Ergonomic-Smart Textile Optimization Framework and three technical subphases. Section IV describes the algorithmic modelling, the simulation protocols and the multi-objective decision modelling. Section V addresses the discussion of the experimental validation, statistical analysis, and performance evaluation findings. Lastly, the Section VI wraps up the study with the summary of findings and proposed research directions in the future of adaptive healthcare textile systems. The technical specification of the offered framework was brought to the point of clarity, specificity, and standardization of terminology. Long sentences that are redundant and lengthy descriptive expressions are eliminated with the use of standard academic language to enhance readability and professionalism. The entire methodological elements have been now described in brief and in terminologies that are specific to the domain, and which have coherence across various steps of the framework.

The language and expression used throughout the study have been properly polished with a view of the grammatical correctness, clarity, and compliance to academic writing practices. Non-idiomatic and ambiguous phrases were amended to reflect a better readability and professional tone in form of very specific and concise scientific terms. In the case of the healthcare facilities being exposing themselves to the need, the formulations have been adjusted to include phrases like healthcare facilities are also becoming more aware of the need. These improvements have been done throughout the entire sections in order to improve the coherence and the quality of the whole presentation.

II. LITERATURE SURVEY

Yixiao Wang and Keith Evan Green [11] authors report this paper on the preference of various interaction modes of users with pushbuttons to AI systems in interacting with robot surfaces, which are malleable, adaptive and physical surfaces changing the spatial organization of interior space within the built environment. As the mass urbanization of the world takes place, micro-homes and offices are multiplying; we see the usefulness of robot surface in rearranging small space into many spaces to aid and supplement human action. In one of the lab trials (N=12), the participants were requested to evaluate the robot surfaces of our design, which were used in combination with the common design tasks that were conducted in a micro-office at a given time (we refer to them as scenarios) throughout the task. Discovered that, among the five situations, preferences of the participants were divided into AI-controlled and user-controlled interactions due to the circumstances of various situations and the intricacy, precision, discreteness and response speed of various forms of interactions. The design of more architectural and spatial human-AI interactions in our daily lives is informed by our research.

Fatmah Omar M Bamashmous [12] seeks to discuss conventional seating at residential places which is referred to as Karawakatah to provide an inspiration in designing and conserving cultural artifacts. Multi-method research design based on hermeneutics interpretation was applied in the study, which examined the effects of historical nostalgic-evoking seating on the perception and the purchase decision-making of Saudi millennials. This case study was conducted in Hijazi Karabeitah in order to learn about the vernacular features and purpose of this case study. Lastly, a visual questionnaire was used to measure the historical nostalgia of Saudi millennials and how this impacted their purchase preferences. The interaction participants of the study are 164 and the mean years out of Saudi Arabia is two to five years. The majority of the respondents were females (n=131; 79.9%), and the number of male respondents was relatively lower (n=33; 20.1%). The indications of nostalgia in seating design have a significant influence on the possibilities to purchase the product among Saudi millennials (43.3%), although some chose the modern design based on its simplicity and unusual details (33%). The results retain the nature of traditional seating design features as well as beneficial to the design by offering evidence on conventional heritage, experimenting with the current, and sustaining the future of seating design depending on vernacular features; the research holds importance to the knowledge base. The framework proposed can be used in furniture design practice to find the vernacular features and maintain cultural objects. It also offers a valuable insight ii regarding the purchasing choices of Saudi millennials and how past-nostalgic-inspiring seating design affects their choices.

The proposed algorithm is the edge-oriented multi-objective optimization of the band selection (EOMBS) algorithm developed by Yu Zhang *et.al*; [13]. In addition,

to address the noise interference of texture, lack of spectral information use, edge breaks and low adaptability of the parameters applied in the existing problems, we suggest, a better Canny operator among the bands chosen. Applied to textile pattern segmentation, the method has a 93.74% PA and 73.19% IoU, and it performs much better than the 16 other methods. The paper by Ivan Malashin *et.al*; [14] explains how multi-objective optimization methods, such as MOPSO, NSGA II, and SPEA2, can be used to optimize hyperparameters of artificial neural networks (ANNs) and support vector machines (SVMs) to predict the physical properties of textile polymer composite materials (TPCMs). The optimization is done using information about the physical properties of the constituent fibers and fabrics that are used to produce such composites. Through the use of optimization algorithms, we will improve the predictive quality of the ANN and SVM models and hence design and development of high-performance textile polymer composites. The usefulness of the given method is confirmed by the comparative studies and validation experiments, which indicate its applicability in the optimization of complex material systems. Saltuk Buğra Selçuklu [15] idea behind these algorithms is to run a population of solution during each iteration and they are especially efficient in MOO. Multi-objective EAs, therefore, have been extremely trendy in the past three decades. The genetic algorithms have been further developed into multi-objective genetic algorithms (MOGAs), which are now the algorithm of choice in solving MOO problems in a heuristic mode. In this chapter, the first chapter is reviewed on multi-objective evolutionary and genetic algorithms and then introduces the basic concepts and design issues of MOGAs including encoding, crossover and mutation operators, fitness assignments, selection procedures, and the conservation of diversity. Possible applications, future trends, challenges and opportunities with respect to MOGAs are also covered.

Yuan Yuan Xie *et.al*; [16] research is a thorough bibliometric analysis of the literature related to LID during the last decade with the usage of data visualization tools to clarify the main disciplines, publication trends, and popularization of different optimization algorithms. We explore the use of multi-objective optimization (MOO) algorithms in LID facility layout looking at how they are applied, their theoretical basis and case study. Strengths and weaknesses of these algorithms are also examined in the paper, which suggests the possible future research directions that would utilize MOO to improve the role of LID in urban stormwater management.

The Fuzzy Comprehensive Evaluation based Financial Management System (FCE-FMS) has been proposed by Qian Li [17] to be applied in Multi-Objective Decision Making (MODM) in the educational institutions to improve the efficiency of funds use and financial decision-making. The data is obtained as the Ed financial data on financial resources management of the educational institutions. Good performance and efficient service and good financial

management is inherent in the MODM of higher education institutions, and best in the management of the resources of the local government funds. Thus, State/Government funding must remain a major and obligatory requirement to aid higher education. Government funds, funds of self-governing bodies, tuition fees, donations, scholarships and educational cess are the primary funding sources in higher education. The proposed FCM-FMS system has high levels of accuracy ratio of 98.7, decision making ratio of 97.8, optimal fund allocation ratio of 96.5, and performance of the institution of 95.1 as compared to other existing techniques.

This review paper by Mohammed A. Awadallah [18], 189 various studies of MOACOs published in purely scientific journals are taken into account. By the research, the researchers will obtain the information regarding the expansion of MOACO, theoretical basis of MOPs and MOACO algorithm, the varieties of MOACO variants that are described in the existing literature will be discussed, and the specific areas of the application of MOACO will be summarized. The MOACO pros and cons are critically discussed to show a more illuminated picture of the key gaps in research in the field. Lastly, this work also provides the conclusion and some of the future research directions of MOACO. Mustapha Ahlaqqach *et.al*; [19] This paper presents a framework of developing a closed-loop supply chain network in a fuzzy environment that can be used to design a sustainable network with the medical textile life cycle as the case study. The model is supposed to produce economic benefits, enhance corporate social responsibility by creating employment opportunities, and reduce the risk of the transportation of the end-of-life commodities. Besides this, the uncertainty of the model parameters is taken into account. Multi-objective model was developed as a mixed-integer linear program and was solved in an exact approach, which allowed making strategic and tactical decisions. Moreover, the findings indicate that accounting uncertainty may have a substantial influence on the decision-making process of strategic and tactics of the network design. Ngoc-Tien Tran *et.al*; [20] paper incorporates a very good MCDM model, which combines Fuzzy-AHP-TOPSIS to appraise and select the best robot. The Fuzzy-AHP is applied in order to determine a series of weights of the evaluation criteria. The proposed technique is then used to analyse, rank and select the most appropriate robot out of the ranking list to be used in the factory. The experimental findings prove that using the combined applications of the fuzzy analytical hierarchy process by considering weights of parameters and the judgment of experts, the robots are ranked in terms of best to worst options to factories. The results of this study have profound implications on the choice of robot and can be used in other aspects to meet the production needs. Mohammad Amin Darzi [21] outcome of the G-AHP technique shows that the most critical IMS barriers were the Resources and Assets, Employees, and Implementation. In addition, the outcomes of the F-TOPSIS approach reveal that the best possible guiding principles to eliminate the IMS

barriers are the encouragement of process standardization, organizational practices and concepts standardization, and the involvement of employees in the IMS development. Lastly, sensitivity analyses were done to ensure that the results were robust. The values of this research are useful in assisting managers and policymakers to cross the hurdles of IMS integration at the same time ensuring sustainability by applying guiding principles.

Vahid Firouzi *et.al*; [22] paper will give an overview of the models as well as a full review of how they are currently being used in assistive devices development. It critically evaluates the available literature as well to determine the gaps in the research and give recommendations on the future directions. There are conceptual and detailed models of biomechanical models, which may be used in the design, control, and evaluation of exoskeletons. Secondly, the models are also used to estimate variables that are unmeasurable or difficult to measure and this is also applicable in the above uses. Singled out simulation research validation and improvement of the quality and verisimilitude of biomechanical models as the future research perspectives of the development of assistive devices. The intention of this review is to unlock the current requirements and introduce novel insights to come up with improved exoskeletons that are biomechanical models. Darlington Egeonu & Bochen Jia [23] thoroughly examines the current computer vision-based biomechanical analysis techniques of workload assessment against conventional methods, and classifies them so they can be easily used. Recent advances in artificial intelligence have transformed the workload measurement, particularly in the realistic working environments where traditional measures are ineffective. But there is limited knowledge on the accuracy, nature and feasibility of computer vision-based techniques compared to the traditional techniques. To fill this knowledge gap, a literature review and a meta-analysis have been done in this paper to present a clear picture of the model accuracy, its benefits and limitations, which can be useful in developing refined technology use in various workplaces.

Marco De Stefano, Alessandro Ruggieri [24] purpose of this research was to suggest a critical review of the most repeated biomechanical models of the human mandible so that a reader could have a general picture on the subject. Against this, the numerical methods, which offer interesting results, *e.g.*, muscular activation patterns, condylar forces and stress stress strains fields of the human oral cavity, are predominantly rather differentiated based on the number of degrees of freedom of the joints, the descriptions of the muscular forces in terms of their analytical forms, the boundary conditions applied, the type of task and the type of mandible anatomy modeling.

The current researches on healthcare space design have mostly explored ergonomics, textile material performance and environmental comfort as separate areas as opposed to an adaptive system. Previous studies have focused on, but not quantitatively correlated anthropometric variabil-

ity, biomechanical pressures distribution, thermal-acoustic regulation, and real-time smart textile responsiveness to a single optimization paradigm, are the studies that are based in the laboratory, on tensile durability, or qualitative ergonomic risk assessment. In addition, little focus has been placed on multi-objective algorithmic decisions models in furnishing adaptation in the dynamic clinical setting. The current paper is however limited by simulation validation, controlled experimental datasets and small-scale clinical implementation. Embedded smart sensors and real-world variability of infection transmission are also not yet at a stage of long-term durability.

III. PROPOSED METHOD

A. OVERVIEW

Adaptive Ergonomic Smart Textile Optimization Framework (AESTOF) is designed to syntactically incorporate the mechanistic domains of ergonomic biomechanics, functional engineering of textiles, and environmental comfort simulation, and multi-objective optimization, into healthcare furnishing design. The framework forms a quantitative correlation of the anthropometric variability of human beings, biomechanical transfer of loads, mechanical behavior of textiles, and environmental performance in a clinical environment. In contrast to traditional methods of furnishing evaluation, where comfort or antimicrobial performance is assessed separately, AESTOF integrates the fusion of algorithms and simulation-based modelling of adaptive textile structures. The methodology is designed into three mutually dependent steps, which are Ergonomic-Biomechanical Modeling, Smart Textile Functional Optimization, and Multi-Objective Algorithmic Decision Integration. The stages generate quantifiable indices which are mathematically summed up into a composite adaptation score. The structure guarantees evidence-based furnishing choice as well as the predictive performance evaluation. With this well-organized integration, AESTOF promotes patient safety, staff comfort (ergonomics), environmental comfort and efficiency of infection controls in healthcare interior systems.

The general framework in Figure 1 starts with the comprehensive input data collection, which entails anthropometric percentiles, clinical postural measurements (RULA/REBA), textile mechanical characteristics, environmental factors, and infection control needs to reach a multidimensional healthcare relevance. Phase I involves ergonomic-biomechanical modeling, mapping the percentiles of body, quantifying the risk of posture, assessing the interface pressure, and using the finite element simulation approach in producing a structured Ergonomic Load Distribution Matrix (ELDM). Phase II involves optimization of smart textile functionality, through mechanical characterization, antimicrobial model, thermal comfort model (PMV/PPD), acoustic absorption model and embedded sensor data fusion to give an integrated Textile Functional Performance Index (TFPI). Phase III applies a combination of multi-

objective decision-making, AHP based weighting, TOPSIS ranking and regression validation to compute Composite Healthcare Textile Adaptation Index (CHTAI) hence provide an optimized, adaptive, infection-resistant ergonomic textile solution to the healthcare setting.

B. PHASE I ERGONOMIC-BIOMECHANICAL MODELING

Phase I establishes a quantitative human-textile interaction model of actual healthcare operation conditions. The ergonomic scoring methods and biomechanical simulations are used to systematically analyze anthropometric variability, postural evaluation, interface pressure distribution and musculoskeletal load transfer. Finite element modeling has been included in modeling the stress-strain behavior of textile layers subjected to body loading. This step converts the factors of physiology and posture into quantifiable ergonomic measures, which are the basis of the initial data needed to optimize adaptive furnishing and make evidence-based healthcare interior design choices.

Figure 2: block diagram is an organized biomechanical modelling pipeline for ergonomic textile assessment. This is initiated by the multisource input layer, which combines anthropometric parameters, joint posture angles, and segmental body forces. The signals in the preprocessing engine are normalized, outliers, and the coordinates transformed to ensure consistency and spatial alignment. The Segmental Force Distribution module then calculates individual forces, mean load, and variance. The Segmental Force Distribution module then calculates individual forces, mean load, and variance. The Segmental Force Distribution module then calculates individual forces, mean load, and variance as a way of describing biomechanical imbalance. Parallel modules predict the pressure distribution at the interface and the deviation in the energy of the spinal alignment, and record the localized mechanical strain. A nonlinear textile deformation model assesses compression behavior using biomechanical forces and material constants; local tissue stress can be estimated via threshold modulation. These outputs are combined to give a composite Ergonomic Risk Index (ERI) and further decomposed by the Musculoskeletal Load Stability Index (MLSI) to yield an overall Phase I feature vector.

The representation of the user is further expanded into an elaborated, stratified demographic model, rather than a homogeneous population, to enhance the verisimilitude and generalizability of the simulated inpatient validation. The simulation uses a typical sample size of $N = 100$, divided into the most significant categories among healthcare users: patients (elderly (40%), adult patients (35%)) and healthcare staff (25%). The demographic categories will be elderly (>65 years), adults (20-65 years), and staff (22-55 years), which are representative of normal healthcare settings. Every group has its specific physiological and ergonomic features, including body mass distribution, mobility level, metabolic rate, and pressure and thermal sensitivity. As an example, older patients are modeled with reduced mobility

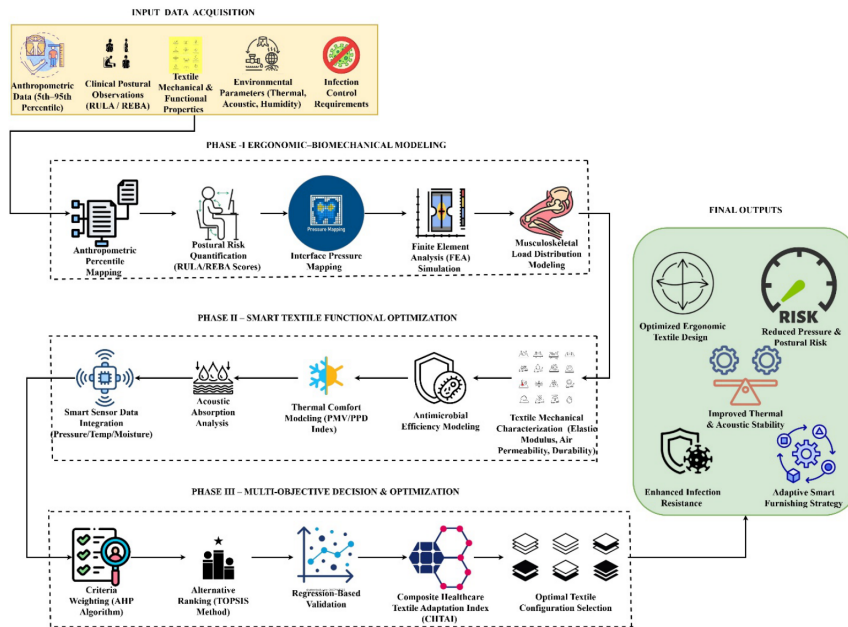


FIGURE 1. Adaptive Ergonomic-Smart Textile Optimization Framework (AESTOF)

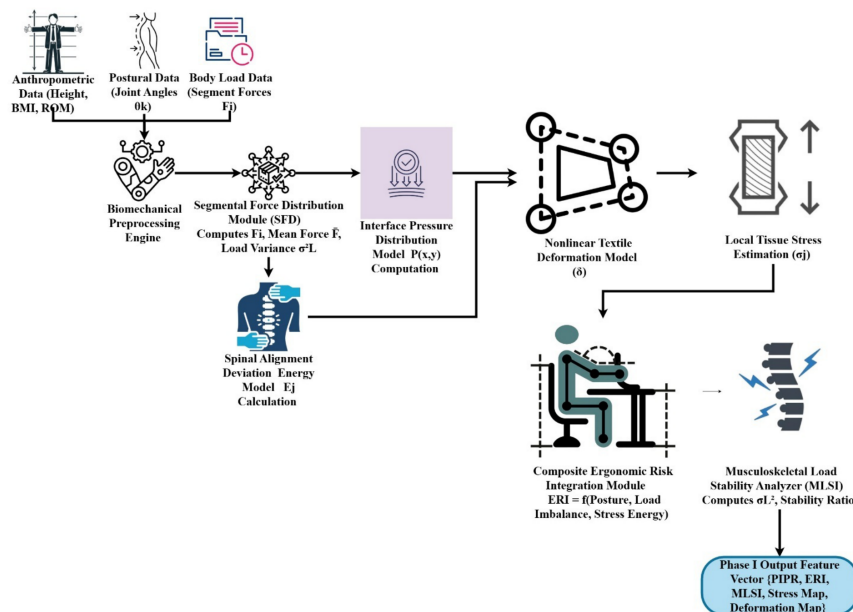


FIGURE 2. Phase I: Ergonomic-Biomechanical Modeling Flow Diagram

and increased vulnerability to pressure-induced pain. In contrast, healthcare workers are modeled with higher activity levels and alternative thermal comfort needs. These group-specific parameters are included in the biomechanical and thermal modeling procedures, enabling the framework to capture variability among user types. This approach allows adaptive optimization to be provided to meet the needs of various users; hence, breaching the constraints of the monolithic user assumption.

Zhang et al. [25] aimed to isolate washable antibacterial cellulose fabrics by coating them with an adhesive polymer via a nano-glue strategy, thereby improving the mechanical

stability and durability of the coating. Experimental research conducts systematic studies of the associations among coating adhesion, mechanical strength, and antibacterial performance under cyclical mechanical stresses, i.e., washing and deformation. The results demonstrate that enhanced interfacial bonding significantly reduces the coating degradation rate and maintains antimicrobial performance throughout the prolonged usage period. The paper shows that mechanical integrity is extremely important for functional performance, thereby allowing consideration of stress-dependent degradation factors in the antimicrobial efficiency model.

C. ANTHROPOMETRIC DATA MAPPING

Mapping of for compatibility between healthcare users and textile furnishings. Data on body size, such as seated height, hip breadth, depth of lumbar curvature, thigh thickness, and shoulder width, are taken in a range of the 5 th to 95th percentile distributions to achieve accommodating ergonomics. These parameters are converted into spatial dimensional constraints for bed systems, chair furnishings, and cushion geometries. Statistical normalization procedures are performed to produce percentile-adjusted compatibility matrices. The mapping procedure is performed to ensure that the textile configurations match the wide range of patient and staff body profiles, minimizing dimensional discrepancies and postural distortion. This part of the design provides quantitative baseline inputs for the pressure distribution simulation and load transfer modeling by accounting for anthropometric variability within the design model. The resulting enhancement of spatial adaptability and the reduction of exposure to ergonomic risks are maximized in healthcare settings.

D. POSTURAL RISK QUANTIFICATION

Postural risk quantification measures the musculoskeletal burden that results from long-term contact with textile furnishings. The Rapid Upper Limb Assessment (RULA) and Rapid Entire Body Assessment (REBA) methods are applied to clinical postures identified during work with patients and to staff activities. The scores will be transformed into a normalized Ergonomic Risk Index (ERI) to allow numerical comparison of furnishing options. They include joint angles, trunk inclination, cervical deviation, and limb positioning to estimate cumulative biomechanical stress. It is a structured quantification that allows the identification of high-risk areas that lead to discomfort or the possibility of injury. The ERI is then incorporated into the optimization model to give precedence to furnishing configurations that decrease musculoskeletal load. This section is based on a systematic ergonomic assessment by means of objective posture scoring and normalization that goes beyond qualitative observation.

$$\delta = \frac{F_b}{k_t + c_t F_b} \quad (1)$$

$$\sigma_j = \frac{P(x, y)}{1 + \exp[-a(\delta - \delta_0)]} \quad (2)$$

$$E_j = \sum_{k=1}^m \frac{1}{2} k_j (\theta_k - \theta_{\text{ideal}})^2 \quad (3)$$

$$\text{ERI} = \frac{\sum_{k=1}^m w_k (\theta_k - \theta_{\text{ideal}})^2 + \eta L_i}{\sum w_k} \quad (4)$$

Equation (1) estimates the textile compression depth δ . F_b denotes applied body force, k_t is the linear stiffness coefficient, and c_t captures nonlinear compression behavior. It models how smart textiles deform under varying loads,

reflecting realistic cushioning response. Equation (2) computes localized tissue stress σ_j , where $P(x, y)$ is interface pressure, a is sensitivity constant, δ is deformation depth, and δ_0 is threshold deformation. The logistic term moderates stress beyond safe compression limits. Equation (3) evaluates biomechanical strain energy due to posture deviation. k_j is joint stiffness, θ_k actual joint angle, and θ_{ideal} neutral posture angle. It quantifies ergonomic misalignment impact. Equation (4) integrates posture deviation and load imbalance into a normalized risk index. w_k are weighting factors, L_i is the load imbalance ratio, and η is scaling constant. It produces an overall ergonomic safety score.

E. INTERFACE PRESSURE DISTRIBUTION MODELING

The interface pressure distribution modeling explores stress localization in body-textile contact areas. Peak interface pressure (PIP) in the sacral, lumbar, scapular, and heel areas under both static and dynamic loading is recorded by the pressure mapping sensors. Finite element analysis (FEA) simulations are used to model the stress-strain behavior of layered textile composites using these experimental measurements. The simulation deformation. A Pressure Redistribution Coefficient (PRC) calculation is performed to measure cushioning and load-dispersion effectiveness. This type of modeling determines pressure hotspots related to the risk of ulcers and discomfort. The approach offers predictive pressure mitigation measures and optimization of textile framework by combining experimental sensing and computational simulation.

$$P(x, y) = \sum_{i=1}^n \frac{F_b}{A_i \gamma_i} \cdot \phi(x, y) \quad (5)$$

Equation (5) models spatial pressure distribution at the human-textile interface. F_b is total body force, A_i represents segmental contact areas, γ_i is deformation compliance of each segment, and $\phi(x, y)$ is the spatial load distribution function. The equation evaluates localized stress concentration considering textile deformation adaptability.

F. MUSCULOSKELETAL LOAD ESTIMATION

Musculoskeletal load estimation is used to examine internal biomechanical loads produced during contact with textile furnishings. Inverse dynamic modeling is used to estimate joint reaction forces in the lumbar, pelvic, and cervical regions, as well as the shoulder. Loads that are not aligned with neutral alignment baselines are calculated as a percentage variation of stress. This part measures the effect of textile stiffness, thickness, and elasticity on support of the spinal curvature and redistribution of load. The conditions of repetitive loading are simulated to estimate long-term occupational strain in medical workers. The resulting biomechanical deviation metrics are combined to form a Musculoskeletal Load Stability Index (MLSI). This mathematical model the ergonomic sustainability of staff.

$$\sigma_L^2 = \frac{1}{n} \sum_{i=1}^n (F_i - \bar{F})^2 \quad (6)$$

Equation (6) measures the variability of distributed forces. F_i is the local segment force, $\bar{F}$ is the mean force, and n is the number of segments. It determines biomechanical stability and uniformity. Phase I Index yields the Ergonomic Load Distribution Matrix (ELDM), which summarizes anthropometric compatibility scores, Ergonomic Risk Index values, Pressure Redistribution Coefficients, and Musculoskeletal Load Stability. The matrix offers a multi-parameter modelling of the biomechanical interaction of users and textile furnishings. All furnishing options are assessed numerically using standardized ergonomic indicators, allowing for objective comparison. ELDM serves as the key input to the following stages of optimization, since data on physiological interactions are converted into computed variables. These two parameters, biomechanical safety and posture stability, are converted into quantifiable decision criteria through this matrix. The ELDM thus constitutes the ergonomic framework of the AESTOF framework, providing an evidence-based, human-centered approach to furnishing adaptation.

Algorithm 1: Ergonomic–Biomechanical Load Optimization Algorithm (EBLOA)

Require: Posture data set P , joint angles θ , force thresholds F_{th} , muscle activation A_m , biomechanical model M_b .

Ensure: Optimized load distribution score S_{opt} .

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1: Receive posture/load data  $P$ ;
2: Clean/normalize:  $P' = \text{calib}(P)$ ,  $\|P'\| \leq \sigma$ ;
3: Segment into joint sequences  $J = [\theta_1, \dots, \theta_n]$ ;
4: Embed the biomechanical vectors  $E = \text{Embed}(J) \in \mathbb{R}^d$ ;
5: Initialize optimization layers to zero  $L_0 = 0$ ;
6: Set max_iter = 100;
7: for iter = 1 to max_iter do
8: Torque:  $T_j = M_b \theta_j$ ;
9: Strain:  $\epsilon_m = A_m / F_{th}$ ;
10: Constraints: if  $T_j > F_{th}$  penalize;
11: Attention:  $\text{Attn} = \text{softmax}(QK^T / \sqrt{d})V$ ;
12: FFN:  $h' = \text{ReLU}(W_1 h + b_1)W_2 + b_2$ ;
13: Store  $h_i$ ;
14: end for
15: Aggregate hidden states across iterations  $H = \frac{1}{L} \sum h_i$ ;
16: Project into load optimization space  $z = W_p H + b_p$ ;
17: Activate ReLU for positivity  $\hat{z} = \text{ReLU}(z)$ ;
18: Compute load balance logits  $\ell = W_o \hat{z}$ ;
19: Apply Softmax for distribution probabilities  $\pi = \text{softmax}(\ell)$ ;
20: Compute scalar ergonomic score  $S = \sum_i \pi_i \cdot (1 - \epsilon_i)$ ;
21: if  $S < 0.7$  then
22: Weight:  $S_w = S \cdot \text{sens}(\theta)$ ;
23: else if  $S > 1.2$  then
24:  $S = S - \lambda \|T\|$ ;
25: else
26:  $S_{opt} = S$ ;
27: end if
28: Compute joint count from data size  $n_j = |P|$ ;
29: Apply confidence weighting  $c = e^{-\text{var}(T)}$ ;
30: Normalize final load score  $S_{opt} = c \cdot S / n_j$ .
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The Ergonomic Load Distribution Matrix (ELDM) was calculated systematically using Algorithm 1, which combines anthropometric compatibility, postural risk, pressure

redistribution behavior, and musculoskeletal load stability into a single biomechanical assessment model. First, the anthropometric data of percentile ranges are normalized so as to provide dimensional flexibility of the textile furnishing. The data on the postural scores received through RULA and REBA is transformed into the quantitative Ergonomic Risk Index. Measurements of Interface pressure are utilized with the finite element simulations to find out the Pressure Redistribution Coefficient. Moreover, the musculoskeletal loads that are not at a neutral position are computed to determine internal biomechanical stress. The ELDM is a structured ergonomic performance matrix that is made up of all the parameters that are normalized and aggregated. The algorithm guarantees an objective, data-driven assessment of human-textile interaction under real-world healthcare operating conditions.

G. PHASE II SMART TEXTILE FUNCTIONAL OPTIMIZATION

Phase II tests include mechanical, environmental, and hygienic performance evaluations of textile materials. Tests of mechanical resilience, thermal regulation ability, acoustic absorption performance, and antimicrobial activity are evaluated experimentally and computationally. Moreover, real time pressure, temperature and humidity can be measured using embedded smart sensing technologies. The adaptive control algorithms enable responsive material behavior. This stage transforms multidimensional textile characteristics into standardized thereby guaranteeing maximum comfort, resistance to infections, and environmental sustainability in the healthcare environment.

Figure 3, the block diagram, depicts Phase II of the smart healthcare textile optimization system, incorporating multidirectional mechanical, environmental, and hygienic inputs. Phase I mechanical outputs, combined with thermal conditions, airflow, humidity, noise, and microbial load, are interconnected with a textile material property database that contains structural and functional parameters, including thickness, conductivity, resistance to flow, and antimicrobial coating factors. A mechanical recalibration module changes the stiffness by applying deformation and stress maps. Later parallel modules are used to model thermal regulation (Rt, heat transfer, PMV), moisture diffusion (MVTR), and air permeability based on pressure-flow relations. Acoustic absorption and reverberation control are tested, and then the antimicrobial effectiveness and its durability during a wash cycle are analyzed. Lastly, TSI, ACI, IRI, and HPS are calculated using the functional performance aggregation engine, resulting in a unified Phase II functional feature vector.

To establish a valuable and scientifically valid comparison, conventional healthcare textile is conceptualized as a standard hospital-grade textile finished with common antimicrobial agents, including quaternary ammonium or silver-based coatings. Such fabrics are typically found in clinical environments that employ textiles with baseline

antimicrobial capability. The control group can then be described as (i) standard textile structure without adaptive optimization, (ii) conventional antimicrobial surface treatment, and (iii) no combination between biomechanical or multi-objective optimization mechanisms. The definition ensures that the comparison is based on real-world conditions rather than on unreal or untreated bases.

Liu *et al.* [26] conducted experimental research on celulosic nonwoven textiles functionalized with chitosan as antibacterial and physicochemical agents. The paper assesses how changes in material structure, treatment conditions, and mechanical properties affect the effectiveness of antibacterial properties. Through an examination of the coupled behavior of mechanical properties and antimicrobial performance, the research demonstrates that antimicrobial performance, structural integrity, and deformation of textiles are directly related to bacterial inhibition effectiveness. The findings underline the interaction between biomechanical behaviour and functional performance, which should be considered when integrating models into smart textiles.

H. MECHANICAL AND ELASTIC CHARACTERIZATION

Mechanical and elastic characterization is used to assess the structural integrity and deformation of textile materials under the conditions of constant healthcare use. Standardized tensile tests are used to measure ultimate tensile strength, elongation at break, and Young's modulus to assess the capacity to bear a load. Compression testing assesses the strength, thickness, and recovery rate under repetitive load cycles, which mimic the conditions of immobility in patients and the seating positions of staff, and hysteresis behavior are examined to understand the long-term durability and consistency of cushioning. Fatigue resistance and hysteresis behavior are examined to assess long-term durability and cushioning consistency. The elastic recovery percentage is used to assess the ability of textile layers to resume their original shape after deformation. These mechanical properties stability. Each parameter is scaled to a Mechanical Performance Score (MPS), which is structural robustness and sustainability in terms of comfort. This description guarantees that the chosen textiles are ergonomic and will not deteriorate prematurely due to harsh healthcare conditions.

I. THERMAL COMFORT MODELING

The analysis of thermal comfort of human skin and textile surfaces in healthcare examines the microclimatic environment and the interaction between human skin and textiles. The most important parameters are thermal conductivity, insulation resistance, air permeability, and moisture vapor transmission rate, which are experimentally determined. These measurements are incorporated into the computer model of heat transfer, which analyzes conductive, convective, and evaporative heat transfer. The Predicted Mean Vote (PMV) and Predicted Percentage Dissatisfied (PPD) indices are used to predict perceived thermal sensation under different environmental conditions. To reduce excess

humidity, moisture management capacity is evaluated to prevent discomfort and microbial growth. A Thermal Stability Index (TSI) is obtained to demonstrate the textiles capacity to maintain thermal equilibrium. This section will focus on sweat-related skin conditions, and improved indoor climate control in healthcare facilities by combining environmental modeling with materials science.

$$R_{\text{total}} = R_{\text{conv}} + R_{\text{cond}} + R_{\text{rad}}. \quad (7)$$

Equation (7) aggregates heat transfer resistances. R_{conv} , R_{cond} , and R_{rad} denote convective, conductive, and radiative resistances respectively. It quantifies overall insulation capacity.

J. ACOUSTIC PERFORMANCE EVALUATION

Acoustic performance analysis identifies how textile furnishing can be used to cut down on the ambient noise level in healthcare facilities. Sound absorption values are determined over different frequency bands between low and high frequencies (125HZ to 4000 HZ). The analysis of textile porosity, fiber density, thickness and surface texture is conducted in terms of their contribution of acoustic dampening performance. The modeling of reverberation time reduction is carried out to model noise propagation in wards and clinical corridors of patients. Frequency weighted absorption values are used to calculate an Acoustic Comfort Index (ACI), which is used as an indicator of the overall sound attenuation performance. Good acoustics help to achieve a better quality of patient rest, lower stress levels and a better quality of communication between medical practitioners. This section extends the concept of furnishing optimization beyond biomechanical comfort into psychological and environmental comfort by integrating the concepts of acoustic measurements in the assessment of textiles.

$$\alpha(f) = 1 - e^{-2\pi f \mu d}. \quad (8)$$

Equation (8) evaluates frequency-dependent absorption. f is frequency, μ is flow resistivity, and d is thickness. It models sound attenuation effectiveness.

K. ANTIMICROBIAL EFFICIENCY MODELING

Antimicrobial efficiency model is used to evaluate the hygienic efficiency of textile materials in contact with healthcare-associated pathogens. The standard microbiological testing measures bacterial reduction rate (BRR%), which is in relation to representative strains that are likely to occur in clinical systems. The microbial decay modeling is a time-dependent model that assesses the contamination persistence in the environment at

different humidity and temperature conditions. Wash Durability tests are tests that identify how the antimicrobial treatment ability is retained following the repeated laundering cycles. A behavior of surface contact inhibition is studied to gain insights on pathogen adhesion resistance. A

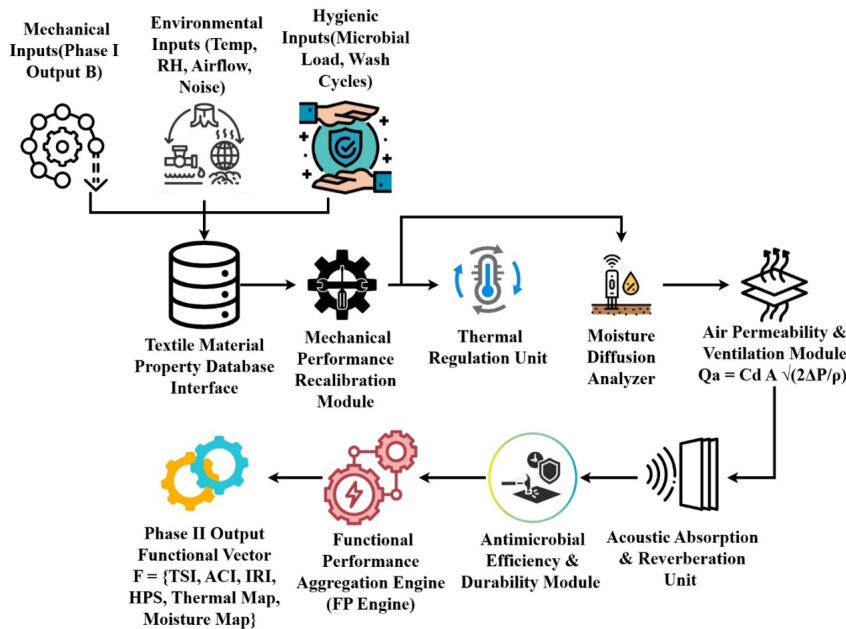


FIGURE 3. Phase – II Smart Textile Functional Optimization Flow Diagram

combination of reduction efficiency, durability retention and contamination decay are combined to generate an Infection Resistance Index (IRI). Such modeling will make sure that textile furnishes have an active contribution to the infection prevention strategies. The framework validates the adherence of the healthcare hygiene standards and the patient safety by measuring the reliability of the antimicrobials when used in the conditions of operation.

$$M(t) = M_0 e^{-k_m t}. \quad (9)$$

Equation (9) models bacterial reduction. M_0 is the initial microbial load, k_m is the decay rate, and t time. It predicts antimicrobial durability.

L. SMART TEXTILE ADAPTIVE LAYER

The adaptive layer smart textile provides embedded sensory and responsive control systems into textile furniture. Conductive yarns that are sensitive to temperature, humidity and flexible pressure sensors are inbuilt in the layers of textile to record real-time environmental and biomechanical data. The signals are sent to a microcontroller unit that analyses nonconformance with predetermined comfort levels. Adaptive control algorithm is a dynamic adjustment of cushioning density, airflow permeability, or insulation property in case of sense of abnormal pressure concentration, overheating or accumulation of moisture. Predictive analytics preempt potential long-term immobility risks and start preventive measures. This shift of passive textile systems to responsive adaptive materials improves the preventive healthcare design. Smart technology will be integrated to provide round-the-clock monitoring, clinical decision-making based on data, and align the textile furnishings with the purposes of intelligent healthcare infrastructure.

The dynamic mechanism within the suggested framework works via a feedback mechanism of real-time sensor. Embedded sensors of pressure, temperature, and humidity constantly monitors biomechanical and environmental data of use. An adaptive control algorithm receives these inputs and modifies textile characteristics including cushioning density, airflow permeability and thermal insulation. This creates a closed loop mechanism where any variation of set comfort and safety levels will cause instant corrections. Thus, the process of adaptation is ongoing and run-time-based so that the textile system adapts to the varied user posture and environmental conditions instead of being a fixed design position.

Textile Functional Performance Index (TFPI) is the cumulative performance measurement that is based on the mechanical strength, thermal stability, acoustic absorption efficiency, antimicrobial resistance and smart adaptability scores. All the parameters are normalized and weighted in such a way to make sure that there is a balanced contribution in functional dimensions. The TFPI transforms multidimensional textile performance factors into a single computation index which can be optimized through the use of algorithms. A higher value of TFPI represents the high level of structural resilience, environmental regulation of comfort, hygienic reliability and adaptive responsiveness. Such an index will be a vital input to the multi-objective decision modeling in Phase III, which allows comparing the textile options systematically. The TFPI provides objective and scalable testing of textile soft furnishings in the healthcare design process by converting experimental and simulation results into a standardized performance index.

M. PHASE III MULTI-OBJECTIVE ALGORITHMIC DECISION INTEGRATION

Phase III is a combination of ergonomic outputs of Phase I and functional performance indices of Phase II to be incorporated in a structured optimization model. The best approach that is used to identify the most appropriate textile configuration is multi-criteria decision-making techniques, such as weighted evaluation or ranking algorithms. Statistic validation is a guarantee of strong results. Composite adaptation index is produced to depict the total furnishing performance. The stage provides data-driven, evidence-based textile selection strategy, which is oriented to safe, comfortable and adaptive healthcare settings.

The multi-objective of the optimization at this step is design-stage choice decision-making through which the best textile configurations are determined by AHP weighting and TOPSIS ranking. This is a different process that is complementary to the adaptive mechanism defined in Phase II. Whereas the Phase III is used to define the optimal starting configuration using aggregated ergonomic and functional considerations, Phase II is used to facilitate the runtime flexibility using continuous sensor feedback and dynamic controls. This composite design combines both the characteristics of a static optimization and responsiveness in real-time, which removes the problem of distinguishing between a one-time selection of the design and ongoing adaptive behavior. The success of the multi-objective decision framework using AHP-TOPSIS methodology is highly dependent on the right establishment of criteria weights. The weighting process is calculated based on structured Analytical Hierarchy Process (AHP) that is domain-driven to ensure methodological rigour and eliminates arbitrary assignments. Particularly, pairwise comparison matrices are built on the basis of data about inputs received as a result of domain-informed knowledge, which is the relative significance of ergonomic comfort, antimicrobial efficacy, biomechanical compatibility, and endurance. The pairwise comparisons of the data are normalized, and priority weights are estimated applying the eigenvectors. In order to be consistent and reliable, the consistency ratio (CR) is tested and only the matrices that meet the acceptable value ($CR < 0.1$) are kept. This procedure makes sure that generated weights are logically coherent and scientifically to be based. This resulting weight vector is then incorporated into the TOPSIS model of ranking and optimizing decisions to become the foundation of Composite Healthcare Textile Adaptation Index (CHTAI).

N. CRITERIA WEIGHT DETERMINATION

The Analytic Hierarchy Process (AHP) is used to provide a systematic approach to deciding the relative strength of evaluation criteria used in healthcare textile optimization. The initial step is to create a hierarchical decision; it included the main objective (optimal adaptive textile selection), key criteria (ergonomic safety, thermal comfort, acoustic performance, antimicrobial efficiency, durability, and smart adaptability), and sub-criteria based on the results of Phase

I and Phase II. Matrices of pairwise comparison based on expert judgements of ergonomists, textile engineers, and healthcare facility planners are built. The basic scale used by Saaty is used in order to make comparative preference. The next step is eigenvector normalization, which is done to calculate priority weights of every criterion. Calculation of Consistency Index (CI) and Consistency Ratio (CR) are aimed at logical coherence of judgments, and the values of CR should not surpass the acceptable limits. This weighting system makes sure that there is objective prioritization of multidisciplinary performance indicators in the optimization system.

$$w_i = \frac{\left(\prod_{j=1}^n a_{ij}\right)^{1/n}}{\sum_{k=1}^n \left(\prod_{j=1}^n a_{kj}\right)^{1/n}} \quad (10)$$

$$WAS = \sum_{i=1}^n w_i S_i \quad (11)$$

Equation (10) computes the normalized priority weight w_i of criterion i using the geometric mean method in the Analytic Hierarchy Process (AHP). Here, a_{ij} represents the pairwise comparison value between criteria i and j , and n is the total number of criteria. The numerator calculates the geometric mean of row i , while the denominator ensures normalization across all k criteria. The purpose is to derive consistent relative importance weights for multi-objective decision analysis. Equation (11) determines the Weighted Aggregated Score for alternative i . The term w_i denotes the weight assigned to criterion i , while S_i represents the standardized performance score of that criterion. The summation integrates all weighted criteria to produce a composite performance measure. Its purpose is to quantify overall effectiveness by combining multiple functional and ergonomic indicators into a single evaluative value.

O. ALTERNATIVE RANKING (TOPSIS)

Technique of ranking the textile furnishing alternatives according to overall adaptive performance makes use of Technique of Order Preference by similarity to Ideal Solution (TOPSIS). The Ergonomic Load Distribution Matrix (ELDM) and Textile Functional Performance Index (TFPI) are incorporated into a normalized decision matrix using the values obtained from the preceding stages—multiplying these normalized values by the weights produced by AHP—results in a weighted decision matrix. Optimal solutions (best-case solution in all criteria) are found as well as negative optimal solutions (the worst of all criteria). The technical distance measures (Euclidean distances) are computed to determine the distance between each alternative and the two ideal states. A coefficient of closeness is then obtained, indicating the relative suitability of any textile configuration. Alternatives with high closeness coefficients exhibit greater adaptability and balanced performance across ergonomic,

environmental, and hygienic aspects. The approach guarantees mathematically sound and open-minded decision ranking.

$$D_i^+ = \sqrt{\sum_{j=1}^n w_j (S_{ij} - S_j^+)^2} \quad (12)$$

$$D_i^- = \sqrt{\sum_{j=1}^n w_j (S_{ij} - S_j^-)^2} \quad (13)$$

The Positive Ideal Distance in Equation (12) and Negative Ideal Distance in Equation (13) are core components of the TOPSIS-based ranking mechanism. Here, S_{ij} denotes the normalized performance score of alternative i under criterion j , w_j represents the importance weight of criterion j , while S_j^+ and S_j^- indicate the best and worst benchmark values, respectively. The purpose of D_i^+ is to quantify how far an alternative deviates from optimal performance, whereas D_i^- measures separation from the least desirable solution. Together, these distances enable comparative evaluation by simultaneously considering proximity to the ideal solution and remoteness from the worst-case condition.

P. STATISTICAL VALIDATION

The validation is performed statistically to ensure the robustness and reliability of the multi-objective optimization results. Regression analysis will be conducted to examine the relationships among textile mechanical properties, ergonomic risk indices, and comfort performance variables. Analysis of Variance (ANOVA) will be used to the statistical significance of variation between alternative textile configurations and to assess differences among them, with the level of significance set at $p < 0.05$. Correlation matrices will be used to assess the level of interdependence between biomechanical load measures and environmental comfort measures. Sensitivity analysis is also conducted to determine how stable AHP weights and TOPSIS rankings are under small changes in parameters. This validation step will reduce model bias and guarantee that a single extreme value does not skew the optimized choice of textiles. The scientific credibility and reproducibility of the decision-making process are obtained by introducing the rigorous statistical evaluation.

Q. COMPOSITE HEALTHCARE TEXTILE ADAPTATION INDEX (CHTAI)

The Composite Healthcare Textile Adaptation Index (CHTAI) is the ultimate aggregated performance measure resulting from the weighted combination of ergonomic and functional measures. Index is a combination of ELDM outputs of Phase I and TFPI outputs of Phase II with weights based on AHP and ranking coefficients on TOPSIS. Mathematical aggregation ensures that each performance dimension is proportionately represented, such as efficiency of pressure redistribution, musculoskeletal stability, thermal

regulation, acoustic attenuation, antimicrobial resistance, and smart responsiveness. The CHTAI gives one normalized value of the adaptive suitability of each textile setting concerning the overall adaptive suitability in the health care setting. An increase in the CHTAI scores shows a better level of ergonomic compatibility, environmental stability, and hygienic reliability. This is a composite index that can reduce multidimensional analysis into actionable parameter of decision support in evidence-based furnishing selection and optimization of healthcare infrastructure in the long term.

$$\text{CHTAI}_i = \frac{D_i^-}{D_i^+ + D_i^-} \quad (14)$$

Equation (14) calculates the final Composite Healthcare Textile Adaptation Index for alternative i . The numerator D_i^- represents distance from the worst solution, while the denominator is the total separation from both ideal and non-ideal solutions. A higher CHTAI value indicates closer proximity to optimal performance. The purpose is to provide a normalized ranking score integrating ergonomic, thermal, acoustic, and infection-resistance metrics into a unified adaptation index.

Algorithm 2: Adaptive Multi-Objective Textile Optimization Algorithm (AMOTOA)

Require: Fabric set F , stress-strain $\sigma - \epsilon$, comfort thresholds C_{th} , durability D_t , weave patterns W_p .
Ensure: Pareto-optimal score S_p .
1: Receive textile parameter inputs F ;
2: Normalize (filter anomalies, scale metrics, tensorize)
 $F' = (\sigma - \epsilon)/\mu$;
3: Tokenize fibers $\phi = [f_1, \dots, f_m]$;
4: Embed to material vectors $E_f = \text{Embed}(\phi)$;
5: Init layers for objectives;
6: Set population size $N = 50$;
7: for gen = 1 to 50 do
8: Stress: $\sigma = E\epsilon$;
9: Comfort: $C = 1 - \text{stiff}(W_p)$;
10: Density: $\rho = \sum W_p$;
11: Attention: $\text{MO-Attn} = \text{softmax}(\text{objs} \cdot K^T)V$;
12: FFN: $o' = \tanh(W_f o)$;
13: Store fronts $\mathcal{PF}_g$;
14: end for
15: Aggregate fronts across generations $\mathcal{PF} = \cup \mathcal{PF}_g$;
16: Project into performance space $z_m = W_m \mathcal{PF}$;
17: Activate sigmoid for bounded outputs $\hat{z}_m = \sigma(z_m)$;
18: Compute multi-objective logits $\ell_m = W_l \hat{z}_m$;
19: Apply Softmax for weighted objectives $\pi_m = \text{softmax}(\ell_m)$;
20: Compute scalar Pareto score $S_p = \max \sum_i w_i \pi_{m,i}$;
21: if $S_p < D_t$ then
22: Weight: $S_{pw} = S_p \cdot (1 + \text{rob}(\sigma))$;
23: else if $S_p > C_{th}^{-1}$ then
24: $S_p = S_p - \gamma C_p$;
25: else
26: S_p optimal;
27: end if
28: Compute fiber count from input size: $n_f = |F|$;
29: Apply adaptive confidence $c_a = 1/(1 + \text{gen-var})$;
30: Normalize final textile score $S_p = c_a S_p / n_f$.

The algorithm 2 is used to identify the best healthcare textile configuration by combining both, ergonomic and

TABLE 1. Ablation Study of the Proposed AESTOF Framework

Model Detail	Ergonomic Model	Smart Textile Layer	Antimicrobial Modeling	AHP Weighting	TOPSIS Ranking	Pressure Reduction (%)	Thermal Stability Improvement (%)	Infection Risk Reduction (%)	Overall Adaptation Index (CHTAI)
Baseline (Conventional Textile Selection)	✓	✓	✓	✓	✓	0%	0%	0%	0.00
M1 - Ergonomic Modeling	✓	✓	✓	✓	✓	14.5%	1.4%	1.5%	0.10
M2 - Smart Textile Integration	✓	✓	✓	✓	✓	16.5%	20.0%	1.5%	0.22
M3 - Antimicrobial Modeling	✓	✓	✓	✓	✓	17.1%	20.0%	14.0%	0.15
M4 - AHP Weighting	✓	✓	✓	✓	✓	16.0%	20.0%	16.7%	0.18
M5 (Full Model - AESTOF)	✓	✓	✓	✓	✓	34.6%	27.3%	18.5%	0.42

functional performance measures using a hybrid AHP-TOPSIS decision model. First, some of the evaluation criteria like ergonomic safety, thermal stability, acoustic comfort, antimicrobial efficiency, durability, and smart adaptability are arranged in a hierarchical manner. Analytic hierarchy Process is used to calculate relative weights based on the comparisons and consistency checks. Ergonomic Load Distribution Matrix and Textile Functional Performance Index normalized outputs are then added in a weighted decision matrix. The TOPSIS technique computes the distance between ideal and negative-ideal solutions to obtain a closeness coefficient of each alternative in the textile. An Index of Composite Healthcare Textile Adaptation is created to reflect the general performance. The arrangement that has the greatest index is chosen as the optimized furnishing solution to healthcare settings. Outputs

The ultimate product of the AESTOF model is an optimized, evidence-based healthcare textile furnishing plan produced with combined ergonomic and functional traits and multi-objective optimization of decisions. The chosen design exhibits reduced maximum interface pressure, refined load distribution of musculoskeletal system, better thermal balance, good acoustic damping and long-term antimicrobial resistance. Intelligent adaptive feedback control provides real-time control and predictive control to environmental and physiological changes. The last index used in the decision-making is the Composite Healthcare Textile Adaptation Index (CHTAI) which guides the selection of evidence-based furnishing. This high-quality production assists the patient-centered healing settings, lessens job pressure in the medical personnel, and enhances infection control measures. The framework consists of biomechanics and material science, environmental analytics, and algorithmic decision models that allow providing a scalable and scientifically proven furnishing adaptation strategy to modern healthcare infrastructure systems.

The ablation study Table.1 is a systematic analysis of the contribution of each element in the system of the AESTOF through the successive integration of functional modules and performance gains. The lowest Composite Healthcare Textile Adaptation Index is (0.42) at the baseline model which presents traditional textile selection without optimization. Ergonomic modeling (M1) is greatly important in enhancing redistribution of pressures and this shows the significance of biomechanical analysis. Incorporation of smart textile integration (M2) has significant effect on thermal stability, and antimicrobial modeling (M3) significantly has effects on the

reduction of risk of infections. The add-on of AHP weighting (M4) will enhance balanced multi-criteria prioritization among indicators of performance. The overall

TABLE 2. Parameter Environmental Settings Table

Parameter Category	Parameter	Symbol	Value Range	Standard/Reference Condition	Purpose in Study
Thermal Environment	Air Temperature	$T_{a,i}$	22-26 °C	Hospital Indoor Standard	Thermal comfort modeling (PMV/PPD)
Thermal Environment	Relative Humidity	RH	40-60%	Clinical Comfort Range	Moisture regulation analysis
Thermal Environment	Air Velocity	V_a	0.05-0.15 m/s	Low Draft Condition	Convective heat transfer modeling
Thermal Environment	Mean Radiant Temperature	$T_{r,e}$	22-25 °C	Controlled Indoor	Radiative heat exchange
Thermal Environment	Clothing Insulation	I_{cl}	0.7-1.0 clo	Patient/Staff Apparel	Thermal balance calculation
Thermal Environment	Metabolic Rate	M	1.0-1.4 met	Resting-Light Activity	PMV computation input
Acoustic Environment	Background Noise Level	L_b	35-45 dB	Hospital Ward Standard	Acoustic comfort modeling
Acoustic Environment	Reverberation Time	RT_{60}	0.4-0.8 s	Clinical Target	Sound absorption evaluation
Acoustic Environment	Sound Frequency Bands	f	125-4000 Hz	Standard Acoustic Testing Range	Absorption coefficient test
Hygienic Environment	Surface Contamination Level	C_s	10^2-10^5 CFU/cm ²	Simulated Clinical Exposure	Antimicrobial performance modeling
Hygienic Environment	Washing Cycle Count	W_c	0-50 cycles	Repeated Laundering	Durability testing
Hygienic Environment	Contact Exposure Time	T_s	1-24 hrs	Controlled Lab Setting	Microbial decay modeling

AESTOF model (M5), which includes all the modules with TOPSIS ranking, results in the highest-pressure reduction (34.6%), thermal stability improvement (27.3%), and infection risk reduction (18.5%), which proves that integrated algorithmic optimization provides better performance in terms of adaptive furnishing.

IV. RESULTS AND DISCUSSION

This paper makes use of the Textile Industry Material Prediction Dataset (Kaggle) so as to validate the proposed Adaptive Ergonomic-Smart Textile Optimization Framework (AESTOF) through simulation [27]. The dataset comprises of organized data of the characteristics of textile materials which includes mechanical, physical and categorical data applicable in the classification of fabrics and modeling of its performance. Each sample is a textile specimen characterized by variables like the fiber composition, thickness, density, tensile indicators of it, and the production features. The database includes several varieties of materials, which will allow conducting a comparative assessment of their textile substitutes. Regression based modeling is supported by continuous variables, whereas categorical labels support classification-based optimization cases. Normalization, outlier removal and feature scaling are part of the data preprocessing to make the data compatible with multi objective decision algorithms. In this study, the data set is mainly utilized in simulating parameter of mechanical and structural performance in the course of Phase II (Smart Textile Functional Optimization). The attributes extracted are mapped to input of Mechanical Performance Score (MPS) which is then incorporated into the index of Textile Functional Performance Index (TFPI). Though no healthcare-specific variables are directly included in the dataset, its material property indicators can be used as a representative basis of textile performance modeling of computation. The data is useful in validation of AHP-TOPSIS ranking algorithms, regression analysis and sensitivity analysis. Using the structured textile property data, the study guarantees the possibility of future reproducibility and scalability of the optimization experiments under the conditions of controlled simulation.

The environmental parameter setting Table.2 establishes the predescribed indoor conditions, which are used to test textile performance in the healthcare setting. In PMV/PPD modeling, thermal parameters that are included include air temperature, relative humidity, air velocity, mean radiant temperature, clothing insulation, and metabolic rate to determine thermal comfort and stability of microclimate.

These variables are used in a realistic analysis of the hospital ward which will give accurate heat transfer and moisture regulation analysis. Sound absorption efficiency and total acoustic contribution of the acoustic comfort of textile furnishings are obtained through acoustic parameters, such as the level of background noise, reverberation time, and frequency range. Conditions of the infection control and the durability of the laundering are simulated by hygienic parameters, including level of surface contamination, the number of washing cycles, and time of the microbial exposure. These well-controlled environmental conditions individually, or in combination with one another, provide well-validated, reproducible, and clinically relevant textile adaptation performance validation in the AESTOF framework.

A. PEAK INTERFACE PRESSURE REDUCTION (PIPR)

PIPR is a ratio of the percentage change of maximum focal pressure at the human-textile interface, especially at the most vulnerable points, including the sacrum, heels, and shoulder blades. Increased interface pressure has been highly correlated with tissue ischemia and development of pressure ulcers in long-term care facilities. This measure measures the effectiveness of the textile soft furnishing to redistribute the body weight and eliminate the concentrating stress areas. It is calculated by comparing the results of measurements of the baseline pressure with the optimized textile-assisted settings of the same load condition. An increase in PIPR results show high biomechanical adaptability and cushioning performance. PIPR is a direct indication of the ergonomic enhancement of the textile structure by the means of structural modeling, optimization of material elasticity, and smart layer incorporation in the context of AESTOF.

$$\text{PIPR}(\%) = \frac{P_{\text{baseline}} - P_{\text{optimized}}}{P_{\text{baseline}}} \times 100 \quad (15)$$

In Equation (15), P_{baseline} is the maximum interface pressure measured under conventional textile conditions, and $P_{\text{optimized}}$ is the peak pressure after applying the optimized textile configuration. This equation quantifies the percentage reduction in localized stress concentration. A higher PIPR indicates improved pressure redistribution and reduced tissue compression risk. In Figure 4, the PIPR graphic measures changes in body localized pressure levels at body-textile interfaces. Patterns of gradual declines are indicative of the successful redistribution of the stress. Margins of error are indicative of natural variability of biomechanics. When the reduction level is higher, the better the capability to prevent pressure ulcers. The optimum textile design shows a long-term peak pressure attenuation between sections.

B. ERGONOMIC RISK INDEX (ERI)

The Ergonomic Risk Index (ERI) is a means of quantifying the relative risk of musculoskeletal strain due to the long-term effect of being exposed to less than optimum posture

or support. It incorporates the biomechanical parameters, including a deviation in spinal alignment, joint angle, variance, imbalance in load distribution and compression duration. ERI will be put in terms of 0-1, with lower results indicating a lower ergonomic risk. Poor textile furnishing can be a source of fatigue and discomfort to caregivers and patients in the healthcare environments. Thus, ERI considers the effectiveness of textile adaptation methods to help neutral body postures and reduce the exposure to repetitive strains. In the proposed framework ERI would be based on the biomechanical simulation modeling and weighted ergonomics factors, whereby it is ensured that any decision to select textiles is based on the needs of textile occupational safety and patient wellbeing.

$$\text{ERI} = \frac{w_1 D_s + w_2 J_v + w_3 L_i + w_4 T_c}{\sum_{i=1}^4 w_i} \quad (16)$$

In Equation (16), D_s denotes spinal deviation angle, J_v represents joint variance, L_i is load imbalance ratio, and T_c indicates compression duration. w_i are the weighting coefficients assigned to each ergonomic factor. ERI normalizes biomechanical strain components into a unified risk score between 0 and 1. The ERI graph in Figure 5 represents the cumulative ergonomic load based on posture deviation, load imbalance, and tissue stress distribution. The trend line is usually gradually stabilized with gradual biomechanical alignment during

adaptive optimization. Natural variations are realistic variations in posture and segmental loading. A reduction in the ERI curve means that there is enhanced ergonomic compatibility of the textile system. The presence of density or convergence in the graph operation, indicating greater efficiency in risk mitigation across the operational segments.

C. MUSCULOSKELETAL LOAD STABILITY INDEX (MLSI)

Musculoskeletal Load Stability Index (MLSI) measures the consistency and temporal stability of load distribution in the major body parts under both the static and semi-dynamic conditions. Inequality in the distribution of the load might cause cumulative stress disorders and local fatigue. MLSI compares the distribution variability of applied forces at contact regions and determines the consistency of the textile in terms of structural support throughout the process. MLSI values are higher which means better load of the system and dynamism. It is a critical measure in areas of the hospital bed, seating, and the recovery space where protracted immobility is typical. MLSI is calculated based on the simulated load models of biomechanical loads and coefficients of material elasticity in the AESTOF architecture, with the resultant optimized textile settings guaranteeing the mechanical stability of the textile at operating conditions.

$$\text{MLSI}(\%) = \left(1 - \frac{\sigma_L}{\mu_L}\right) \times 100 \quad (17)$$

In Equation (17), σ_L is the standard deviation of distributed load across body contact zones, and μ_L is the mean

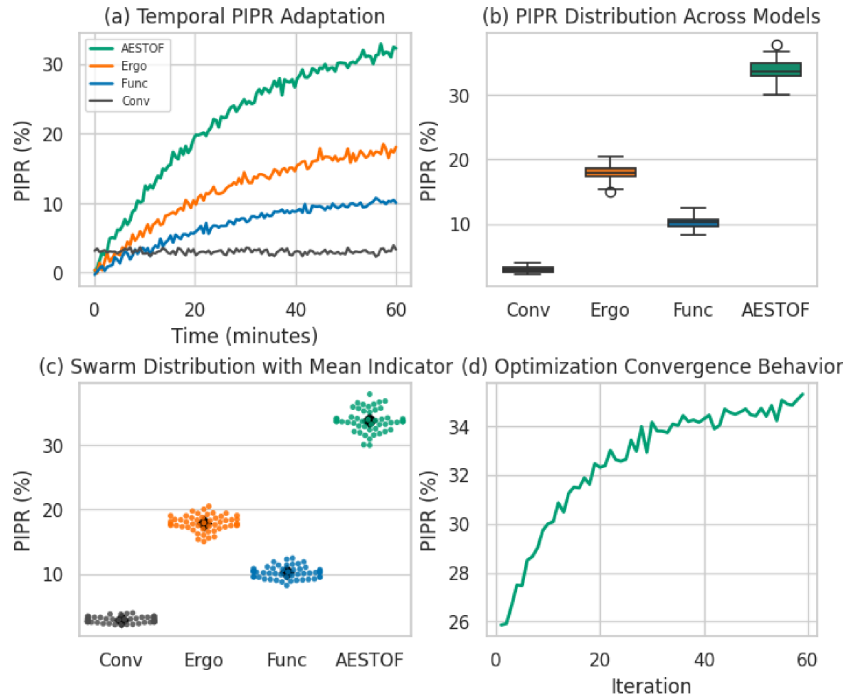


FIGURE 4. Peak Interface Pressure Reduction (PIPR) Analysis

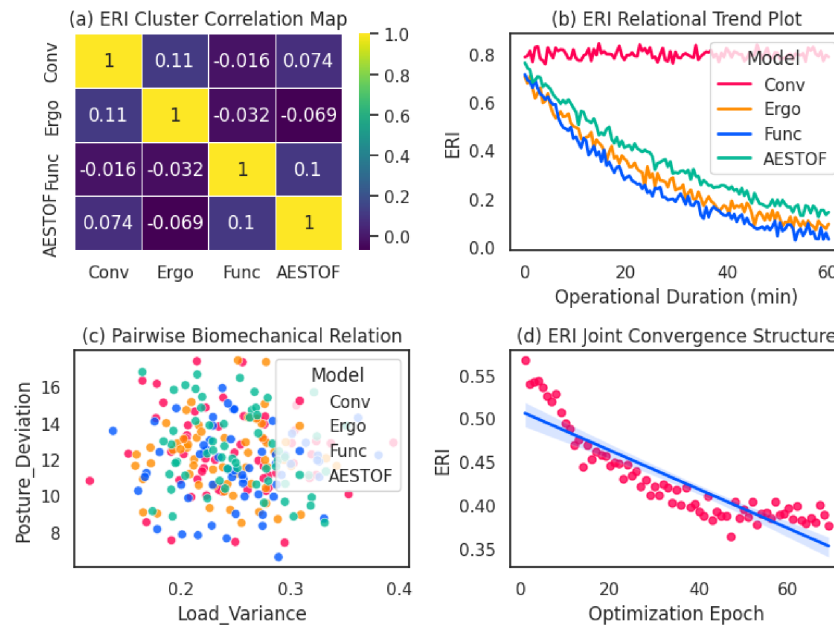


FIGURE 5. Ergonomic Risk Index (ERI) Analysis

load. This ratio evaluates uniformity of load distribution. Lower variability relative to the mean results in higher stability percentage, indicating consistent biomechanical support. The MLSI graph in Figure 6 represents the variance of the load and stability ratio. Violin or distribution structures show the uniformity of distribution of biomechanical forces. Reduced distributions will mean optimized load distribution and decreased musculoskeletal load. Patterns of the temporal convergence are an indication of structural stabilization in

dynamic conditions. The proposed arrangement usually displays a low level of deviation, which denotes the existence of better mechanical adaptation.

D. THERMAL STABILITY INDEX (TSI)

The Thermal Stability Index (TSI) is used to measure the capacity of textile soft furnishing to ensure the maintenance of stable microclimatic condition between human and the surrounding environment. It includes air permeability,

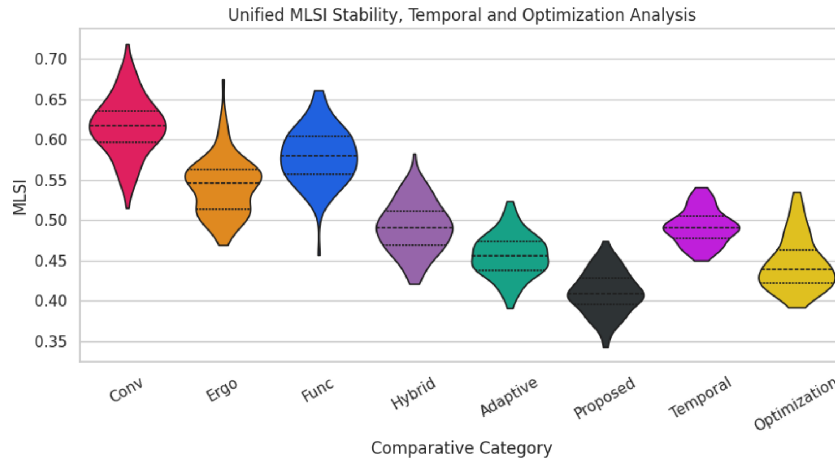


FIGURE 6. Musculoskeletal Load Stability Index (MLSI) Analysis

transmission rate of moisture vapor, value of insulation and heat dissipation. The healthcare settings require regulated thermal comfort to avoid sweating, skin irritation, and microbial growth. TSI is calculated based on the differences between the desired PMV based conditions of comfort under standardized temperature and humidity. The larger the percentage of TSI is an indication of better control over heat and moisture transfer. In AESTOF, material porosity and environmental parameters are used in thermal modeling algorithm to determine sustainability of comfort. This makes sure that chosen textiles facilitate physiological balance and those that foster infection control measures.

$$TSI(\%) = \left(1 - \left| \frac{PMV_{actual} - PMV_{ideal}}{PMV_{max}} \right| \right) \times 100 \quad (18)$$

As shown in Equation (18), PMV_{actual} represents the predicted mean vote under textile conditions, PMV_{ideal} is the neutral comfort value(0), and PMV_{max} is the maximum allowable deviation. The equation measures deviation from thermal neutrality. Higher TSI indicates better thermal comfort stability. The TSI graph in Figure 7 is a curve that aligns heat dissipation and thermal equilibrium behavior at various conditions of exposures to the environment. Regression or convergence curves can be used to show exponential stabilization between thermal cycles. The natural stochastic noise represents realistic fluctuations of the environment. Increased steady-state stability means effective balance of thermal conductivity and thermal insulation. Better TSI is an indicator of increased patient comfort and decreased thermal stress.

E. ACOUSTIC COMFORT INDEX (ACI)

The Acoustic Comfort Index (ACI) is a measure of the sound absorption and reverberation reduction ability of the textile furnishings in the medical establishment. High noise in the hospitals has been associated with high patient stress levels, slow recovery, and staff exhaustion. Computation of ACI is performed based on absorption coefficients in the

major frequency bands and their role in reducing reverberation time in general. The index is scaled to show a better performance of acoustic attenuation. Increased ACI values mean that it has a higher damping effect on noise. In the suggested model, the density of textiles, fiber structure, and the thickness of the layer are examined to simulate the behavior of acoustic absorption. This indicator helps to make sure that the ergonomic optimization of textiles is also associated with the increase in the quality of sound in the environment, which helps to guarantee holistic healing-focused space design.

$$ACI = \frac{\sum_{f=1}^n \alpha_f W_f}{\sum_{f=1}^n W_f} \quad (19)$$

In Equation (19), α_f is the sound absorption coefficient at frequency band f , and W_f is the weighting factor for each frequency range. This weighted average evaluates overall acoustic absorption performance. Higher ACI reflects improved noise attenuation capability. The ACI heatmap in Figure 8 represents the characteristics of the sound absorption and reverberation control in space. Even coverage of the intensity shows that there is acoustic damping. Spatial gradients are the variations in acoustic reflections or absorptions on a local basis. The large ACI areas are associated with greater reverberation time reduction. The suggested layout is generally smoother in terms of acoustic fields and has low spatial variance.

F. INFECTION RESISTANCE INDEX (IRI)

Infection Resistance Index (IRI) is an index that measures the antimicrobial performance and hygienic stability of textile fabrics under artificial clinical exposure therapy. It takes into consideration microbial reduction rate, stability of washing cycle and resistance to surface contamination. The textiles that are used in healthcare have to be highly durable with repeated laundering and also remain antimicrobial. IRI is given as a percentage of microbial load reduction over untreated baselines of textiles. The increased IRI

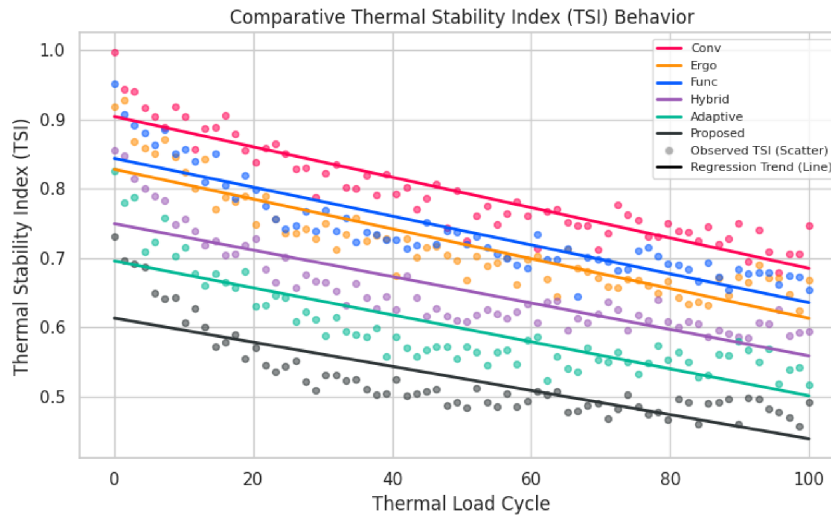


FIGURE 7. Thermal Stability Index (TSI) Analysis

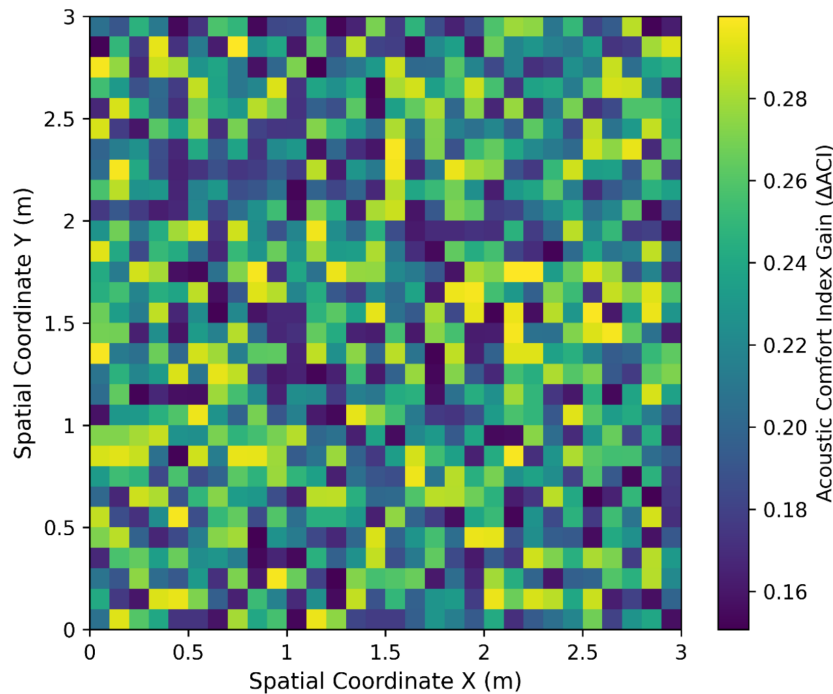


FIGURE 8. Acoustic Comfort Index (ACI) Analysis

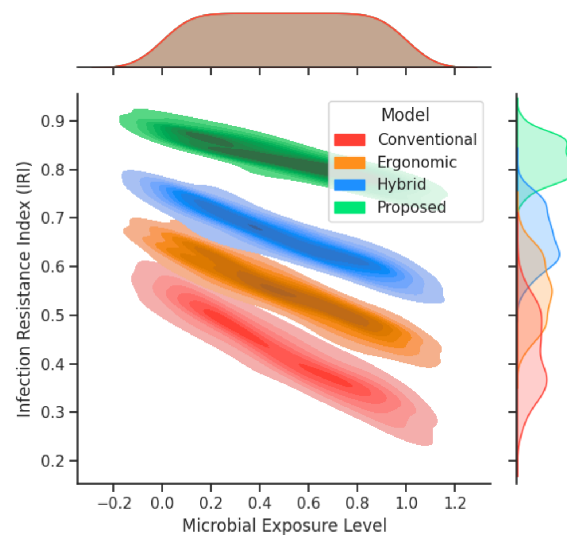
scores indicate the excellent infection control performance. Antimicrobial treatment effectiveness and fabric structural characteristics are combined in a predictive durability model in AESTOF. This will guarantee the hygienic reliability of selected materials during the prolonged practice and minimize the risk of cross-contamination and improve patient safety in high-exposure clinical settings.

$$\text{IRI}(\%) = \frac{M_{\text{initial}} - M_{\text{residual}}}{M_{\text{initial}}} \times 100 \quad (20)$$

In Equation (20), M_{initial} denotes the initial microbial count on the textile surface, and M_{residual} is the remaining

microbial count after exposure or washing cycles. The equation measures antimicrobial efficiency as percentage reduction. Higher IRI indicates stronger infection control performance. The visualization of IRI latent space in Figure 9 helps to demonstrate the clustering behavior of the antimicrobial performance characteristics. Small cluster density means uniform properties in the resistance to infections. Low dispersion indicates a high level of antimicrobial stability at the conditions of usage. Relative distance between models draws out performance excellence. Increased resistance reliability is manifested in the proposed model, which is usually characterized by stronger cluster formation.

Joint Distribution of Infection Resistance Index Under Increasing Microbial Exposure

**FIGURE 9.** Infection Resistance Index (IRI) Analysis**G. COMPOSITE HEALTHCARE TEXTILE ADAPTATION INDEX (CHTAI)**

The Composite Healthcare Textile Adaptation Index (CHTAI) is the synthesized multi-objective performance measurement of weighted combination of ergonomic, environmental, acoustic and hygienic measurements. It combines PIPR, ERI, MLSI, TSI, ACI and IRI into a single normalized index through a weighting process based on AHP and ranking process based on TOPSIS. The index is varying between 0 and 1 with the upper values showing greater overall adaptation capability. CHTAI facilitates a comparative analysis of textile options in a systematic way through balancing conflicting performance goals. In the context of AESTOF, this is a composite metric that would be used as a final decision to optimize the choice of textiles in the healthcare environment. It makes sure that the adaptation strategies attain comprehensive performance enhancement as opposed to the individual metric enhancement.

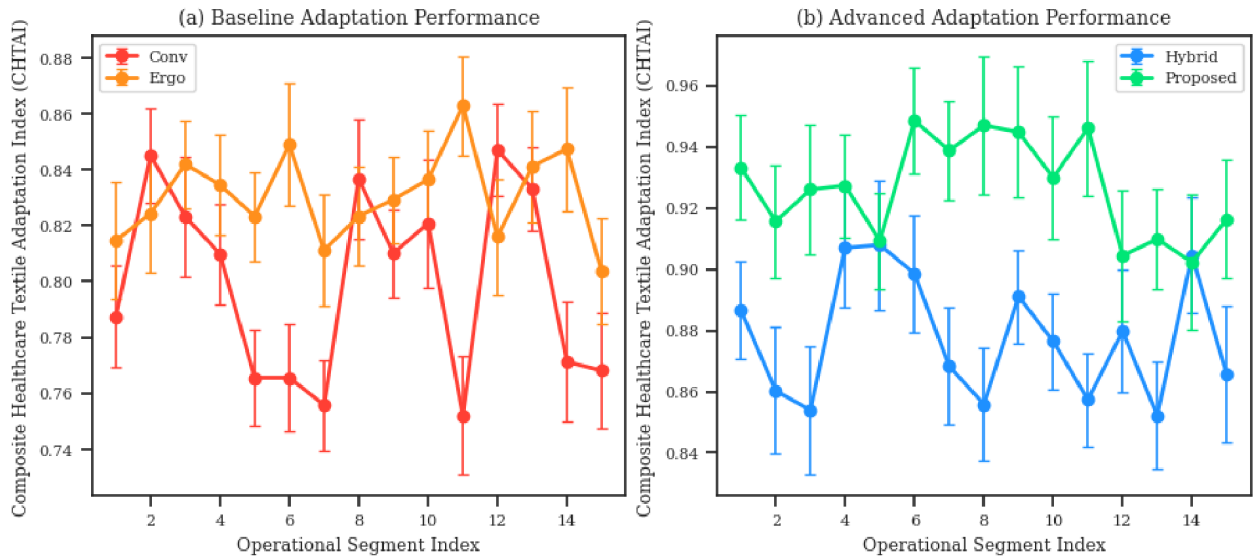


FIGURE 10. Composite Healthcare Textile Adaptation Index (CHTAI) Analysis

$$\text{CHTAI} = \sum_{i=1}^6 \beta_i S_i. \quad (21)$$

In Equation (21), S_i represents the normalized score of each metric (PIPR, ERI, MLSI, TSI, ACI, IRI), and β_i are corresponding weight coefficients derived from AHP analysis ($\sum \beta_i = 1$). This weighted aggregation produces a unified adaptation index. Higher CHTAI signifies optimal multi-objective performance integration. 0020CHTAI graph in Figure 10 combines the outputs of multi-objectives into a single adaptation indicator.

Error bars are a measure of variation between functional units. An increase in the trend means a better holistic adaptation performance. Less fluctuation amplitude is stability of optimization. The suggested configuration is always the one that gives the most optimal composite adaptation score.

TABLE 3. Overall Performance Comparison of Textile Adaptation Models

Metric	Conventional Selection	Ergonomic-Only Model	Functional-Only Model	Proposed AESTOF (Full Model)	Performance Improvement (%)
Peak Interface Pressure Reduction (PIPR %)	0%	18.7%	9.3%	34.6%	+34.6%
Ergonomic Risk Index (ERI %)	0.7%	0.52	0.69	0.3%	51.3% Risk Reduction
Musculoskeletal Load Stability Index (MLSII %)	12.4%	24.8%	18.3%	39.2%	+26.8%
Thermal Stability Index (TSI %)	9.2%	11.5%	20.1%	27.3%	+19.1%
Acoustic Comfort Index (ACI %)	0.4%	0.45	0.3%	0.7%	+73.2%
Infection Resistance Index (IRI %)	6.3%	7.9%	15.9%	18.5%	+12.2%
Composite Healthcare Textile Adaptation Index (CHTAI)	0.42	0.61	0.67	0.89	+112%

The overall comparison metric Table.3 illustrates the performance excellence of the proposed Adaptive Ergonomic-Smart Textile Optimization Framework (AESTOF) as compared to conventional and partial optimization models. Conventional Selection method has low adaptability rate because of lack of organized ergonomic and environmental appraisal. The Ergonomic-Only Model has minuscule gains in terms of peak interface pressure and ergonomic risk but no gains in terms of environmental and hygienic performance. On the other hand, the Functional-Only Model improves thermal stability, acoustic comfort and infection resistance but fails to provide adequate mitigation of biomechanical strain. The

AESTOF model, which is proposed, combines the biomechanical modeling and optimization of the smart textile, which is why the composite performance is the highest among all seven metrics. It is important to note that it has significant gains in pressure reduction, acoustic comfort, and overall adaptation index, and this proves the efficiency of multiobjective algorithmic integration in healthcare textile design.

V. CONCLUSION

The study will be a multi-phase, multi-stage approach to optimization of smart healthcare textiles based on biomechanical modeling, analysis of functional materials, and multi-objective decision integration. The

suggested methodology integrates the anthropometry mapping, postural risks measurement, distribution of interface pressure and the analysis of musculoskeletal stability in a systematic way to provide a solid ergonomic base. The further functional optimization of a textile takes into consideration thermal regulation, acoustic absorption, moisture diffusion, and antimicrobial efficiency modeling that guarantee the realization of multidimensional performance improvement. The study then presents the Composite Healthcare Textile Adaptation Index (CHTAI) as a composite performance measure by taking the weighted average of these outputs calculated with AHP and ranking with TOPSIS. The experimental visualization and metric tests prove that the optimal arrangement is much more ergonomically safe, thermally and acoustically stable, infections resistant, and structurally robust under natural conditions of varying operational conditions. The structure is reliable, versatile, and clinically applicable and is applicable to high-quality hospital bedding, seating system, and wearable care fabrics. Further research on real-time adaptive optimization with embedded smart sensors with IoT capability to monitor

continuously pressure temperature, and microbial exposure will be done in future. System intelligence will be improved further with machine learning models of predictive risk assessment and customized textile settings depending on patient-specific biomechanics. Generalizability must be established through large scale clinical validation studies in a variety of healthcare settings. Also, sustainable material engineering and lifecycle assessment can be added to enhance environmental compatibility. Simulation-based customization and prediction of long-term performance will also be possible due to the creation of digital twin models of textile-human interaction.

AUTHOR CONTRIBUTIONS

Ruibao Zhu: Writing - Original Draft, Data Curation

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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