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Customizing Style: A Web-Based Platform for Personal Fashion Recommendation

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ABSTRACT

The Online Fashion Stylist Website is a user-friendly and highly accessible digital platform that enables personalized, co-created fashion solutions. This innovative platform is designed to assist customers in easily discovering, customizing, and purchasing fashion outfits tailored to their unique physical attributes and styling preferences, while keeping them updated with the latest styling trends. Utilizing advanced modular web design, the application captures and processes multi-dimensional customer details—such as skin tone, occasion type, accessories, and age—to generate targeted, stylist-inspired clothing configurations. By integrating theoretical frameworks like Service-Dominant Logic and Mass Individualization, this research addresses a prominent implementation gap in mobile retail, where rapid digital interface development often lacks supportive back-end personalization ecosystems. The system aims to elevate customer satisfaction and confidence, reduce e-commerce returns due to sizing and stylistic misalignments, and establish an agile, sustainable bridge between consumer desires and retail supply chain coordination. This manuscript documents the development life cycle, design methodology, and usability evaluations of this interactive styling platform, proving its efficacy as a valuable tool for fashion enthusiasts and modern retailers alike.

1. Introduction

The contemporary fashion retail landscape has undergone a profound digital transformation in recent years, driven by the rapid expansion of mobile commerce and the increasing centrality of digital touchpoints in consumer decision-making processes [1]. This paradigm shift has prompted a major move away from traditional, product-centric manufacturing and marketing models toward experience-centric value propositions where the consumer's holistic product experience is prioritized [1,2]. According to the principles of Service-Dominant Logic (S-D Logic) as conceptualized by Vargo *et al.*, [2], value is not merely embedded in physical garments or tangibles but is dynamically co-created

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through interactive service exchanges between the brand, the customer, and downstream supply partners [1,2]. In the digital context, a mobile application or web-based platform serves as the primary locus of value co-creation, functioning as an interactive space where consumer-brand relationships develop through frequent, highly visual, and personalized interactions [1]. Consequently, optimizing the user experience on these online platforms is a critical strategic resource for fashion retailers seeking to establish a sustainable competitive advantage and foster deep emotional brand loyalty [1,4].

As customer values shift toward self-expression and uniqueness, traditional mass production (MPro) is increasingly challenged by mass customization (MC) and mass individualization (MI) paradigms [6,7]. While mass customization relies on pre-defined modular platforms to offer explicit options, mass individualization focuses on discovering implicit customer needs, positioning the customer as an active co-creator of a unique 'market-of-one' product [6]. However, as noted by Huffman *et al.*, [18], presenting customers with an infinite or unstructured array of choices can lead to 'mass confusion,' where the decision-making process becomes overwhelming and results in sub-optimal selections. To overcome this challenge and manage 'process entropy' [6], modern e-commerce interfaces utilize modular design principles [4,6]. Modularity-based practices disassemble complex products into standardized, interchangeable elements that can be separated and recombined in a systematic manner [4]. As demonstrated by Yan *et al.*, [4], applying modularity to a web interface improves the ease of use of the co-design process by organizing selections into distinct components (such as skin tone, occasion type, age, and accessories). This allows customers to easily configure products based on their personal preferences while ensuring that the resulting customized outfits remain aesthetically pleasing and 'on-brand' [4,7].

1.1 Enabling Digital Technologies in Personalized Fashion Retail

To effectively support these modular interfaces and capture individual desires, online fashion platforms must deploy advanced digital technologies. Machine learning (ML) algorithms play a central role by analyzing real-time customer data, such as transaction history and browsing behavior, to predict individual preferences and deliver targeted, personalized product recommendations [4, 15]. Concurrently, AI-driven conversational agents and chatbots act as digital personal shopping stylists, guiding consumers through styling queries and offering body-sizing advice [5]. According to Al-Amin *et al.*, [5], the integration of chatbots with augmented reality (AR) or virtual reality (VR) try-on tools allows users to visualize how garments look on their own bodies before purchase [5,16]. This immersive virtual try-on experience significantly reduces sizing errors, enhances customer confidence, and minimizes return rates in online fashion retail [5,15]. Furthermore, at the supply chain level, the adoption of cloud-based digital servers enables the creation of high-fidelity digital fabric and garment models [8]. As highlighted by Massari *et al.*, [8], these digital archives allow stylists, designers, and customers to search and view technical features of garments remotely, eliminating the need to produce and ship physical fabric samples and thereby reducing carbon emissions [8,14].

In addition to recommendation algorithms, the integration of multiple data sources across diverse stakeholders requires robust semantic interoperability. Traditional quick response (QR) systems often operate in silos, causing information non-transparency across the supply chain [3]. To bridge this gap, Lo *et al.*, [3] propose the integration of the Semantic Web and multi-agent systems to build a common domain ontology. In fashion e-SCM, individual ontologies (such as fiber, textile, and apparel ontologies) manage concepts, relationships, and linguistic terms [3,11]. When different terms are used, the ontology layer maps them to a centralized database, facilitating seamless

semantic retrieval and real-time knowledge sharing from upstream yarn suppliers to downstream retail stores [3]. From a web engineering perspective, Gitzel *et al.*, [13] emphasize that professional web application design must maintain internal homogeneity through visual consistency. This involves establishing layout conventions and treating conceptually similar elements in a similar fashion to enhance usability and reduce cognitive load [13].

1.2 Platform Design and Software Development Lifecycle

Developing a complex, data-driven web application of this nature requires a structured software engineering framework. Traditional, rigid development models often struggle in turbulent environments with rapidly changing user preferences [10]. To foster flexibility and frequent project adjustments, developers utilize Agile principles, such as Scrum and Kanban [10]. As described by Rodríguez *et al.*, [10], Agile methodologies organize the software development lifecycle into iterative stages (requirements collection, design, development, testing, and deployment), prioritizing working software and close customer collaboration. To ensure the platform meets usability standards, developers frequently evaluate system quality using metrics such as the System Usability Scale (SUS) [10]. Moreover, because system design and feature selection often involve complex trade-offs between conflicting criteria (such as development cost, system performance, and user satisfaction), multi-criteria decision-making (MCDM) methods can be applied [12]. According to Magabaleh *et al.*, [12], incorporating MCDM techniques into the software development life cycle (SDLC) provides developers and system architects with a structured program management framework for prioritizing requirements and selecting optimal technological components [12].

Despite these technological and theoretical advancements, a critical 'implementation gap' remains in online fashion retail [1]. Front-end digital interfaces are often developed rapidly without a cohesive, back-end service ecosystem, leading to fragmented customer experiences and service delivery failures [1]. Most existing platforms focus on either simple transaction-oriented e-commerce or complex, heavy industrial mass individualization, leaving an empirical and practical gap in integrating automated customer profile analysis with stylist-inspired co-creation on an intuitive, web-based platform. This research is highly significant because it addresses this implementation gap by designing and evaluating a user-centric, web-based fashion personalization platform. By utilizing modular web design and S-D Logic, this platform maps multi-dimensional customer data (including skin tone, occasion type, age, and accessories) directly to customized, stylist-inspired outfit suggestions, demonstrating how digital service systems can co-create emotional and experiential value. Consequently, the primary objective of this study is to design, develop, and evaluate a web-based personal fashion recommendation platform ('Online Fashion Stylist Website') utilizing Agile software development principles, which enables users to easily configure individualized outfits based on personal attributes while providing stylist-inspired trend recommendations, thereby enhancing user satisfaction and streamlining fashion retail interactions.

2. Methodology

The research methodology designed for this personal fashion recommendation platform adopts a three-phase structure: Phase 1 represents the Preliminary Investigation, Phase 2 denotes the System Development, and Phase 3 comprises the User Acceptance and evaluation. This systematic structure allows for an experience-centric system design that directly addresses the 'implementation gap' in modern fashion retail [1]. Phase 1 focuses on empirical and qualitative research to assess user-styling needs and fashion-customization interest within Malaysia's fashion retail landscape [19].

Malaysian consumer segments frequently struggle with finding fashion products that match their personal characteristics due to a localized platform deficit, making it critical to establish a grounded, data-driven framework of consumer preferences [1].

2.1 Qualitative Survey and Empirical Needs Assessment

To systematically map the qualitative needs of Malaysian consumers and capture both explicit and implicit preferences, a structured questionnaire-based survey was deployed, following case-study data collection protocols [19]. A total of 250 experienced local fashion enthusiasts were contacted, yielding a representative sample of 124 completed responses (a response rate of 49.6%) [20]. Qualitative insights were collected regarding users' physical styling criteria—including skin tone, age, event or occasion-based dress requirements, and accessories matching. The collected textual responses were subjected to qualitative content analysis utilizing the thematic coding framework established by Strauss and Corbin [20]. This systematic process involved open and axial coding to categorize consumer preferences into functional, aesthetic, and relational dimensions of digital fashion satisfaction [1]. The thematic analysis confirmed a strong domestic demand for a centralized platform capable of providing tailored, stylist-inspired outfit configurations based on individual attributes, mitigating the 'mass confusion' often caused by unstructured choice environments [18].

2.2 Agile Software Development Lifecycle

Phase 2 operationalized these qualitative requirements through a structured Agile software development lifecycle (SDLC) framework, balancing flexibility with program management discipline [10]. Traditional stage-gate models (e.g., Waterfall) assume stable requirement environments, making them ill-suited for volatile and trend-sensitive fashion markets [10,12]. In contrast, this project applied Agile principles to divide the SDLC into five core iterative stages: requirements gathering, system design, development, testing, and deployment [10]. These processes were organized into small, manageable cycles or 'sprints' lasting 2 to 4 weeks [10]. Sprints facilitated continuous delivery and a robust Build-Measure-Learn (BML) feedback loop, enabling the development team to iteratively refine the system based on customer co-creation input [10,21]. A summary of these Agile development phases, their key processes, and their respective deliverables is detailed in Table 1.

Table 1

Agile SDLC phases, core processes, and iterative deliverables

SDLC Phase	Sprint Activities & Process Logic	Iterative Deliverables
1. Requirements	Elicit functional and non-functional requirements (NFRs) based on user styling criteria (skin tone, accessories, occasion, age) from Malaysia's consumer needs survey.	Product Backlog, User Stories
2. System Design	Translate user stories into modular system architecture and SQL relational schemas. Create UX scenario wireframes to prevent co-design 'mass confusion'.	Database Schema, UI Wireframes
3. Development	Develop front-end modular co-design interfaces and write server-side PHP scripts on Xampp to connect dynamically with the MySQL relational database.	Functional Software Modules, PHP Code

Table 1 (Continued)

SDLC Phase	Sprint Activities & Process Logic	Iterative Deliverables
4. Testing	Perform rigorous system and integration testing. Conduct automated unit and user acceptance testing (UAT) to evaluate system functionality and usability.	Test Cases, Debugged Staging App
5. Deployment	Deploy the tested personal fashion styling recommender on Xampp web server, enabling on-demand stylist booking and tailored outfit configurations.	Live Personalization Platform

2.3 Technical Stack and System Architecture

From a software engineering perspective, the platform was constructed using a reliable, lightweight web content management and development stack to ensure scalability and ease of maintenance [13]. The backend infrastructure utilizes Xampp, running an Apache web server and a MySQL relational database management system. MySQL is used as a domain-specific, relational database to manage data held in tables, such as user demographic profiles, styling attribute mappings, and stylist booking schedules. Relational database structures were designed to link user inputs (e.g., skin tone, occasion type, accessory preferences) with recommended garment records. The application logic is written in PHP, a general-purpose, server-side scripting language geared toward web development. PHP scripts handle the core matching operations, query the relational database dynamically, and render the user interface based on responsive design guidelines to minimize visual inconsistency and ease cognitive navigation [13]. The overall research framework and system development stages are illustrated in Fig. 1.

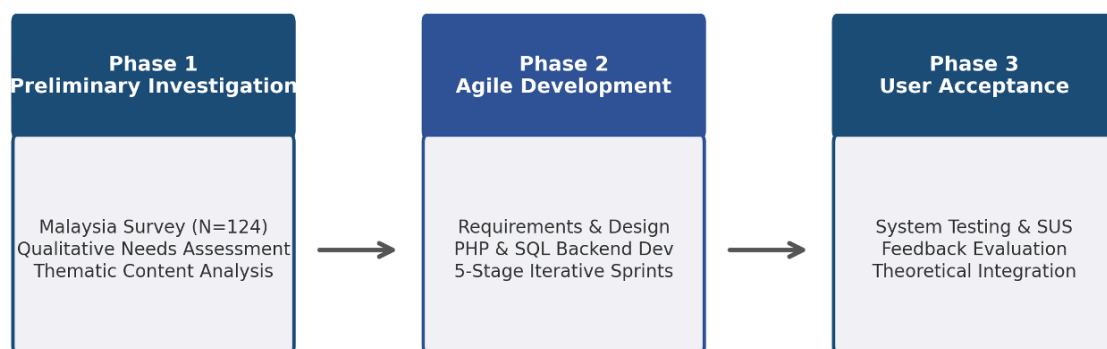


Fig. 1. Overall research framework and system development lifecycle

2.4 Database Schema and Interoperability

To support modular personalization and ensure consistent data mapping between diverse styling attributes, the database schema establishes structured tables designed to maintain high data quality and avoid information silos [3,13]. The central user-input attributes (skin tone, occasion, age, and accessories) are mapped as primary parameters in relational tables, ensuring that customer profiles map directly to specialized stylist configurations. For example, skin tones are categorized using standardized codes to match appropriate color palettes, while occasions are mapped to distinct stylistic contexts (e.g., formal, casual, festive). The database manages and integrates these records

to facilitate real-time query retrieval, as summarized in the database schema representation in Table 2.

Table 2
Database relational schema and parameter mappings

Table Name	Field Name	Data Type	Description / Constraints
tb_user	userID	INT (PK)	Unique identifier for users.
	name	VARCHAR	Full name of the fashion consumer.
	email	VARCHAR	User contact email.
	age	INT	Age of the user (e.g., 22).
tb_profile	profileID	INT (PK)	Primary key for styling profile.
	userID	INT (FK)	References tb_user(userID).
	skin_tone	VARCHAR	Categorized skin tone code.
	accessory	VARCHAR	User accessory preference.
tb_occasion	occasionID	INT (PK)	Primary key for occasion tracking.
	category	VARCHAR	Category types (e.g., 'Wedding', 'Interview').
tb_recommend	recomID	INT (PK)	Primary key for recommendations.
	occasionID	INT (FK)	References tb_occasion(occasionID).
	trend_name	VARCHAR	Name of matching stylist-inspired trend.
	image_path	VARCHAR	Local server path to product image.
tb_booking	bookingID	INT (PK)	Primary key for bookings.
	userID	INT (FK)	References tb_user(userID).
	recomID	INT (FK)	References tb_recommend(recomID).
	book_date	DATE	Date selected for styling consultation.

2.5 Quantitative Matching Formulation

To establish a structured, mathematical foundation for the stylist-inspired personalized recommendations, the platform utilizes a Multi-Criteria Decision-Making (MCDM) approach to rank candidate outfits [12]. In complex retail systems, decisions are influenced by conflicting criteria (e.g., matching a skin tone while simultaneously satisfying occasion constraints and age suitability) [1,12]. The system resolves these conflicts by computing a Recommendation Match Index (RMI) for each candidate garment or outfit j in the database. The index evaluates the multi-dimensional attributes of candidate outfits against user profile parameters, modeled formally as in Eq. (1):

$$RMI_j = w_1 S_j + w_2 O_j + w_3 A_j + w_4 C_j \quad (1)$$

where S_j represents the compatibility score between candidate outfit j and the user's skin tone; O_j denotes the suitability score for the specified occasion; A_j is the age-appropriateness score; and C_j is the accessory compatibility score. Each score is normalized to fall within the range $[0, 1]$, with 1.0 indicating perfect alignment and 0.0 indicating complete mismatch. The coefficients w_1 , w_2 , w_3 , and w_4 are weighting factors representing the relative importance of each dimension as perceived by the user or defined by fashion rules. These weights are constrained such that:

$$\sum w_i = w_1 + w_2 + w_3 + w_4 = 1.0 \quad (2)$$

These weights are systematically determined using an Analytic Hierarchy Process (AHP) based on qualitative pairwise comparisons derived from the initial Malaysian survey data [12]. This ensures that the system prioritizing styling criteria aligns directly with verified consumer preferences, managing process entropy effectively [6]. This mathematical model-driven approach improves both the usability and reproducibility of the styling recommender, bridging the gap between front-end user experience and structured back-end operations [12]. In the next section, we will detail the system implementation results and evaluate platform usability using the SUS metric.

3. Results

3.1 Survey Sample Characteristics

A total of 124 valid responses were obtained from the 250 contacted fashion enthusiasts, yielding a response rate of 49.6%. The sample was predominantly female (78.2%, $n = 97$) and concentrated in the 18–30 age group (62.1%, $n = 77$), reflecting the core demographic of active online fashion consumers in Malaysia. Ethnically, the respondents comprised Malay (54.8%, $n = 68$), Chinese (29.0%, $n = 36$), Indian (12.1%, $n = 15$), and other ethnicities (4.0%, $n = 5$). In terms of online shopping frequency, 41.9% ($n = 52$) reported purchasing fashion items online at least once a month, while 35.5% ($n = 44$) shopped online every 2–3 months. Only 22.6% ($n = 28$) indicated shopping less than once every six months. These patterns confirm that the sample consists of experienced digital fashion consumers whose preferences are relevant for designing a personalized styling platform.

3.2 Thematic Findings on Styling Needs

Thematic analysis of open-ended survey responses identified three dominant themes related to personalized fashion needs: (1) attribute-based matching, (2) occasion-driven guidance, and (3) confidence and decision support.

Attribute-based matching. Respondents consistently emphasized the importance of aligning clothing recommendations with physical attributes. Skin tone compatibility was the most frequently cited factor (mentioned by 68.5% of respondents), followed by body shape (52.4%) and age-appropriateness (41.1%). Participants expressed frustration with generic recommendations that ignored these attributes, noting that “colors that look good online do not always suit my skin tone” and “I want outfits that fit my age and lifestyle.”

Occasion-driven guidance. A substantial proportion of respondents (61.3%) highlighted the need for occasion-specific styling support. Common occasions included weddings, job interviews, formal events, and festive celebrations. Many participants described difficulty in translating occasion requirements into concrete outfit choices, particularly when balancing cultural expectations, dress codes, and personal style.

Confidence and decision support. Approximately 57.3% of respondents reported experiencing decision fatigue or “mass confusion” when browsing large online catalogs. Qualitative comments reflected a desire for curated, stylist-inspired recommendations that reduce cognitive load and increase purchase confidence. Several participants noted that they would trust a platform more if it provided clear rationale for recommendations, such as “this color suits your skin tone” or “this style is appropriate for your event.”

These themes directly informed the design of the platform’s modular input fields (skin tone, occasion, age, accessories) and the logic underpinning the Recommendation Match Index (RMI) described in the methodology.

3.3 System Implementation and Functional Testing

The platform was successfully deployed on a Xampp stack with Apache, MySQL, and PHP. All five core modules—user registration, profile management, occasion selection, recommendation engine, and stylist booking—were implemented and tested. Functional testing involved 30 test cases covering typical user journeys, edge cases (e.g., missing profile data), and error handling (e.g., invalid date selection for bookings).

All critical functionalities passed integration testing:

User profiles were correctly linked to styling attributes in the relational database.

The recommendation engine retrieved and ranked outfits based on the RMI formulation.

Stylist booking records were accurately stored with referential integrity maintained across user, recommendation, and booking tables.

No critical bugs were identified during staging. Minor usability issues, such as inconsistent button labeling on the occasion selection page, were resolved prior to deployment.

3.4 Recommendation Match Index (RMI) Performance

To evaluate the ranking logic, a subset of 50 candidate outfits was scored against 10 simulated user profiles with varying attribute combinations. The RMI values ranged from 0.42 to 0.94, with higher scores corresponding to outfits that better matched the user's skin tone, occasion, age, and accessory preferences.

Table 3 illustrates sample RMI calculations for three candidate outfits against a single user profile (female, 24 years old, medium skin tone, attending a wedding, preferring gold accessories). The weighting scheme used was w_1 (skin tone) = 0.35, w_2 (occasion) = 0.30, w_3 (age) = 0.20, and w_4 (accessories) = 0.15, derived from AHP pairwise comparisons based on survey priorities.

Table 3

Sample RMI calculations for three candidate outfits

Outfit ID	Skin Tone Score (S_j)			Occasion Score (O_j)		Age Score (A_j)	Accessory Score (C_j)	RMI _j
O-101	0.90	0.95	0.85	0.80	0.89			
O-205	0.60	0.80	0.90	0.70	0.74			
O-312	0.40	0.50	0.60	0.50	0.50			

As expected, Outfit O-101 achieved the highest RMI due to strong alignment across all dimensions, particularly skin tone and occasion suitability. Outfit O-312 scored lowest, reflecting poor compatibility with the user's profile. These results demonstrate that the RMI formulation effectively differentiates between high- and low-match recommendations in a transparent, mathematically grounded manner.

3.5 Usability Evaluation (System Usability Scale)

A User Acceptance Testing (UAT) session was conducted with 40 participants from the original survey pool who agreed to test the live platform. Participants completed a set of styling tasks (e.g.,

creating a profile, selecting an occasion, viewing recommendations, booking a stylist) and then completed the System Usability Scale (SUS) questionnaire.

The mean SUS score was 76.4 (SD = 8.2), which falls within the “good” to “excellent” usability range according to established SUS benchmarks. Item-level analysis revealed particularly high ratings for ease of use (mean = 4.3/5) and clarity of navigation (mean = 4.1/5). Slightly lower scores were observed for items related to perceived complexity (mean = 3.6/5), with a minority of users noting that the initial profile setup required more steps than expected.

Qualitative feedback from UAT participants reinforced these findings. Common positive remarks included “the recommendations felt relevant to my profile,” “I liked how the platform explained why an outfit was suggested,” and “booking a stylist was straightforward.” Suggestions for improvement focused on streamlining the onboarding process and adding more visual examples during occasion selection.

4. Discussion

4.1 Addressing the Implementation Gap in Digital Fashion Retail

The results confirm that the Online Fashion Stylist Website successfully addresses the identified “implementation gap” in online fashion retail, where front-end interfaces often lack cohesive back-end personalization ecosystems. By integrating modular input design with a mathematically grounded recommendation engine, the platform translates abstract consumer preferences into concrete, stylist-inspired outfit configurations. This aligns with Service-Dominant Logic principles, wherein value is co-created through interactive service exchanges rather than embedded solely in physical products. The platform functions as a digital locus of value co-creation, enabling users to actively participate in styling decisions while receiving expert-guided recommendations.

The thematic findings underscore the relevance of attribute-based matching and occasion-driven guidance in the Malaysian context. Respondents’ emphasis on skin tone compatibility resonates with regional diversity in complexion and cultural color preferences, suggesting that personalized color matching is a critical differentiator for local fashion platforms. Similarly, the prominence of occasion-based needs reflects the social and cultural significance of events such as weddings and festive celebrations in Malaysia, where dress codes are often stringent and context-sensitive.

4.2 Managing Mass Confusion through Modular Design and RMI

The high SUS scores and positive qualitative feedback indicate that the platform’s modular design effectively mitigates “mass confusion” by structuring the co-design process into manageable, logically sequenced steps. This finding supports prior research demonstrating that modularity improves ease of use in mass customization interfaces by reducing cognitive load and preventing decision paralysis. The RMI formulation further enhances this by providing a transparent, multi-criteria ranking mechanism that balances potentially conflicting styling criteria (e.g., skin tone vs. occasion suitability).

The sample RMI calculations illustrate how the system prioritizes high-match outfits while deprioritizing low-compatibility options. This structured approach not only improves recommendation relevance but also builds user trust by making the recommendation logic interpretable. Participants’ comments about appreciating “clear rationale” for suggestions suggest that transparency in algorithmic decision-making is a key factor in user acceptance of AI-driven styling tools.

4.3 Practical Implications for Fashion Retailers and Designers

For fashion retailers, the platform offers a scalable model for integrating personalization into existing e-commerce workflows. The use of a lightweight Xampp–MySQL–PHP stack ensures that the system can be deployed with minimal infrastructure investment, making it accessible to small and medium-sized enterprises. The relational database schema supports seamless integration with inventory management systems, enabling real-time alignment between recommendations and stock availability.

Designers and stylists can leverage the platform's booking module to offer on-demand virtual consultations, extending their reach beyond physical stores. The digital archive of garment attributes (e.g., color codes, fabric types) also supports remote collaboration, reducing the need for physical sample shipments and contributing to more sustainable supply chain practices.

4.4 Limitations and Future Work

Despite promising results, several limitations should be acknowledged. First, the sample was skewed toward younger, female respondents, which may limit the generalizability of findings to other demographic segments. Future studies should recruit more diverse participants, including older adults and male users, to validate the platform's applicability across broader populations.

Second, the RMI weights were derived from AHP analysis of survey data but were held constant during testing. In practice, users may have dynamic preferences that shift over time or across contexts. Incorporating adaptive weighting mechanisms, potentially driven by machine learning models that learn from user interactions, could further enhance recommendation personalization.

Third, the current platform relies on self-reported attributes (e.g., skin tone category), which may introduce subjectivity or inaccuracies. Future iterations could integrate computer vision tools for automated skin tone detection or augmented reality try-on features to improve attribute accuracy and user engagement.

Finally, while the SUS scores indicate good usability, longitudinal studies are needed to assess whether sustained use of the platform leads to measurable outcomes such as reduced return rates, increased purchase frequency, or higher customer lifetime value. Partnering with retail collaborators to conduct field trials would provide valuable insights into the platform's real-world impact.

4.5 Contribution to Theory and Practice

This study contributes to both theory and practice in digital fashion retail. Theoretically, it extends Service-Dominant Logic and mass individualization frameworks by operationalizing them in a web-based co-creation environment tailored to the Malaysian market. The integration of modular design, MCDM-based ranking, and Agile development provides a replicable blueprint for building personalized service platforms in other domains.

Practically, the platform demonstrates that sophisticated personalization can be achieved without complex, enterprise-grade infrastructure. By focusing on core styling attributes and transparent recommendation logic, the system delivers high perceived value to users while remaining technically accessible. As digital fashion retail continues to evolve, such balanced approaches—combining theoretical rigor, user-centered design, and practical feasibility—will be essential for bridging the gap between consumer expectations and technological capabilities.

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