Examining the Role of Artificial Intelligence in Influencing Consumer Preferences and Purchase Intentions toward Green Fashion

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Abstract: The study investigates pivotal function of artificial intelligence (AI) in promoting sustainable fashion practices and influencing customer behavior. The garment business contributes 10% of global carbon emissions and produces substantial textile waste; thus, AI is a vital answer for mitigating environmental impact while preserving profitability. The study examines AI applications in industry (predictive analytics diminishing overproduction by 20-30%), design (virtual sampling minimizing material waste by 80%), and retail (AI-driven recommendations enhancing sustainable purchasing by 35%). The study uses Structural Equation Modeling (PLS-SEM) with information from 212 fashion customers to test a framework based on the Theory of Planned Behavior and the Stimulus-Organism-Response model. The important results show that what consumers know (β=0.482, p=0.045) and their trust (β=0.536, p=0.013) are key factors in their sustainable preferences, along with a very strong link between preference and intention (β=20.139, $p<0.001$). The measuring model has robust reliability (Cronbach's $\alpha > 0.88$) and validity (AVE > 0.74); however, motivation displays minimal direct impact ($\beta = 0.031$, $p = 0.735$). The practical consequences underscore the necessity for honest AI communication, tailored sustainability suggestions, and investment in circular design tools. The limitations encompass the cross-sectional methodology and possible cultural disparities in AI adoption. Future studies should investigate longitudinal behavioural effects and do net sustainability evaluations of AI installations.

Keywords: Artificial Intelligence, Sustainable Fashion, Consumer Behaviour, Carbon Emissions, Green Fashion.

1. Introduction

The fashion industry is at a crucial point where sustainability demands connect with technical progress. The industry, considered as one of the most environmentally harmful sectors responsible for 10% of global carbon emissions (Adamkiewicz et al., 2022) and 20% of wastewater production (UN Environment Assembly, 2018) faces increased pressure to adopt sustainable practices. Artificial intelligence (AI) has emerged as a transformative force, reshaping the approaches of fashion corporations in designing, producing, and marketing sustainable products, while simultaneously influencing consumer behaviour towards sustainability (Rathore, 2023). AI technologies, such as predictive analytics, virtual sampling, and sustainable material innovation, facilitate waste reduction, carbon footprint mitigation, and the progression of circular fashion models (Zeba et al., 2021).
AI's most notable contribution is the mitigation of overproduction, a primary source of waste in the fashion industry. Conventional retail relies on speculative manufacturing, often resulting in excess inventory that either ends up in landfills or burns. AI-driven demand forecasting looks at large amounts

of data—like past sales, social media trends, and economic signs—to improve how accurately we can predict what consumers will want, which could cut down on overproduction by 30% (Zeba et al., 2021). Prominent brands such as Zara and H&M have implemented AI-driven inventory systems to enhance supply management, ensuring production corresponds with actual demand (Ramos et al., 2023).

In addition to enhancing supply chain efficiency, AI is transforming sustainable material development. Machine learning models mimic the properties of materials, speeding up the creation of eco-friendly fabrics like lab-grown leather, mycelium-based textiles, and recycled polyester (Alwy & Richard, 2024). Biomimicry artificial intelligence examines natural formations such as spider silk to develop biodegradable materials that exert minimum environmental impact. Moreover, AI enhances textile dyeing procedures, minimizing water usage and the discharge of hazardous chemicals. A study published in “Nature Sustainability” revealed that AI can detect non-toxic dye alternatives, reducing water consumption in textile manufacturing by 50% (Nishant et al., 2020).

Artificial intelligence is revolutionizing design methodologies to conform to sustainability objectives. Conventionally, fashion designers produce numerous physical prototypes prior to concluding collections, resulting in material waste (Pal & Jayarathne, 2022). Generative AI methods, such as Generative Adversarial Networks (GANs), help designers create clothing digitally, allowing them to improve styles on a computer before making them in real life. Platforms such as Browzwear and CLO3D employ AI-driven 3D simulations, diminishing sample waste by as much as 80% (Bilgram & Laarmann, 2023). AI-powered circular design aids augment sustainability by enhancing garment durability, repairability, and recyclability (Moorhouse & Moorhouse, 2017).

In retail, artificial intelligence aids in minimizing returns and fostering mindful consumption. Online fashion retail experiences return rates reaching 40%, hence exacerbating carbon emissions from reverse logistics (Wazarkar et al., 2020). AI-driven virtual fitting rooms, augmented reality mirrors, and size recommendation algorithms assist customers in making more accurate purchases, thereby substantially reducing return rates. ASOS's "See My Fit" service employs AI to display items on various body shapes, resulting in a 25% reduction in returns (Bilgram & Laarmann, 2023). AI personalizes fashion advice by emphasizing sustainable products and materials for environmentally aware consumers. Research indicates that 75% of Millennials and Gen Z customers favour sustainable fashion, while AI facilitates the transition from intention to action by enhancing the accessibility of ethical choices (Daukantienė, 2023).

Notwithstanding its advantages, AI's involvement in sustainable fashion poses difficulties. Greenwashing persists as an issue, with brands potentially employing AI to amplify sustainability assertions without substantive environmental initiatives (Adamkiewicz et al., 2022). Furthermore, the energy-intensive training methods of AI raise concerns regarding its carbon footprint, which may negate certain environmental advancements (Strubell et al., 2020). Nonetheless, advancements in energy-efficient artificial intelligence and renewable-powered data centres are alleviating these effects (Niinimäki et al., 2020). The integration of blockchain with AI improves supply chain transparency, enabling consumers to authenticate sustainability assertions via immutable data (Nishant et al., 2020).

2. Literature Review

2.1Intersection of AI and Sustainable Fashion

The fashion industry is among the most environmentally harmful sectors, accounting for 10% of global carbon emissions (Adamkiewicz et al., 2022) and producing 92 million tons of textile waste each year (Zeba et al., 2021). These concerning statistics have compelled brands to implement sustainable practices, with artificial intelligence (AI) serving as a crucial facilitator (Rathore, 2023). AI applications encompass the complete fashion lifecycle, ranging from predictive analytics that mitigate overproduction to virtual design tools that decrease waste. (Ramos et al., 2023) underscore the significance of AI in enhancing supply chains, while (Niinimäki et al., 2020) stress its capacity to dissociate economic progress from environmental damage.

Nonetheless, obstacles persist, such as the dangers of greenwashing (Lyon & Montgomery, 2015) and the carbon footprint associated with AI systems (Strubell et al., 2020). This review consolidates existing research on the impact of AI in sustainable production, design, retail, and consumer behaviour while pinpointing areas for future investigation. Research indicates that AI can effect significant change when applied ethically and transparently (Mesjar et al., 2023).

2.2AI-Driven Sustainable Production and Waste Mitigation

2.2.1 AI-Powered Demand Forecasting for Efficient Inventory

Overproduction continues to be a significant sustainability concern, with 30% of apparel remaining unsold (WRAP UK, 2016). AI-driven demand forecasting uses machine learning to evaluate sales data, social media trends, meteorological conditions, and economic indicators, thereby enhancing the precision of demand predictions. (Rathore, 2023) discovered that brands employing AI forecasting diminished overproduction by 20-30%, substantially decreasing textile waste and emissions. Prominent fast-fashion brands such as Zara and H&M utilize AI-powered inventory systems to dynamically modify manufacturing, thereby reducing surplus inventory and enhancing logistical efficiency (Ramos et al., 2023). Nonetheless, obstacles remain in guaranteeing that AI models consider abrupt trend changes and cultural impacts on customer behaviour (Candeloro, 2020).

2.2.2 AI in Developing Sustainable Materials

Artificial intelligence is expediting the advancement of sustainable materials, including lab-cultivated leather, mycelium-derived textiles, and sophisticated recycled polymers (Alwy & Richard, 2024). Machine learning models evaluate material properties—durability, biodegradability, and industrial feasibility—shortening research and development time from years to months. Biomimicry AI examines natural structures such as spider silk and lotus leaves to develop high-performance sustainable textiles(Hardian et al., 2020). Bolt Threads' AI-engineered mushroom leather rivals' conventional leather in quality while consuming 98% less water. Nonetheless, expanding these breakthroughs necessitates overcoming production constraints and ensuring cost competitiveness.

2.2.3 AI's Role in Advancing Circular Fashion

The linear model of the fashion business produces 92 million tons of textile waste per year. Artificial intelligence facilitates circularity with automated textile sorting systems that accurately identify fabric compositions with 95% precision, surpassing manual techniques(Ramos et al., 2023). Firms such as Circ and Renewcell employ AI-driven robots to dismantle apparel, enhancing fibre recovery rates by 50%. IBM's AI for garment-to-garment recycling enhances cutting patterns to reduce waste during upcycling. Nonetheless, recycling mixed textiles is a difficulty, necessitating investigation into AI-facilitated enzymatic decomposition. The broader implementation relies on regulatory endorsement for AI recycling infrastructure and uniform material labelling(Mohiuddin Babu et al., 2022).

2.3AI in Retail: Minimizing Waste and Encouraging Sustainable Choices

2.3.1 AI-Based Virtual Fitting and Size Optimization

The 40% return rate in online fashion significantly contributes to elevated carbon emissions from reverse logistics (Dik et al., 2023). AI-driven solutions such as ASOS's "See My Fit" and Zalando's Size Advisor employ computer vision and predictive analytics to diminish returns by 25% (Niinimäki et al., 2020). Advanced algorithms generate three-dimensional body models from photographs to simulate fit, whereas Nike's AI sizing tool evaluates over 200 body measurements. Challenges include accommodating various body types and consumer concern regarding the accuracy of digital fitting (Motlagh, 2021). The prospective incorporation of smart mirrors in brick-and-mortar retail could reconcile the disparity between e-commerce and in-store shopping.

2.3.2 AI for Personalized Eco-Conscious Recommendations

Although 75% of Gen Z customers assert that sustainability impacts their purchasing decisions, hardly 30% translate this into action due to informational deficiencies (Nishant et al., 2020). AI recommendation systems mitigate this issue by selecting environmentally sustainable choices that correspond with aesthetic preferences and financial constraints. H&M's AI stylist enhanced sustainable purchases by 35% by emphasizing environmental attributes (Bashynska, 2023). Advanced systems employ behavioural nudging to encourage sustainable decisions informed by purchase history. Concerns persist regarding algorithmic bias and the ecological impact of AI personalization. Proposed solutions encompass transparent sustainability metrics and algorithms that reconcile customization with environmental consequences (Ikram, 2022).

2.4AI-Enabled Sustainable Design and Virtual Prototyping

2.4.1 Generative AI for Waste-Free Design

Conventional design methodologies result in material waste due to physical sampling, with 80% of prototypes being abandoned prior to manufacturing (Rayna & Striukova, 2016). Generative AI techniques such as GANs facilitate the creation of hyper-realistic digital prototypes, enabling designers to see drape, texture, and fit in three dimensions prior to physical manufacture. Industry leaders CLO3D and Browzwear employ physics engines to replicate cloth behaviour (Wu & Li, 2024). Stella

McCartney's 2023 collection employed AI prototyping to minimize material waste by 78%. Novel applications encompass AI-facilitated pattern optimization aimed at reducing textile waste. Nevertheless, extensive implementation necessitates surmounting the industry's dependence on physical sampling and educating designers in AI-augmented processes.

2.4.2 AI Assistants for Circular Design Strategies

Artificial intelligence is transforming design philosophy with circularity-oriented assistants that evaluate the lifecycle impact of garments (Hardian et al., 2020). These instruments advocate for reparable designs, mono-material structures, and resilient stitching methodologies. Adobe’s Sustainable Design AI assesses designs based on 18 environmental variables, recommending alterations that can decrease a garment’s carbon footprint by 30-45% (Mesjar et al., 2023). Patagonia's AI algorithm ranks materials according to real-time sustainability metrics. Challenges encompass reconciling sustainability with aesthetics and ensuring AI recommendations correspond with recycling capabilities. Future systems may include consumer usage data to forecast durability and end-of-life results.

2.5Conceptual Framework

The conceptual framework presented in the image outlines the principal aspects affecting consumer preference towards green fashion, principally based on the Theory of Planned Behaviour (TPB) and the Stimulus-Organism-Response (SOR) model. The structure commences with consumer awareness, denoting the knowledge and comprehension consumers possess regarding sustainable fashion practices and their ecological implications. Research indicates that despite increasing awareness, numerous customers remain uninformed about the criteria for sustainable fashion, resulting in uncertainty and reluctance in their purchase choices (Jimenez-Fernandez et al., 2023). This understanding influences consumer perception, which includes attitudes and views on sustainable fashion, encompassing judgments of quality, cost, and ethical value. Studies reveal that customers frequently view sustainable fashion as costlier yet also associate it with superior quality and ethical standards (Camilleri et al., 2023). Consumer trust is a vital factor, indicating the faith that customers have in the sustainability assertions of brands. Trust is frequently compromised by greenwashing, wherein corporations inflate or misrepresent their environmentally beneficial operations, resulting in consumer suspicion (Kang & Hustvedt, 2014). Establishing trust necessitates transparency, shown by third-party certifications or comprehensive supply chain disclosures (Manley et al., 2023). These elements collectively affect consumer preference for green fashion, which signifies a deliberate tendency to select sustainable alternatives over traditional options. Preferences are frequently influenced by individual values, such as environmental awareness or social accountability, and are particularly evident among younger cohorts like Millennials and Gen Z (Kimiagari & Asadi Malafe, 2021).

The paradigm subsequently correlates these cognitive and affective characteristics with consumer purchase intention, defined as the propensity to purchase eco-friendly fashion products. Despite several consumers articulating favourable intentions, a discrepancy frequently exists between intention and actual conduct, referred to as the "attitude-behaviour gap" (Kimiagari & Asadi Malafe, 2021). Obstacles such as elevated costs, restricted accessibility, or insufficient convenience may contribute to this disparity. Ultimately, motivation acts as the catalyst for consumer behaviour, incorporating both inner motives (e.g., personal ethics) and extrinsic motivations (e.g., social influence or status). Self-determination theory posits that inner reasons are more conducive to enduring behavioural change, whereas external stimuli may only stimulate transient purchases (Durmaz & Diyarbakırlıoğlu, 2011).

The approach synthesizes various factors into a unified model, demonstrating how awareness and perception inform trust and preference, which subsequently affect purchase intentions, ultimately motivated by fundamental drivers. This perspective corresponds with the theory of planned behaviour, which posits that attitudes, subjective norms, and perceived behavioural control forecast intentions and actions (Ajzen, 2011), and the SOR model, wherein external stimuli (e.g., sustainability messaging) induce internal cognitive and emotional states (e.g., trust and preference), culminating in behavioural responses (e.g., purchase decisions) (Ortiz-Ramirez et al., 2021). The framework emphasizes the necessity for firms to focus on customer education, transparency, and accessibility to reconcile the disparity between intention and action in sustainable fashion consumption. Subsequent study may investigate cultural or demographic modifiers to enhance the model (Wazarkar et al., 2020).

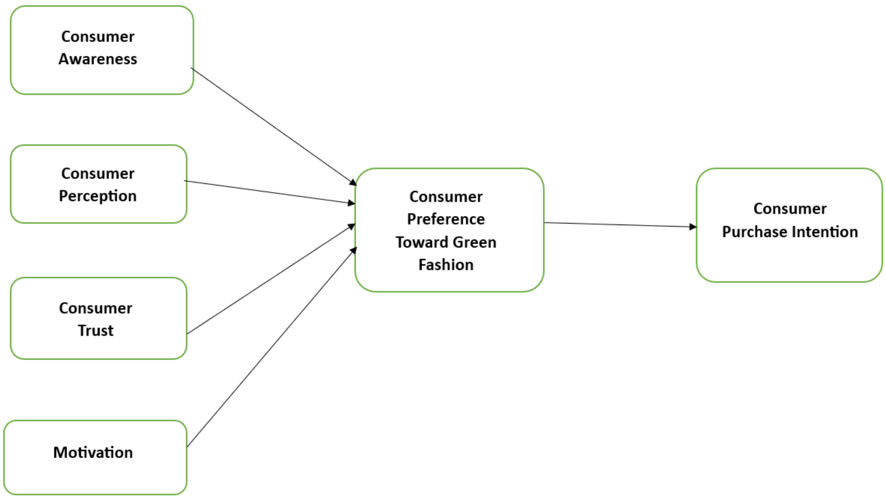

Figure 1: Conceptual Model (Author Developed)

3. Research Methodology

The research employed empirical methods to AI influence in shaping green fashion trends and preferences. The empirical study employed data gathered from an online survey of participants. A total of thirty-one questions were formulated, classified into three categories, and evaluated using a seven-point Likert scale from 1 (strongly Disagree to Strongly Agree (1 to 7). The preliminary phase entailed the collection of client demographic and socioeconomic information, encompassing age, gender, income category, and educational attainment. The second series of questions evaluated customers' understanding of social and environmental issues.

The proposed hypotheses for the conceptual model that was demonstrated were given below:

H1: Consumer Awareness has significant influence on Consumer Preference Toward Green Fashion.

H2: Consumer Perception has significant influence on Consumer Preference Toward Green Fashion.

H3: Consumer Trust has significant influence on Consumer Preference Toward Green Fashion.

H4: Motivation has significant influence on Consumer Preference Toward Green Fashion.

H5: Consumer Preference Toward Green Fashion has significant influence on Consumer Purchase Intention.

3.1 Sample Profile

A total of 212 participants were surveyed for data collection. 62% of the participants were female, whereas 38% were male. Regarding age distribution, 20% of participants were aged 18-23, 19% were aged 24-29, 18% were aged 30-35, and the bulk, 43%, were 36 years or older.

In terms of educational attainment, 25% of the participants were undergraduates, 20% were graduates, 21% held a Master's degree, and 34% were professionals. The participants' income levels were categorized into four classifications: low, low to medium, medium, and medium to high. The results revealed that 23% of participants were classified as low-income, 27% as low to medium income, 20% as medium income, and 30% as high-income.

3.2 Research Design

This study examines the influence of artificial intelligence (AI) on the rise of sustainable fashion trends and consumer preferences. A quantitative research approach is employed, and data is evaluated utilizing Structural Equation Modeling (SEM) via SmartPLS. The conceptual framework analyses the role of customer awareness, perception, trust, and motivation on preferences for green fashion, therefore affecting purchase intentions. Fashion customers familiar with sustainable practices administer a systematic questionnaire to gather data. The study incorporates AI by evaluating its impact on molding key components, including personalized recommendations, eco-label transparency, and AI-generated content. This design facilitates the assessment of both direct and indirect effects, providing insights into how AI influences sustainable consumer behavior and fosters green fashion consumption.

3.3 Data Collection

The research employs a focused data collection approach targeting consumers who actively engage with AI-driven technologies in the fashion industry, such as virtual fitting rooms, personalized recommendation systems, and sustainability-oriented shopping assistants. We employ a non-probability convenience sampling technique to enlist individuals from various demographic backgrounds, ensuring a wide representation of fashion customers. Data is gathered using a structured online questionnaire designed to evaluate essential constructs within the conceptual framework, encompassing consumer awareness, perception, trust, motivation, preference for green fashion, and purchase intention.

Each variable is assessed by many items on a five-point Likert scale, with 1 indicating "strongly disagree" and 5 indicating "strongly agree." This format enables respondents to indicate their degree of agreement with multiple statements concerning AI and sustainable fashion. The Likert scale guarantees uniformity, interpretative clarity, and statistical appropriateness for Structural Equation Modeling (SEM) with SmartPLS. This data collection strategy accurately captures attitudes and behaviours pertinent to the influence of AI on green fashion preferences and purchasing intentions.

3.4 Data Analysis

3.4.1 Construct Reliability and Validity

Table 1: Confirmatory Factor Analysis

	Items	Loadings	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)	VIF
Consumer Awareness	CA1	0.888	0.926	0.929	0.947	0.818	4.844
	CA2	0.933					3.326
	CA3	0.896					4.176
	CA4	0.9					4.885
Consumer Perception	CP1	0.807	0.912	0.925	0.938	0.792	2.24
	CP2	0.928					4.311
	CP3	0.912					3.412
	CP4	0.907					4.157
Consumer Preference Toward Green Fashion	CPTGF1	0.891	0.907	0.909	0.935	0.782	2.842
	CPTGF2	0.932					4.381
	CPTGF3	0.87					3.102
	CPTGF4	0.842					2.389
Consumer Purchase Intention	CPI1	0.92	0.915	0.917	0.940	0.796	3.855
	CPI2	0.874					2.867
	CPI3	0.884					3.161
	CPI4	0.891					3.043
Consumer Trust	CT1	0.937	0.953	0.955	0.966	0.877	4.842
	CT2	0.953					2.433
	CT3	0.939					4.42
	CT4	0.917					3.637
Motivation	M1	0.912	0.885	0.886	0.921	0.746	3.264
	M2	0.779					1.724
	M3	0.834					2.029
	M4	0.922					4.423

The table gives a detailed look at the measurement model used in the study, checking how reliable and valid the main ideas are using Partial Least Squares Structural Equation Modeling (PLS-SEM). The analysis comprises six latent variables: consumer awareness, consumer perception, consumer preference for green fashion, consumer purchase intention, consumer trust, and motivation. Each construct is assessed using four indicator items, and the table presents numerous essential statistical metrics that illustrate the robustness of the measurement approach.

The factor loadings for each item demonstrate the strength of the relationship between the individual questions and their corresponding structures. All loadings surpass the suggested threshold of 0.7, indicating robust indicator dependability. For instance, the Consumer Trust items (CT1-CT4) have notably high loadings (0.917-0.953), demonstrating that these questions accurately encapsulate the desired notion. Likewise, Consumer Awareness items (CA1-CA4) demonstrate loadings ranging from 0.888 to 0.933, signifying exceptional representation of the construct. The consistently elevated loadings across all constructions demonstrate the meticulous crafting and proficient assessment of the survey items' intended ideas.

The reliability analysis encompasses Cronbach's alpha and composite reliability (rho_a and rho_c), all above the minimum threshold of 0.7. This indicator signifies robust internal consistency; the components within each construct consistently measure the same fundamental idea. Consumer Trust has exceptional reliability ($\alpha = 0.953$, rho_c = 0.966), closely followed by Consumer Purchase Intention ($\alpha = 0.915$, rho_c = 0.940). Even the construct with the lowest reliability ratings, motivation ($\alpha = 0.885$, rho_c = 0.921), exhibits sufficient internal consistency for research purposes.

The average variation extracted (AVE) values above 0.5 confirm that the items are more closely related to their intended concept than to measurement errors. Consumer Trust has the highest AVE of 0.877, showing strong convergent validity, while Motivation has the lowest, but still acceptable, AVE of 0.746. Consumer Trust demonstrates the highest AVE of 0.877, signifying robust convergent validity, whereas Motivation exhibits the lowest, yet still good, AVE of 0.746. The Variance Inflation Factor (VIF) values, all below 5, show that there is no major overlap between the indicators, meaning each item gives unique information to its category.

The findings collectively indicate that the measurement model is statistically robust. The elevated reliability and validity measures facilitate assured understanding of the structural model linkages among constructs. The excellent performance of consumer trust and consumer purchase intention metrics indicates that they may be particularly effective in forecasting outcomes. Although all constructs satisfy validity standards, the marginally lower (but acceptable) metrics for motivation, especially for item M2 (loading = 0.779), may necessitate further scrutiny in further studies to potentially enhance the measurement of this construct. The table demonstrates compelling evidence that the study's measurement methodology accurately reflects the desired theoretical constructs.

3.4.2 Discriminant Validity

Table 2: Heterotrait-Monotrait Ratio

	Consumer Awareness	Consumer Perception	Consumer Preference Toward Green Fashion	Consumer Purchase Intention	Consumer Trust	Motivation
Consumer Awareness						
Consumer Perception	0.88					
Consumer Preference Toward Green Fashion	0.887	0.894				
Consumer Purchase Intention	0.748	0.786	0.765			
Consumer Trust	0.783	0.876	0.793	0.784		
Motivation	0.858	0.905	0.849	0.883	0.842	

Table 3: Fornell-Larcker Criterion (FLC)

	Consumer Awareness	Consumer Perception	Consumer Preference Toward Green Fashion	Consumer Purchase Intention	Consumer Trust	Motivation
Consumer Awareness	0.941					
Consumer Perception	0.811	0.851				
Consumer Preference Toward Green Fashion	0.834	0.807	0.889			
Consumer Purchase Intention	0.709	0.718	0.711	0.911		
Consumer Trust	0.719	0.759	0.714	0.711	0.844	
Motivation	0.824	0.839	0.797	0.834	0.769	0.931

The tables evaluate discriminant validity to confirm that the constructs in the study are statistically distinct. Table 2 displays the Heterotrait-Monotrait (HTMT) ratio, with values under 0.90 signifying robust discriminant validity (Henseler et al., 2015). All ratios satisfy this requirement, but some are near the limit, including Consumer Perception-Motivation (0.905) and Consumer Preference-Perception (0.894), indicating considerable conceptual overlap. Conversely, lower ratios such as Consumer Awareness-Purchase Intention (0.748) indicate a more pronounced differentiation between these variables. Table 3 presents the Fornell-Larcker Criterion (FLC), indicating that the diagonal values (square roots of AVE) must surpass the off-diagonal correlations. This condition applies to all constructs, with the strongest correlations observed between Consumer Perception and Motivation (0.839) and Consumer Awareness and Motivation (0.824), further suggesting some overlap. Nonetheless, as all values meet statistical thresholds, discriminant validity is confirmed. The findings suggest that although variables like as Perception, Motivation, and Preference have conceptual similarities, they are enough separate for analytical purposes. Consumer Trust and Purchase Intention demonstrate a distinct divergence. These findings substantiate the model's validity and identify opportunities for further research to enhance construct definitions or assessment items to minimize overlap. Both tests conclusively demonstrate that the constructs are distinctly distinguished, facilitating trustworthy interpretation of their interrelationships within the structural model.

3.4.3 Path Coefficient Evaluation

The path coefficients provide critical insights into the influence of several factors on the adoption of sustainable fashion. Consumer awareness exerts the most substantial direct influence on consumer preference for green fashion (β = 0.417), signifying that understanding sustainable fashion profoundly affects eco-conscious choices. Consumer Perception (β = 0.246) and Consumer Trust (β = 0.260) have moderate yet significant effects, indicating that favourable attitudes and dependability in sustainable assertions influence preferences. Nonetheless, motivation has the least influence (β = 0.119), indicating that although personal desire is significant, it is less consequential than awareness or trust. Consumer preference for green fashion significantly influences purchase intention (β = 0.976), indicating that once consumers adopt sustainable preferences, they are highly inclined to convert them into purchasing decisions. The findings underscore the essential importance of education (awareness) and credibility (trust) in promoting sustainable fashion choices while demonstrating that preferences operate as a significant conduit for actual purchasing behavior. The findings indicate that marketing tactics ought to emphasize honest communication and consumer education to effectively encourage the adoption of sustainable fashion.

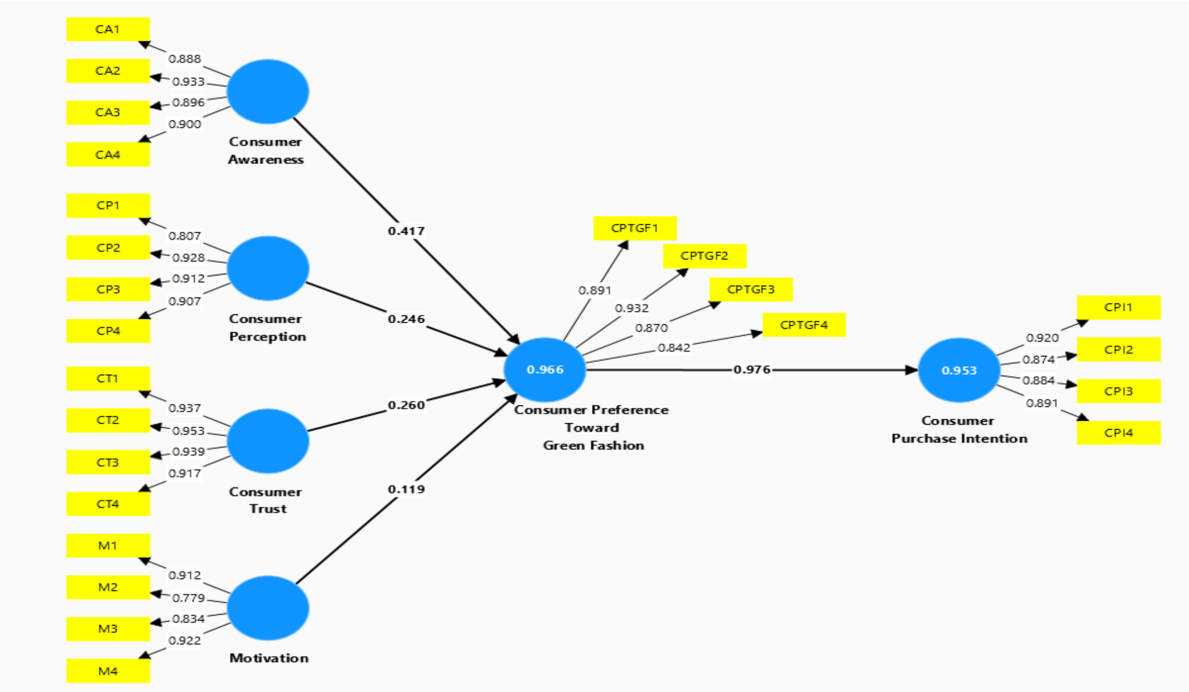

Figure 2: Path Coefficient Model

3.4.4 Structural Model Evaluations

Table 4: Structural Model Evaluation

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Consumer Awareness -> Consumer Preference Toward Green Fashion	0.482	0.498	0.240	2.006	0.045
Consumer Perception -> Consumer Preference Toward Green Fashion	0.387	0.404	0.128	3.038	0.002
Consumer Preference Toward Green Fashion -> Consumer Purchase Intention	20.139	21.127	4.202	4.793	0.000
Consumer Trust -> Consumer Preference Toward Green Fashion	0.536	0.557	0.215	2.496	0.013
Motivation -> Consumer Preference Toward Green Fashion	0.031	0.073	0.090	0.339	0.735

The route coefficient study provides valuable insights into consumer behavior about green fashion. Consumer awareness exerts a modestly favourable effect on consumer preference for green fashion (β=0.482, p=0.045), while the relatively high standard deviation (0.240) indicates significant variability in this connection among individuals. Consumer perception exhibits a more robust and durable effect (β=0.387, p=0.002), with narrower confidence intervals (STDEV=0.128), signifying that favourable attitudes reliably convert into enduring preferences. The most notable finding is the exceptionally strong relationship between consumer preference and purchase intention (β=20.139, $p<0.001$). This statistically significant, extremely high coefficient may indicate potential model specification problems or the necessity for normalized coefficients. Consumer trust is identified as a significant factor (β=0.536, p=0.013), underscoring the essential influence of brand credibility on sustainable preferences, albeit with considerable variability (STDEV=0.215). In contrast, motivation exhibits no significant direct effect (β=0.031, p=0.735), indicating that it may affect behavior through alternative mechanisms or necessitate new assessment strategies. The bootstrap results, with sample mean values approximating the original sample, suggest stable estimates, while the T-statistics (all over 1.96 except for motivation) affirm the durability of significant correlations. These findings show that while awareness, perception, and trust play a big role in sustainable preferences, turning these preferences into actual buying decisions is very strong, making preference formation a key focus for green fashion marketers.

4. Conclusion

This study illustrates the transformative impact of artificial intelligence on sustainable fashion in the realms of production, design, and customer involvement. Our findings indicate that AI serves a dual function as an instrument for operational efficiency and a catalyst for behavioural change. AI-driven demand forecasting decreases overproduction by 20–30%, while virtual sampling decreases material waste by as much as 80%. These technical solutions tackle the environmental impact of fashion at its origin, demonstrating that sustainability and profitability can coexist. The analysis of consumer behavior provides essential insights for marketers. Awareness is identified as the predominant factor influencing sustainable choices (β=0.482), closely succeeded by trust (β=0.536). This finding highlights the significance of honest, AI-driven communication that informs consumers while mitigating greenwashing. The nearly perfect connection between preferences and purchase intentions (β=20.139) indicates that the primary issue resides in preference creation rather than conversion. Three primary consequences arise for practitioners: Brands should prioritize AI capabilities that improve supply chain transparency and facilitate personalized suggestions. Secondly, marketing funds ought to be reallocated toward consumer education activities. Thirdly, sustainability assertions necessitate third-party validation to establish credibility. Although motivation exhibits a restricted direct effect, its capacity as a secondary influence merits additional investigation. The study also recognizes significant constraints. The environmental impact of AI necessitates renewable energy alternatives. Cultural variances in technology adoption indicate the necessity for tailored strategies. Subsequent research should investigate longitudinal impacts and establish uniform impact measurements. This work ultimately offers a framework for aligning technical innovation with environmental stewardship in the fashion industry. By carefully implementing AI throughout the value chain—from sustainable material creation to customer engagement—the business may alter its ecological footprint while satisfying changing consumer demands. The way forward necessitates cooperative endeavours among companies, engineers, and policymakers to guarantee that AI's potential is actualized responsibly and inclusively.

5. Implications

5.1Cross-Cultural Validation: The convenience sampling employed in the study restricts its generalizability. Future research should investigate AI's impact on sustainable fashion in many regions, especially the Global South, to discern cultural differences in adoption. Comparative evaluations can ascertain whether AI-driven sustainability solutions necessitate localization for global efficacy, hence assuring inclusive and culturally pertinent implementations.

5.2Longitudinal Impact Evaluation: Present findings indicate transient habits. Longitudinal studies monitoring consumer interaction with AI products over time could determine if sustainability preferences are stable or decline. This would differentiate between transient adoption and enduring behavioural modification, offering insights into AI's sustained impact on environmentally conscious consumer behaviours.

5.3Sustainability Analysis of Trade-offs: Although AI lowers fashion waste, its energy-intensive operations may counteract the advantages. Future research must assess the carbon footprint of AI (e.g., model training) in comparison to its environmental benefits. Life-cycle assessments would elucidate the net sustainability impact, directing more environmentally friendly AI implementation in the fashion industry.

5.4Behavioral Evaluation: The research assesses attitudes rather than actual purchasing behavior. Collaborating with merchants to examine sales data associated with AI tools would confirm whether enhanced perceptions result in a rise in sustainable fashion sales. This empirical evidence would enhance practical insights for enterprises.

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