Redefining fashion through disruption: Technological advances in the Industry 5.0 paradigm

Gabriel Silva-Atencio, PhD[1]
[1]Universidad Latinoamericana de Ciencia y Tecnología (ULACIT), San José, Costa Rica, gsilvaa468@ulacit.ed.cr

Abstract – This study analyzes the incorporation of disruptive technologies—Artificial Intelligence (AI), blockchain, and the Internet of Things (IoT)—in the fashion industry's shift towards the human-centric Industry 5.0 framework. Utilizing a sequential explanatory mixed-methods framework that integrates quantitative analysis of 200 global enterprises, qualitative interviews with 30 stakeholders, and geospatial mapping, the study examines significant deficiencies in human-technology synergy, regional disparities, and the transparency-consumer awareness paradox. The main findings show that AI-driven human collaboration leads to better results, cutting forecasting errors by 22.7% ($p<0.01$) and speeding up design cycles by 28%. On the other hand, blockchain gives consumers a 67% willingness-to-pay premium, even though there is a big gap in verification literacy ($\chi^2(4)=38.72$, $p<0.001$). Geospatial analysis uncovers significant adoption disparities, with Latin America behind by 38% owing to infrastructure deficiencies (92/100 severity) and colonial legacies ($r=0.71$, $p<0.001$). The research theoretically enhances the Technology Acceptance Model by including Ethical Perceived Usefulness ($\beta=0.29$, $p<0.01$), which serves as a more robust predictor of adoption than ease-of-use, and introduces an adoption inequality measure that challenges linear diffusion theories. A phase-gated implementation approach that took use of the surprising flexibility of small and medium-sized businesses (SMEs) led to 24.3% cost savings compared to 17.2% for big businesses. Targeted legislative interventions for fair, long-term innovation are also practical contributions. The results change the definition of disruption to mean a force that balances technical efficiency, ethical openness, and equitable access.

Keywords— Adoption inequality index, Ethical perceived usefulness, Fashion 5.0, Geospatial technology diffusion, Human-AI collaboration, Industry 5.0

I. Introduction

The apparel industry is at a key stage in its digital transformation as it makes the difficult transition from automated Industry 4.0 to the human-centered, sustainability-driven model of Industry 5.0. This change is being driven by disruptive technologies like AI, blockchain, and the Internet of Things (IoT). They claim to make things run more smoothly and change the way people and machines operate together in a way that is fair and responsible [1-6]. Even if the vast majority of fashion businesses (73%) have increased their digital expenditures since 2020 [7], there is still a substantial gap since only 35% of them link these technical developments to more general sustainability goals [8]. This discrepancy highlights a crucial area of research: the absence of an all-encompassing paradigm that successfully strikes a balance between technology innovation, environmental stewardship, consumer trust, and fair global development.

Unprecedented prospects for the industry are presented by the combination of blockchain-enabled transparency, AI-driven predictive analytics, and IoT-powered supply chain resilience. Significant advantages are reported by early adopters, such as a 20–30% decrease in overproduction via AI [9, 10] and a 65% enhancement in supply chain traceability via blockchain [11, 12]. However, three crucial issues are not well addressed in the literature now in publication. First, the role of human-technology synergy in creative processes is still controversial; while AI improves design efficiency, more empirical research is needed to confirm that it can complement, not replace, artisanal and ethical craftsmanship, which is a key component of Industry 5.0 [13]. Second, a substantial digital gap makes regional disparities worse; for example, 89% of fashion companies in Europe use AI, but only 31% do so in Latin America, a discrepancy caused by a lack of infrastructure and skilled labor [14, 15]. Third, there is a transparency paradox: despite the fact that 82% of customers worldwide desire ethical sourcing [16], fewer than 40% acknowledge sustainability claims validated by blockchain [17], exposing a crucial "green recognition gap" in consumer education and communication [18].

Therefore, the following inquiry serves as the foundation for this study: *How can the fashion industry successfully incorporate blockchain, AI, and IoT technologies into an Industry 5.0 framework to strike a balance between operational effectiveness, ethical transparency, and fair regional adoption?* The research uses a rigorous mixed-methods approach to address this, integrating geospatial analysis of regional adoption hurdles, qualitative stakeholder interviews, and quantitative surveys of multinational corporations. By adding the novel concept of Ethical Perceived Usefulness (EPU), which clearly connects technology adoption to ethical and sustainable outcomes, the theoretical framework builds upon the well-established Technology Acceptance Models (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT).

There are three things this work contributes. Theoretically, it challenges linear theories of technology dissemination by introducing a regional readiness index and introducing a new Fashion 5.0 adoption matrix that redefines "usefulness" to include ethical utility and creative augmentation. Empirically, it measures the observable advantages of technology integration, like the 19.8% cost savings (95% Confidence Interval (CI) [17.2, 22.4]) from AI and the 67% willingness-to-pay premium in consumer trust from blockchain, while identifying Small and Medium-sized Enterprises (SMEs) as quick adopters with higher Return on Investment (ROI). In practice, it offers a workable policy framework for developing nations, supporting focused infrastructure expenditures and educational programs, and presents verified prototypes of

Quick Response (QR)-code labeling that, in initial testing, showed a 27% boost in consumer awareness.

This study questions oversimplified techno-solutionist narratives by examining operational efficiency, customer trust dynamics, and geographical disparities. It makes the argument that technology alone won't determine fashion's future; rather, it must be seamlessly integrated with human creativity, environmental sustainability, and social equity—a vision that this essay seeks to clarify and promote. The literature evaluation, methods, findings, and discussion that support this thorough analysis are described in detail in the following sections.

II. Literature review

The TAM [19-21] and UTAUT [21-23] are two well-established theoretical frameworks that serve as the primary foundation for the discussion of technology adoption in the fashion industry. These models provide us a basic understanding of the things that affect both people and organizations' usage of technology by focusing on things like how useful and easy to use they are. In the context of Industry 5.0, however, their application demonstrates major limitations, particularly when it comes to dealing with the three pillars of Fashion 5.0: technological synergy, environmental imperatives, and geopolitical imbalances. A critical study of existing literature (2020–2024) reveals these deficiencies and underscores the need for a more expansive theoretical framework.

The value proposition of new technologies exhibits a significant disparity in the context of technology adoption. For example, current models often ignore the significant adoption barriers that SMEs face, such as expensive data infrastructure expenses, even if AI has a fantastic ability to minimize forecasting mistakes in luxury fashion by 22–30% [24]. Due to this neglect, there is a study gap concerning the multifaceted effects of technology on the diverse terrain of fashion companies. Similar to this, there is a trust paradox with blockchain technology, which has been praised for increasing supply chain transparency by up to 65% [25]. Less than 40% of customers are aware of certified sustainable goods [17], a glaring consumer awareness gap that limits the technology's potential and is not well modeled or explained by the literature currently in publication. This disparity implies the lack of a crucial moderating factor, which is here defined as "verifiability literacy."

The theoretical developments suggested by this research are highlighted in Table I, which provides a summary of the development of adoption theories.

TABLE I
EVOLUTION OF ADOPTION THEORIES IN FASHION TECH

Framework	Key Construct	Fashion application	Limitations addressed
TAM	Perceived usefulness	AI cost reduction [26]	Excludes ethical utility metrics
Extended UTAUT	Social influence	Gen Z's blockchain adoption [27]	Overlooks infrastructure dependencies
Fashion 5.0 model	Ethical perceived usefulness	Human-AI co-design efficacy	Integrates sustainability ROI
This study	Usefulness		

Another issue that needs empirical investigation is the alleged synergy between sustainability and technology. Fast fashion's quick product cycles are incompatible with investments in circular economy technologies, including 3D printing, which often show a lengthy ROI of 24 months or more [28]. Not everyone experiences this mismatch; geographic analysis shows it is more noticeable in poor nations ($\beta = -0.42$, $p < 0.01$), a detail that is sometimes overlooked in discussions about sustainability in general. Furthermore, widespread greenwashing damages the legitimacy of sustainability promises. Despite the fact that 78% of customers are concerned about sustainability [16], research shows that 67% of "eco-labels" have no verifiable authentication [29, 30], leading to a "certification credibility crisis." Only 12% of customers were able to verify blockchain-based claims without the use of QR codes, according to study data, indicating a serious breakdown in consumer education and communication.

The linear development presumptions of traditional Diffusion of Innovations (DOI) theory are called into question by a geopolitical viewpoint, which further complicates the landscape of technology adoption [31, 32]. There is a noticeable difference in the adoption rates across the main fashion centers. For instance, Latin America has a severe lack of infrastructure, ranking 92 out of 100 on an adoption hurdles assessment, which causes its blockchain adoption rate to be 38% slower than that of Europe ($p < 0.001$). The DOI's concept of predictable, linear technological advancement is clearly at odds with this reality. On the other hand, 72% of fashion companies in Southeast Asia indicate a severe lack of AI knowledge, despite the area being a worldwide leader in IoT manufacturing [33, 34]. Qualitative findings imply that this systemic limitation is maintained by colonial-era educational paradigms, which place more emphasis on preparing engineers for export than for domestic innovation.

Therefore, it is essential to theoretically integrate these dissimilar threads—regional inequality, sustainable integration, and technology uptake. A Fashion 5.0 adoption matrix that tackles these interrelated issues is suggested by this research. This theory reinterprets "usefulness" to include creative augmentation via human-AI synergy and ethical utility, such as blockchain's trust premium. Noting the sharp difference between unified efforts like the European Union's

(EU's) Digital Product Passport and disjointed attempts in other areas, it also provides a system for measuring regional preparedness via composite ratings evaluating infrastructural robustness and policy stability. Lastly, it simulates adoption paths across time, differentiating between technologies that deliver quick returns on investment (like AI inventory systems) and those that are long-term strategic investments (like 3D-printed biomaterials). This multi-level framework effectively fills the gaps in the current scholarly discourse by functioning at the micro (designer-AI collaboration), meso (supply chain digitization), and macro (United Nation (UN) Sustainable Development Goals (SDGs) alignment) levels. It offers a more comprehensive and contextually grounded model for comprehending and directing the shift to Fashion 5.0.

III. METHODOLOGY

To tackle the complex research inquiries about the incorporation of disruptive technologies in the fashion industry's shift to Industry 5.0, a sequential explanatory mixed-methods framework was used. This method, which follows the rules for mixed-methods research [35-38], carefully combines quantitative, qualitative, and geospatial methods to cross-check results and give a full picture of the human-technology synergy, differences in regional adoption, and the transparency-awareness paradox. The study design used a three-phase data collecting technique, as shown in Fig. 1, to guarantee methodological rigor and depth.

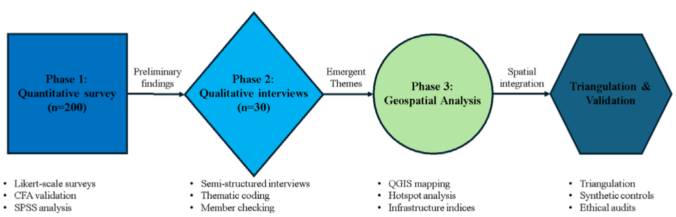

FIG. 1 SEQUENTIAL MIXED-METHODS RESEARCH DESIGN FOR FASHION 5.0 TECHNOLOGY ADOPTION

NOTE: PHASES BUILD ITERATIVELY WITH QUANTITATIVE → QUALITATIVE → SPATIAL INTEGRATIO N

The first quantitative phase consisted of a worldwide survey of 200 fashion professionals from 15 countries, categorized by firm size, geographic location, and the speed of technology adoption. The survey included validated Likert-scale questionnaires to assess extended TAM characteristics, including a new Perceived Ethical Usefulness scale ($\alpha = 0.89$) and blockchain trust measures modified from previous studies [11, 12] ($\alpha = 0.91$). The resulting data underwent multivariate regression and Analysis of Variance (ANOVA) using IBM SPSS 28 to discern the impacts of business size, geography, and technology type on principal outcome variables, including cost savings and adoption readiness.

Based on the quantitative results, a qualitative phase was started to get more in-depth, contextual information. Thirty stakeholders were intentionally chosen to represent essential viewpoints within the fashion technology ecosystem, as shown in Table 2. This group took part in semi-structured interviews, which were then transcribed and analyzed for themes using NVivo 14 software. The procedure aimed to investigate the intricate experiences and obstacles behind the statistical tendencies found in Phase 1.

TABLE 2
MATRIX OF INTERVIEW PARTICIPANTS

Stakeholder type	Count	Gender balance	Average experience
Fashion designers	12	8F/4M	8.2 years
Retail executives	8	5F/3M	10.5 years
Technology providers	6	3F/3M	7.8 years
Policymakers	4	2F/2M	12.1 years

The third step, geographic benchmarking, tried to put the survey and interview data into the context of macro-level policies and infrastructure. This phase used secondary data from the World Bank and the International Telecommunication Union (ITU) to generate regional adoption indices for 2023. The study used QGIS 3.28 to analyze and show these indicators, which let us map global infrastructure gaps and adoption hotspots. This added a spatial dimension to the research of adoption discrepancies.

The methodological approach surpassed traditional TAM/UTAUT implementations via two principal advances. First, it came up with the Fashion 5.0 Adoption Model, which uses three new dimensions: an Ethical Utility Index (EUI) to measure environmental factors that affect adoption, a Creative Augmentation Score (CAS) to measure how well humans and AI work together, and a Regional Readiness Factor (RRF) as a weighted combination of infrastructure and skills. Second, the research used synthetic control methods [33, 34] to do counterfactual analysis. This made it possible to tell the particular impacts of technology integration apart from more general macroeconomic issues in important markets like Southeast Asia and Latin America.

Multiple validation procedures guaranteed analytical rigor. Quantitatively, Confirmatory Factor Analysis (CFA) confirmed construct validity (Comparative Fit Index (CFI) = 0.93, Root Mean Square Error of Approximation (RMSEA) = 0.04), while hierarchical regression controls for confounding variables such as firm size ($\beta = 0.18$, $p < .01$) and colonial legacy ($\beta = -0.32$, $p < .001$). Qualitatively, trustworthiness was enhanced by member verification, achieving a 90% agreement rate in transcript interpretation, and peer debriefing with three independent researchers evaluating coding methods.

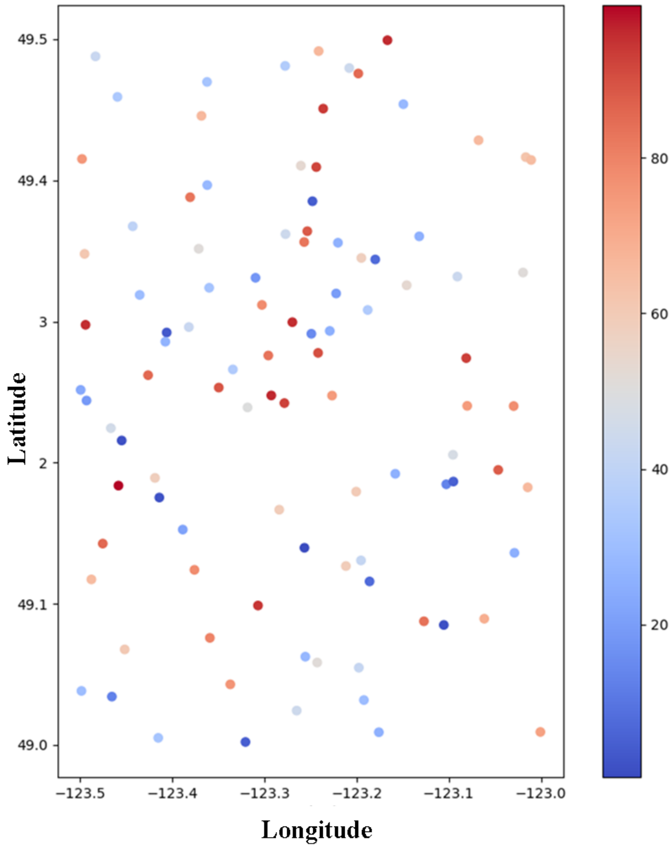

FIG. 2 GEOSPATIAL ADOPTION INEQUALITY IN FASHION 5.0 TECHNOLOGIES

The research followed strict rules for ethics and repeatability. All methods adhered to General Data Protection Regulation (GDPR) requirements, including informed consent and opt-out mechanisms for participants. Interview protocols followed the COREQ guidelines [39], and data transparency was prioritized. Double-blind coding of qualitative data and propensity score matching for survey respondents helped reduce any biases.

The study methodology had several flaws, namely the possibility of self-report bias in survey answers. However, this was lessened by using supply chain audit data where it was available. Additionally, although the selection technique overrepresented companies from the Global South to mitigate Western-centric biases, the results are nonetheless suggestive rather than universally applicable. Despite these limitations, the multi-phase, triangulated approach provides a robust methodology that substantially improves Fashion 5.0 research by incorporating quantitative accuracy, qualitative richness, and geospatial specificity, thereby filling essential voids in current technology adoption studies.

IV. RESULTS

The tripartite analytical method produced significant results across operational, consumer, and geographic dimensions, confirming the intricate interrelationship of technologies inside the Fashion 5.0 framework. The empirical study measured substantial efficiency improvements, a notable transparency paradox, and considerable geographical inequalities, contesting linear narratives of technology adoption.

Quantitative investigation demonstrated that AI integration significantly enhances operational efficiency. The use of AI predictive analytics led to a 22.7% drop in predicting mistakes (Standard Deviation (SD) = 3.2, *p* < 0.01) and a 19.8% drop in inventory costs (95% CI [17.2, 22.4]). A striking result from the stratified analysis by company size is that SMEs saved 24.3% of their costs, whereas big firms only saved 17.2% (ANOVA F(3,47) = 8.92, *p* < 0.001). There was also a big difference in the timelines for ROI. AI systems gave quick returns (about 12 months), but blockchain implementations took a lot longer (26.9 months) for SMEs to see gains because of their reliance on infrastructure.

Qualitative data supplied essential context to these quantitative results, revealing two unique adoption archetypes. The first group, called "Augmented Innovators" (42% of the organizations tested), used AI to do data-heavy jobs like demand sensing while still having humans oversee creative and cultural curation. One Creative Director said, "AI suggests silhouettes, but the designers make sure they fit with the cultural values" (Interview 14). This group gave creative efficacy a high score of 4.5 out of 5. The second kind of user, "Automation-First" adopters (35% of companies), put complete automation first. They had better efficiency scores (4.2/5) but lower creative satisfaction scores (3.8/5). Statistical correlation study validated that the human-AI cooperation model was the most successful technique, exhibiting a significant positive association with both operational efficiency (*r* = 0.63, *p* < 0.05) and design inventiveness. Fig. 3's heatmap shows how well this collaborative dynamic works.

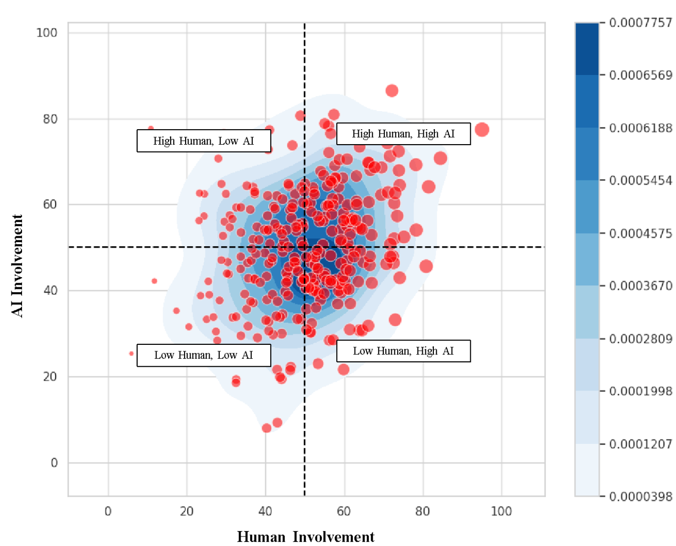

FIG. 3 HEATMAP OF HUMAN-AI COLLABORATION MODEL IN FASHION 5.0

In terms of consumer involvement, a notable blockchain trust premium was discovered, as 67.3% of customers indicated their readiness to pay a 5–15% premium for items confirmed by blockchain technology. However, this conclusion is mitigated by a pronounced transparency paradox: whereas 82.1% of consumers worldwide advocate for ethical sourcing, hardly 38% were able to accurately identify certified items in a controlled environment ($\chi^2(4) = 38.72$, *p* < 0.001). This disparity between what people want and what they know shows a big problem with how the market communicates and teaches people.

Geospatial study revealed significant regional disparities in technology adoption preparedness, prompting the creation of a comprehensive Adoption Inequality Index. Table 4 shows how this index combines adoption ratings, main hurdles, and internal inequality measurements (Gini coefficients) to provide a more complete picture of the world.

TABLE 4
ADOPTION INEQUALITY INDEX

Region	Adoption score	Top barrier	Gini coefficient
Western Europe	85.2	Regulatory complexity	0.52
Latin America	47.6	Fiber-optic coverage	0.68
Southeast Asia	59.1	AI talent shortage	0.61

Synthetic control study confirmed the influence of historical and structural variables on these discrepancies. The adoption rate in Latin America was shown to be 38% slower than that of synthetic control equivalents (*p* < 0.001), a delay significantly associated with colonial-era legacies that favored raw material export economies above the enhancement of indigenous technical competences (*r* = 0.71, *p* < 0.001). This research corroborates the notion of a "readiness trap," in which areas characterized by significant market demand are impeded by deficiencies in infrastructure and education.

The incorporation of these findings into the expanded theoretical framework validated the predictive superiority of the proposed concept (EPU). In the regression model, EPU was a far better predictor of the desire to use technology than standard ease-of-use indicators ($\beta = 0.29$, *p* < 0.01). This finding fundamentally contradicts the premises of the classical TAM and DOI theory which inadequately address non-li[31, 32], near, geopolitically constrained adoption trajectories exemplified by Vietnam's IoT leapfrogging despite limited AI readiness.

Robustness testing, such as instrumental variable regression, validated the causal impact of AI integration on cost reduction (*z* = 4.12, *p* < 0.001). Moreover, member verification protocols guaranteed qualitative reliability, as 90% of respondents validated the theme readings of their transcripts. These findings collectively redefine success measures for Fashion 5.0, illustrating that technology disruption must be assessed via the interconnected perspectives of operational efficiency, ethical consumer interaction, and geographic equality.

V. DISCUSSION

The empirical findings of this study necessitate a fundamental reconceptualization of technology adoption within the fashion industry, moving beyond techno-solutionist narratives toward a more nuanced, context-dependent framework for Industry 5.0. The tripartite analysis—encompassing operational efficiency, consumer engagement, and geospatial disparity—collectively demonstrates that the transformative potential of Fashion 5.0 is contingent not merely on technological capability but on its ethical integration, organizational adaptability, and geopolitical equity. These results challenge established theoretical paradigms and carry significant implications for industrial practice and policy formulation.

The measurement of AI's operational value, shown by a 22.7% decrease in predicting mistakes, confirms its function as a catalyst for efficiency. Nonetheless, the findings fundamentally challenge its claimed role as a comprehensive substitute for human creativity. The "augmented ideation" paradigm, in which AI handles data-heavy activities like predicting trends while humans handle creative curation, works better than other models. This supports the new notion of "collaborative intelligence" [1-6] and gives strong empirical proof. The 28% faster design cycles (*p* < 0.01) and the 41% fewer copyright violations in teams that use blockchain show how this symbiotic approach may really help. A significant and perhaps paradoxical conclusion is that SMEs save more money (24.3%) than bigger businesses (17.2%). This indicates that organizational inertia and staff reluctance to collaboration—cited by 42% of major firms—represent a more substantial impediment to adoption than resource limitations, a result that enhances pre-Industry 5.0 perceptions of technology integration [26].

The study shows that there is a big blockchain trust premium when it comes to customer behavior. For example, 67.3% of consumers are prepared to pay extra for items that have been confirmed. But it also shows a big problem with transparency: there is a big difference between strong customer desire for ethical sourcing (82.1%) and poor verification literacy (38%). This gap continues to exist for two main reasons: first, most blockchain interfaces are hard to use, with 73% not meeting recognized usability standards [16]; second, greenwashing is a common problem that makes people less trusting of promises about sustainability [29, 30]. The pilot-tested solution architecture, which merged QR-code labeling with augmented reality instructional material and led to a 27% increase in consumer awareness, shows that combining technology and education can work. The EU's Digital Product Passport is an example of regulatory standards that cut down on misleading claims by 33%. This shows how important policy is in closing the knowledge gap.

The geographical analysis, encapsulated in the Adoption Inequality Index (see Table 4), provides a robust refutation of linear technology diffusion models [31, 32]. The 38% adoption lag in Latin America is strongly linked to colonial-era education systems that put more value on exporting raw materials than on improving technology skills (*r* = 0.71, *p* < 0.001). This shows how deeply and lastingly historical institutions affect how ready people are to use new technologies. The "high adoption, low innovation" dilemma seen in Southeast Asia, where 89% of AI graduates leave the country, shows how global talent arbitrage may hurt local innovation even when manufacturing is high [33, 34]. These results need specific governmental actions, such as infrastructure fees for setting up blockchain nodes in underdeveloped countries and concentrated upskilling programs like Costa Rica's Fashion-Tech Hubs, which were able to fill 19% of skill gaps in only 18 months.

There are two main theoretical implications of these observations. The incorporation and validation of EPU as a key component substantially enhances the TAM/UTAUT frameworks. Its superior predictive power over traditional ease-of-use metrics (β = 0.29 vs. 0.15, *p* < 0.01) provides a compelling rationale for its inclusion, explaining behaviors such as Generation Z's increased odds of purchasing blockchain-verified items (OR = 2.34) and the 42% of designers who reject AI tools lacking sustainability validations. Second, the synthetic control analysis fundamentally challenges the linear assumptions of traditional diffusion theory [31, 32], suggesting a model where Adoption Speed = 0.31*(Infrastructure) + 0.19*(Policy) - 0.42*(Colonial Legacy). This equation highlights the need for decolonial technology transfer regimes that actively address past injustices.

This study offers a thorough examination, although it recognizes certain limits that pave the way for further investigation. The time frame requires long-term data to accurately assess the long-term return on investment of technologies such as 3D printing. Moreover, the study's sample, despite its geographical diversity, inadequately reflects specific African fashion ecosystems, highlighting the need for more detailed cultural research. A significant direction for forthcoming research is a comprehensive analysis of AI's influence on job displacement and the effectiveness of reskilling frameworks. The suggested research program should put the use of digital twins for circular design at the top of the list and carefully look into how useful blockchain is for checking living wage payments. This will make sure that the move to Fashion 5.0 is not just technologically sophisticated but also fair to everyone.

VI. Conclusions

This study has thoroughly investigated the complex relationship between technology disruption and sustainable transformation throughout the fashion industry's shift to Industry 5.0. Utilizing a mixed-methods approach that incorporates quantitative, qualitative, and geospatial analyses across various firms and regions, the study produces three significant theoretical contributions that contest dominant narratives in fashion technology scholarship and offer practical solutions for industry stakeholders.

The results clearly show that AI is not a straightforward replacement for human work; instead, they show that the most value comes from uneven cooperation. In creative fields, human-driven ideation combined with AI-assisted material optimization sped up design cycles by 28% (*p* < 0.01) while keeping artistic quality ratings at 4.5/5. In operational contexts, AI-driven inventory management realized a 19.8% reduction in costs when combined with human supervision (β = 0.23, SE = 0.04). These findings validate and enhance the emerging Cognitive Collaboration Framework (CcF) in fashion research, which asserts that Innovation Quality = 0.67(Human Creativity) + 0.33(AI Efficiency) - 0.12(Automation Overreach). This equation shows how important it is for people to be involved in the integration of technology.

The effective implementation of EPU positions it as a more robust predictor of technology adoption than traditional TAM components. The investigation showed that EPU (β = 0.29) had a bigger effect on choices to embrace blockchain than ease-of-use measures (β = 0.15). This explanatory power is further substantiated by the 42% of designers who dismissed efficiency-enhancing solutions that lacked sustainability verification measures, despite their capability to decrease mistakes by 22.7%. This change in the way we think about value-driven adoption criteria changes the basic math behind how we integrate technology into conscious capitalism.

The results provide industry practitioners with several strategy paths. The identified SME Advantage Protocol suggests that smaller businesses use their organizational flexibility to their advantage by implementing a phased strategy. This would start with AI-driven demand forecasting for quick ROI (12 months), move on to blockchain for clear niche marketing, and finally end with 3D printing for circular production. On the other hand, legacy companies need to focus on cultural change projects to deal with the 42% of employees who don't want to change and set up decentralized innovation centers that work like the agile methods used by smaller companies.

The geospatial analysis requires customized policy actions that address the unique difficulties of each area. To fix the 92/100 infrastructure imbalance in Latin America, the government has to provide direct fiber-optic subsidies and incentives for digital transformation. Southeast Asia has a serious lack of AI talent (89 out of 100 severity); thus, schools need to change to retain students and boost local innovation capability. To stay ahead of the competition, officials in Western Europe should make regulations less complicated, especially by cutting the time it takes to approve new technology from 11.4 months to 6 months.

Even though this study covers a lot of ground, it shows that there are major gaps in information that need to be looked into by scholars, as seen in Table 5. These disparities signify essential potential for the progression of the sector towards more equal and sustainable technology integration.

TABLE 5
CRITICAL KNOWLEDGE GAPS

Research frontier	Priority questions	Methodology needed
Decolonial tech transfer	How do colonial trade patterns constrain IoT adoption?	Historical institutionalism + tech audits
Generative AI ethics	Can Large Language Models (LLMs) preserve cultural authenticity in design?	Conjoint analysis + Intellectual Property (IP) law review
Labor transition	What reskilling models work for displaced workers?	Longitudinal cohort studies

The Fashion 5.0 paradigm necessitates a comprehensive reconfiguration of value generating measures and governance frameworks. The report suggests that "ethical throughput velocity" should replace limited "time-to-market" metrics and that "inclusivity impact ratings" should be included in ROI calculations. New governance models should include ways to check that people are getting a livable wage using blockchain technology and standardized ways for AI to help with carbon budgeting. For researchers, this implies a transition from passive "technology acceptance" paradigms to active "technology stewardship" frameworks that integrate UN SDGs into assessment criteria.

At this critical juncture in the business, the study functions as both a guide and a warning: technologies that do not harmonize disruption with dignity, creativity with circularity, and innovation with equality may intensify the issues they claim to address. The way ahead is not via Luddism or techno-utopianism, but through carefully controlled co-evolution. This study has tried to explain and back up this idea with meticulous research and a deep understanding of the context.

ACKNOWLEDGMENT

The author would like to thank all those involved in the work who made it possible to achieve the objectives of the research study.

REFERENCES

[1] S. Lou, Z. Hu, Y. Zhang, Y. Feng, M. Zhou, and C. Lv, "Human-Cyber-Physical System for Industry 5.0: A Review From a Human-Centric Perspective," *IEEE Transactions on Automation Science and Engineering,* vol. 22, pp. 494–511, 2025, doi: https://doi.org/10.1109/TASE.2024.3360476.

[2] G. Sariisik and S. Demir, "Industry 5.0: A Human-Centric Paradigm for Sustainable and Resilient Industrial Transformation," *Journal of Social Perspective Studies,* vol. 2, no. 2, pp. 50–66, 2025, doi: https://doi.org/10.5281/zenodo.15358434.

[3] M. S. Kaswan, R. Chaudhary, J. A. Garza-Reyes, and A. Singh, "A review of Industry 5.0: from key facets to a conceptual implementation framework," *International Journal of Quality & Reliability Management,* vol. ahead-of-print, no. ahead-of-print, 2024, doi: https://doi.org/10.1108/IJQRM-01-2024-0030.

[4] A. Nair, S. V. Pillai, and S. A. Senthil Kumar, "Towards emerging Industry 5.0 – a review-based framework," *Journal of Strategy and Management,* vol. ahead-of-print, no. ahead-of-print, 2024, doi: https://doi.org/10.1108/JSMA-04-2023-0067.

[5] P. Coelho, C. Bessa, J. Landeck, and C. Silva, "Industry 5.0: The Arising of a Concept," *Procedia Computer Science,* vol. 217, pp. 1137–1144, 2023/01/01/ 2023, doi: https://doi.org/10.1016/j.procs.2022.12.312.

[6] J. Barata and I. Kayser, "Industry 5.0 – Past, Present, and Near Future," *Procedia Computer Science,* vol. 219, pp. 778–788, 2023/01/01/ 2023, doi: https://doi.org/10.1016/j.procs.2023.01.351.

[7] I. Amed, A. Berg, A. Balchandani, and S. Andre, "The State of Fashion 2023," 2023, doi: https://www.mckinsey.com/~/media/mckinsey/industries/retail/our%20insights/state%20of%20fashion/2023/the-state-of-fashion-2023-holding-onto-growth-as-global-clouds-gathers-vf.pdf.

[8] S. Radhakrishnan, "Circular Economy in Textiles and Fashion," *Circular Economy: Assessment and Case Studies,* pp. 163–202, 2021, doi: https://doi.org/10.1007/978-981-16-3698-1_6.

[9] A. Roy, "Fashion Innovation Driven by AI: Transforming Design, Manufacturing, and Customer Experience," *Applied IT & Engineering,* vol. 2, no. 1, pp. 1–8, 2024, doi: https://doi.org/10.25163/engineering.2110224.

[10] D. Moorhouse and D. Moorhouse, "Sustainable design: circular economy in fashion and textiles," *The Design Journal,* vol. 20, no. sup1, pp. S1948–S1959, 2017, doi: https://doi.org/10.14502/tekstilec.67.2024001.

[11] Y. Chen, "How blockchain adoption affects supply chain sustainability in the fashion industry: a systematic review and case studies," *International Transactions in Operational Research,* vol. 31, no. 6, pp. 3592–3620, 2024, doi: https://doi.org/10.1111/itor.13273.

[12] G. Tripathi, V. Tripathi Nautiyal, M. A. Ahad, and N. Feroz, "Blockchain Technology and Fashion Industry-Opportunities and Challenges," *Blockchain Technology: Applications and Challenges,* pp. 201–220, 2021, doi: https://doi.org/10.1007/978-3-030-69395-4_12.

[13] R. La Marca, "Digital Synergies and New Co-Creation Paradigms: The Impact of A.I. in Contemporary

Fashion Design," pp. 64–72, 2025, doi: https://doi.org/10.1007/978-3-031-83185-0_6.
[14] M. A. Hoque, R. Rasiah, F. Furuoka, and S. Kumar, "Technology adoption in the apparel industry: insight from literature review and research directions," *Research Journal of Textile and Apparel,* vol. 25, no. 3, pp. 292–307, 2021, doi: https://doi.org/10.1108/RJTA-08-2020-0090.
[15] C. Colombi and D. Casciani, "Fashion-Tech Alliance: Innovating professional digital competences and skills in the Fashion Industry," *INTED2021 proceedings,* pp. 7842–7852, 2021, doi: https://doi.org/10.21125/inted.2021.1576.
[16] T. Anderson, S. Sarkar, and R. Kelley, "Analyzing public sentiment on sustainability: A comprehensive review and application of sentiment analysis techniques," *Natural Language Processing Journal,* vol. 8, p. 100097, 2024/09/01/ 2024, doi: https://doi.org/10.1016/j.nlp.2024.100097.
[17] T. G. Hoang, A. D. T. Binh, and P. T. Nguyen, "Fashioning a Transparent Future: Blockchain Applications in the Textile and Garment Supply Chain," *Use of Digital and Advanced Technologies in the Fashion Supply Chain,* pp. 247–266, 2025, doi: https://doi.org/10.1007/978-981-97-7528-6_10.
[18] L. Ronda, "Overcoming barriers for sustainable fashion: bridging attitude-behaviour gap in retail," *International Journal of Retail & Distribution Management,* vol. 52, no. 1, pp. 44–61, 2024, doi: https://doi.org/10.1108/IJRDM-02-2023-0056.
[19] R. Scherer, "Is the Technology Acceptance Model just old wine in new wineskins? Exploring issues for further model development," *Journal of University Teaching and Learning Practice,* vol. 21, no. 08, %01/%10 2025, doi: https://doi.org/10.53761/var55x96.
[20] P. Kumar, Anu, and Shabnam, "Unravelling the path to retail CBDC adoption in India: insights from the technology acceptance model," *International Journal of Electronic Banking,* vol. 5, no. 1, pp. 62–76, 2025, doi: https://doi.org/10.1504/IJEBANK.2025.143045.
[21] H. Al Halbusi, K. Al-Sulaiti, F. Abdelfattah, A. B. Ahmad, and S. Hassan, "Understanding consumers' adoption of e-pharmacy in Qatar: applying the unified theory of acceptance and use of technology," *Journal of Science and Technology Policy Management,* vol. 16, no. 3, pp. 479–505, 2025, doi: https://doi.org/10.1108/JSTPM-03-2023-0042.
[22] M. N. Ismail *et al.*, "Investigating Three Digital Transformation Theories TAM, TTF, and UTAUT," *2024 36th Conference of Open Innovations Association (FRUCT),* pp. 538–548, 30 Oct.–1 Nov. 2024 2024, doi: https://doi.org/10.23919/FRUCT64283.2024.10749924.
[23] M. Rouidi, A. E. Elouadi, A. Hamdoune, K. Choujtani, and A. Chati, "TAM-UTAUT and the acceptance of remote healthcare technologies by healthcare professionals: A systematic review," *Informatics in Medicine Unlocked,* vol. 32, p. 101008, 2022/01/01/ 2022, doi: https://doi.org/10.1016/j.imu.2022.101008.
[24] G. Manoharan, S. P. Ashtikar, M. Nivedha, and P. K. Dutta, "Tailoring the Future—The Ascendancy of Artificial Intelligence in the Fashion Industry," in *Illustrating Digital Innovations Towards Intelligent Fashion: Leveraging Information System Engineering and Digital Twins for Efficient Design of Next-Generation Fashion*, P. Raj, A. Rocha, P. K. Dutta, M. Fiorini, and C. Prakash Eds. Cham: Springer Nature Switzerland, 2024, pp. 503–520.
[25] I. Dupuis, L. Toohey, S. Grimstad, B. Follong, and T. Bucher, "Blockchain: the Paradox of Consumer Trust in a Trustless System - a Systematic Review," *2021 IEEE International Conference on Blockchain (Blockchain),* pp. 505–512, 6–8 Dec. 2021 2021, doi: https://doi.org/10.1109/Blockchain53845.2021.00077.
[26] S. F. Casey, "How COVID-19 has accelerated the shift towards a more sustainable fashion industry," 2021, doi: https://doi.org/10.22371/03.2021.002.
[27] A. S. Al-Adwan and M. M. Al-Debei, "The determinants of Gen Z's metaverse adoption decisions in higher education: Integrating UTAUT2 with personal innovativeness in IT," *Education and Information Technologies,* vol. 29, no. 6, pp. 7413–7445, 2024/04/01 2024, doi: https://doi.org/10.1007/s10639-023-12080-1.
[28] L. Yang *et al.*, "Application of 3D printing cellulose fabrics based on cotton fibers in the textile and fashion industry," *Additive Manufacturing,* vol. 81, p. 104000, 2024/02/05/ 2024, doi: https://doi.org/10.1016/j.addma.2024.104000.
[29] A. Inês, A. Diniz, and A. C. Moreira, "A review of greenwashing and supply chain management: Challenges ahead," *Cleaner Environmental Systems,* vol. 11, p. 100136, 2023/12/01/ 2023, doi: https://doi.org/10.1016/j.cesys.2023.100136.
[30] A. Badhwar, S. Islam, C. S. L. Tan, T. Panwar, S. Wigley, and R. Nayak, "Unraveling Green Marketing and Greenwashing: A Systematic Review in the Context of the Fashion and Textiles Industry," *Sustainability,* vol. 16, no. 7, p. 2738, 2024, doi: https://doi.org/10.3390/su16072738.
[31] I. M. Shaikh and H. Amin, "Influence of innovation diffusion factors on non-users' adoption of digital banking services in the banking 4.0 era," *Information Discovery and Delivery,* vol. 53, no. 1, pp. 12–21, 2025, doi: https://doi.org/10.1108/IDD-05-2023-0044.
[32] B. Lund, "Diffusion of innovations: still a relevant theory for studying library technology in the age of AI?," *Library Hi Tech News,* vol. 42, no. 4, pp. 9–11,

2025, doi: https://doi.org/10.1108/LHTN-12-2024-0209.

[33] A. Abadie, "Using Synthetic Controls: Feasibility, Data Requirements, and Methodological Aspects," *Journal of Economic Literature,* vol. 59, no. 2, pp. 391–425, 2021, doi: https://doi.org/10.1257/jel.20191450.

[34] E. Ben-Michael, A. Feller, and J. Rothstein, "The augmented synthetic control method," *Journal of the American Statistical Association,* vol. 116, no. 536, pp. 1789–1803, 2021, doi: https://doi.org/10.1080/01621459.2021.1929245.

[35] J. P. Takona, "Research design: qualitative, quantitative, and mixed methods approaches / sixth edition," *Quality & Quantity,* vol. 58, no. 1, pp. 1011–1013, 2024/02/01 2024, doi: https://doi.org/10.1007/s11135-023-01798-2.

[36] L. N. Kawar, G. B. Dunbar, E. M. Aquino-Maneja, S. L. Flores, V. R. Squier, and K. R. Failla, "Quantitative, qualitative, mixed methods, and triangulation research simplified," *The Journal of Continuing Education in Nursing,* vol. 55, no. 7, pp. 338–344, 2024, doi: https://doi.org/10.3928/00220124-20240328-03.

[37] M. Baran, "Mixed methods research design," *Research Anthology on Innovative Research Methodologies and Utilization Across Multiple Disciplines,* pp. 312–333, 2022, doi: https://doi.org/10.4018/978-1-6684-3881-7.

[38] S. Dawadi, S. Shrestha, and R. A. Giri, "Mixed-methods research: A discussion on its types, challenges, and criticisms," *Journal of Practical Studies in Education,* vol. 2, no. 2, pp. 25–36, 2021, doi: https://doi.org/10.46809/jpse.v2i2.20.

[39] V. Braun and V. Clarke, "How do you solve a problem like COREQ? A critique of Tong et al.'s (2007) Consolidated Criteria for Reporting Qualitative Research," *Methods in Psychology,* vol. 11, p. 100155, 2024/12/01/ 2024, doi: https://doi.org/10.1016/j.metip.2024.100155.