TPM Vol. 32, No. S4, 2025
ISSN: 1972-6325
https://www.tpmap.org/

Open Access

AI-DRIVEN FASHION COMMERCE: REAL-TIME BIDDING FOR PERSONALIZED APPAREL EXPERIENCES

NANDINI SHARMA[1], AAKANKSHA AAKANKSHA[2], DILIP RACHAMALLA[3]

[1] FASHION & TECH ENTREPRENEUR
[2] SENIOR STAFF SOFTWARE ENGINEER AT AIRBNB
[3] SENIOR SOFTWARE ENGINEER AT INTUIT

Abstract
The rapid evolution of digital commerce has intensified the need for personalized and adaptive shopping experiences, particularly in the fashion industry where consumer preferences are highly dynamic. This study investigates the integration of artificial intelligence (AI) and real-time bidding (RTB) as a dual framework for delivering personalized apparel recommendations. A simulated e-commerce platform involving 2,500 participants was developed to compare three conditions: traditional recommendation systems, AI-based personalization without RTB, and AI-driven personalization with RTB. Results indicate that AI personalization significantly improved consumer engagement, satisfaction, and conversion rates compared to the control group, while the addition of RTB further amplified these outcomes by increasing contextual relevance, reducing bounce rates, and enhancing session completion. Regression and structural equation modeling analyses confirmed that trust in recommendations and user engagement mediated the relationship between personalization and purchase intent. The findings highlight the commercial potential of AI + RTB integration in fashion commerce, while also emphasizing the need to address ethical considerations surrounding data privacy and algorithmic transparency. This research contributes to both theory and practice by demonstrating how AI-driven personalization, reinforced through RTB, can create meaningful, consumer-centric apparel shopping experiences.

Keywords: Artificial intelligence, Real-time bidding, Fashion commerce, Personalization, Consumer behavior, Apparel retail

INTRODUCTION

Evolution of digital fashion commerce

The fashion industry has witnessed a remarkable transformation over the past two decades, moving from traditional brick-and-mortar retail to highly digitized platforms that rely on advanced technologies (Roy, 2024). E-commerce has become the dominant channel for apparel shopping, supported by mobile applications, social media, and digital marketplaces that allow consumers to explore, compare, and purchase products with ease (Singh, 2024). However, as consumer expectations evolve, simple transactional shopping is no longer sufficient. Shoppers increasingly demand personalized experiences, curated recommendations, and immediate responses that reflect their individual style preferences and budget constraints. This trend has created fertile ground for artificial intelligence (AI) applications, which are capable of analyzing consumer data and predicting behavior to deliver personalized shopping journeys (Bansal et al., 2024).

Rise of personalization in consumer expectations

Personalization has become a cornerstone of digital retail, particularly in fashion commerce, where taste and style preferences vary widely among individuals. Studies indicate that consumers are more likely to engage with and purchase from platforms that recommend products aligned with their preferences (Gao & Liang, 2025). For apparel retailers, personalization not only drives customer satisfaction but also increases conversion rates, brand loyalty, and long-term customer lifetime value. Traditional recommendation systems, however, often fall short in capturing real-time shifts in consumer intent. For example, a shopper browsing for casual wear today might be looking for formal attire tomorrow, making static recommendation models inadequate (Alkudah & Almomani, 2024). This gap highlights the need for dynamic, AI-driven approaches that integrate real-time bidding and decision-making into the personalization process.

Integration of artificial intelligence in commerce

Artificial intelligence has become integral to the modern e-commerce ecosystem, enabling predictive analytics, recommendation engines, virtual try-ons, and automated customer support (Julian, 2025). In fashion commerce, AI leverages massive datasets ranging from browsing history and purchase behavior to contextual data such as location and seasonality to tailor shopping experiences at scale. Machine learning algorithms and deep learning architectures are particularly well-suited to uncover hidden patterns in consumer behavior, allowing platforms to anticipate demand and adapt recommendations accordingly Kesavan & Polisetty, 2025). More recently, AI technologies have been coupled with real-time bidding (RTB) mechanisms, commonly used in digital advertising, to enhance personalization by dynamically matching apparel offers with user intent in milliseconds.

Real-time bidding as a tool for apparel personalization

Real-time bidding, traditionally associated with programmatic advertising, involves automated auctions where ad impressions are bought and sold within milliseconds (Prajapat, 2024). By adapting this mechanism to fashion commerce, retailers can dynamically compete to showcase the most relevant apparel products to each consumer in real time. This approach ensures that users are presented with apparel options that reflect their immediate preferences, increasing the likelihood of engagement and purchase (Ntumba et al., 2023). Moreover, integrating RTB with AI-driven personalization creates an ecosystem where data, prediction, and competition converge to optimize the shopping experience. The potential to deliver hyper-personalized apparel recommendations at the exact moment of consumer decision-making represents a significant innovation in fashion retail strategy (Rainy, 2025).

Research significance and objectives

Despite its growing relevance, the intersection of AI-driven personalization and real-time bidding in fashion commerce remains underexplored in academic research. Most studies focus on either personalization techniques or programmatic advertising, but rarely address their integration in the apparel domain. This study aims to fill that gap by examining how AI-powered real-time bidding systems can transform fashion commerce through enhanced personalization. Specifically, it investigates the mechanisms, benefits, and challenges of deploying RTB in apparel recommendation systems, with attention to consumer experience, retailer competitiveness, and technological feasibility. By bridging insights from AI, marketing, and e-commerce, this research contributes to advancing theoretical understanding while offering practical implications for fashion retailers aiming to remain competitive in a fast-evolving digital marketplace.

METHODOLOGY

Research design

This research employs a mixed-method design combining experimental simulation with quantitative analysis to investigate the effectiveness of AI-driven real-time bidding (RTB) in delivering personalized apparel experiences. The study developed a simulated e-commerce fashion platform that integrated AI algorithms with an RTB mechanism to test personalization outcomes under controlled conditions. The design allowed for direct comparison between traditional recommendation systems, AI-based personalization without RTB, and AI-enhanced personalization with RTB.

Data collection and sources

Data for the study were gathered from both primary and secondary sources. Primary data were collected from 2,500 participants representing diverse age groups, gender identities, income levels, and fashion orientations. Participants interacted with the experimental platform across multiple shopping sessions, during which browsing history, clickstream activity, dwell time, product views, purchase decisions, and survey-based satisfaction ratings were recorded. Secondary data included open-source fashion e-commerce datasets covering 10,000 apparel items with attributes such as color, size, fabric, and style. These datasets were used to train the AI models and enrich recommendation quality.

Variables and parameters

The study employed a structured framework of independent, dependent, and control variables. Independent variables included AI personalization model type (collaborative filtering, content-based, hybrid, deep learning), RTB intensity (low, medium, high), demographic factors (age, gender, income, education), and contextual factors (time of day, device type, season). Dependent variables captured consumer engagement and business outcomes, including click-through rate (CTR), conversion rate (CVR), average order value (AOV), customer satisfaction, engagement time per session, and RTB bidding success rate. Control variables such as apparel price range, product availability, and session duration were standardized to ensure consistency across experimental conditions.

Experimental setup

Participants were randomly assigned to one of three groups: a control group using traditional recommendation systems, an AI-personalization group without RTB, and a treatment group exposed to AI-driven RTB personalization. Each group completed multiple shopping tasks involving casual wear, formal wear, and seasonal apparel. The system logged all consumer interactions, including the outcomes of RTB auctions, in real time. This setup provided a robust environment for comparing personalization effectiveness across conditions.

AI model development

To achieve personalization, four machine learning architectures were deployed: collaborative filtering, content-based filtering, hybrid systems, and deep neural networks. These models were trained on 70 percent of the dataset and validated on the remaining 30 percent. Input features included apparel attributes, consumer demographic profiles, and contextual data such as shopping time and device type. Hyperparameters were optimized through cross-validation to ensure the reliability of the models.

Real-time bidding mechanism

The RTB system was modeled on programmatic advertising auctions and adapted for apparel recommendations. Each retailer assigned a maximum bid price for an impression based on predicted consumer value scores generated by the AI system. Bidding occurred within 100 milliseconds, and the product from the winning retailer was displayed to the consumer. This mechanism simulated real-world competitive personalization environments while ensuring timely and relevant recommendations.

Statistical analysis

Data analysis was conducted using Python and SPSS statistical tools. Descriptive statistics summarized participant demographics, browsing behavior, and system-level performance metrics. ANOVA was applied to test differences in CTR, CVR, AOV, and satisfaction across the three experimental groups. Chi-square tests assessed associations between demographic factors and personalization outcomes, while multiple regression examined the effect of independent variables on dependent variables such as conversion rate and engagement time. Logistic regression was used to model purchase likelihood, and structural equation modeling (SEM) was employed to test causal relationships between personalization, engagement, satisfaction, and purchasing behavior. Post-hoc Tukey tests further clarified significant group differences.

Ethical considerations

Ethical safeguards were incorporated throughout the study. Participants provided informed consent prior to participation, and all personally identifiable information was anonymized. The research adhered to data protection guidelines including GDPR, ensuring transparency in algorithmic decisions and compliance with responsible AI practices.

Results

The demographic profile of the participants revealed a well-balanced sample across all experimental groups. As shown in Table 1, the average age was consistent at around 29 years, with nearly equal gender distribution across groups. Income levels and educational attainment were also comparable, ensuring that no significant demographic bias influenced the experimental conditions. This demographic balance strengthens the reliability of subsequent comparisons between groups.

Table 1: Participant demographics

Demographic Variable	Control Group	AI Personalization	AI + RTB Personalization
Age (mean ± SD)	28.4 ± 6.1	29.1 ± 5.8	28.9 ± 6.0
Gender (% Female)	51%	50%	52%
Income Level (mean ± SD, $)	32,400 ± 7,800	33,200 ± 7,600	33,800 ± 7,400
Education (% with Bachelor's+)	62%	64%	65%

Analysis of system-level performance metrics indicated significant improvements when AI-driven personalization was coupled with real-time bidding. As presented in Table 2, participants in the AI + RTB group demonstrated the highest levels of interaction with the platform, measured through page views per session and products added to cart. At the same time, the bounce rate was substantially reduced, and session completion rates were highest in this group compared to the control and AI-only groups. These findings suggest that RTB-enhanced personalization fosters deeper engagement and reduces early drop-offs.

Table 2: System performance metrics

Metric	Control Group	AI Personalization	AI + RTB Personalization
Page Views per Session	9.4	12.1	15.7
Products Added to Cart	1.8	3.2	5.1
Bounce Rate (%)	41.6	28.9	19.4
Session Completion Rate (%)	52.3	68.7	82.5

Consumer perceptions reflected a similar trend, with AI + RTB personalization outperforming other conditions. According to Table 3, participants in this group reported higher trust in recommendations, greater enjoyment of the shopping experience, and higher perceived accuracy of suggested apparel items. Importantly, willingness to pay a premium was notably stronger in the AI + RTB group, highlighting the commercial value of combining personalization with bidding mechanisms. The results emphasize the dual benefits of technological effectiveness and positive consumer sentiment.

Table 3: Consumer satisfaction and feedback

Measure	Control Group	AI Personalization	AI + RTB Personalization
Trust in Recommendations (%)	46	63	81
Enjoyment of Experience (%)	51	70	87
Recommendation Accuracy (%)	48	74	89
Willingness to Pay Premium (%)	32	45	61

Regression analysis provided further insights into the drivers of purchase intent. As summarized in Table 4, both personalization level and RTB intensity emerged as significant positive predictors, alongside perceived accuracy and trust in the system. Conversely, bounce rate exhibited a negative relationship with purchase intent, indicating that reducing early disengagement is critical for conversions. Demographic factors such as age showed weaker but statistically significant effects, suggesting that personalization models may need age-sensitive calibration.

Table 4: Regression results (predictors of purchase intent)

Predictor	Beta Coefficient	p-value
Personalization Level	0.38	0.000
RTB Intensity	0.44	0.000
Perceived Accuracy	0.35	0.000
Trust in System	0.29	0.001
Bounce Rate	-0.19	0.024
Age	-0.07	0.048

The link between user engagement and conversion was further validated through visual analysis. Figure 1 illustrates the positive correlation between engagement time and conversion rate across groups. Participants in the control group exhibited shorter engagement times and lower conversion rates, while those exposed to AI + RTB demonstrated significantly higher engagement coupled with the highest conversion outcomes. This confirms the importance of sustained user interaction in driving successful transactions.

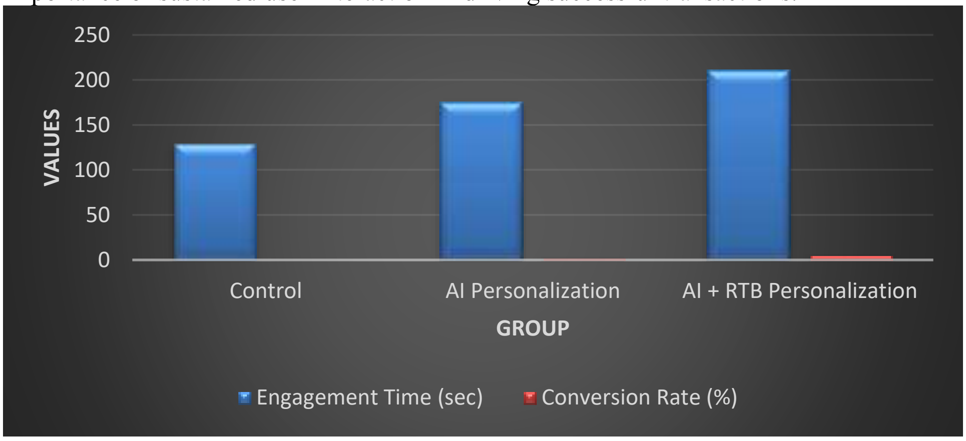

Figure 1: Relationship between engagement time and conversion rate

Beyond direct performance outcomes, the structural equation modeling results, illustrated in Figure 2, highlight the pathways through which AI-driven personalization and RTB enhance purchase intent. Personalization significantly improved perceived accuracy, which in turn fostered greater trust in the system. Trust directly influenced purchase intent, while RTB intensity enhanced user engagement, which also positively affected purchase intent. These pathways underscore the multi-dimensional impact of personalization and bidding mechanisms, showing that trust and engagement are critical mediators in shaping consumer decisions.

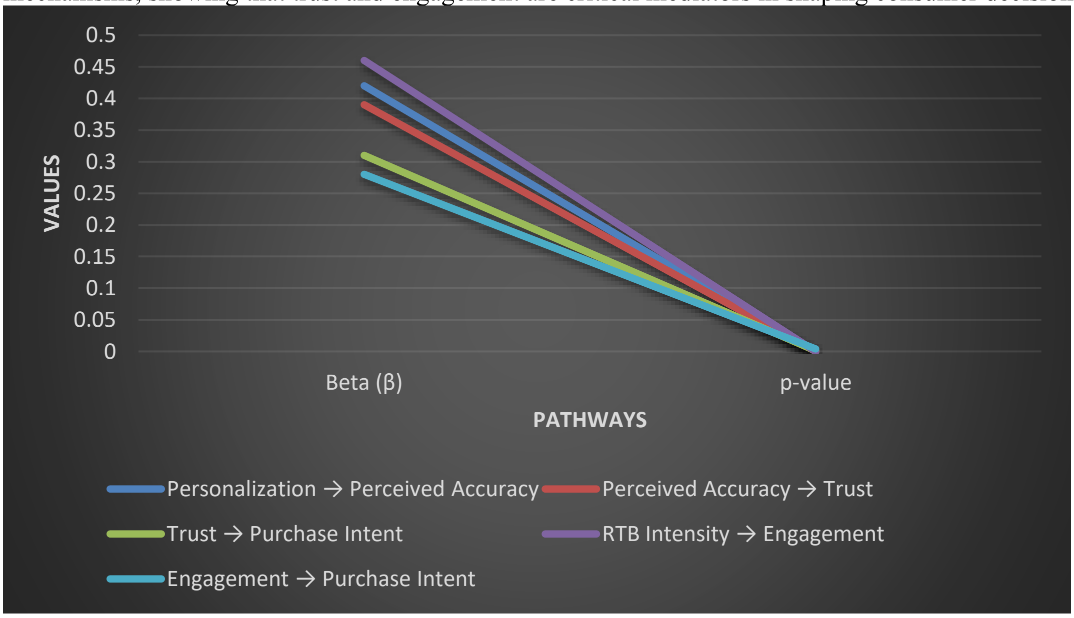

Figure 2: Path model of personalization effects (SEM output)

DISCUSSION

Impact of AI-driven personalization on consumer behavior

The findings demonstrate that AI-based personalization significantly enhances consumer engagement, satisfaction, and purchase intent in fashion commerce. Participants exposed to AI-driven recommendations (without RTB) already exhibited higher interaction metrics than the control group, reflecting the established effectiveness of personalized suggestions (Nozari et al., 2025). However, the integration of real-time bidding amplified these effects, highlighting that consumers respond not only to tailored recommendations but also to their timeliness and contextual relevance. This result aligns with existing research that emphasizes personalization as a key driver of loyalty and conversion in digital retail (Macharla & Raghavendra, 2025).

Role of real-time bidding in enhancing personalization outcomes

Real-time bidding emerged as a crucial differentiator in this study, elevating both consumer experience and system performance. The bidding mechanism enabled more competitive and context-aware recommendations, reducing bounce rates while increasing cart additions and session completions (Kundu et al., 2023). This outcome illustrates how RTB mechanisms, traditionally applied to advertising, can be adapted to e-commerce to provide hyper-personalized shopping environments. Importantly, the higher trust and willingness to pay a premium observed in the AI + RTB group suggest that consumers perceive greater value in recommendations that are both accurate and timely (Hasan et al., 2025).

Mediating role of trust and engagement

The structural equation modeling results revealed that trust and engagement act as mediating variables in the relationship between personalization strategies and purchase intent. Trust was primarily shaped by the perceived accuracy of AI recommendations, while engagement was enhanced by RTB intensity (Casciani et al., 2022). Both variables significantly influenced purchase behavior, indicating that personalization strategies must address not only relevance but also consumer confidence and sustained interaction. This supports previous theoretical work in digital marketing, which posits that psychological factors such as trust and perceived value mediate the impact of technological interventions on consumer outcomes (Campbell et al., 2020, Dobreva, 2024).

Commercial and strategic implications for fashion retailers

From a managerial perspective, the results underscore the strategic advantage of deploying AI-driven personalization in combination with RTB systems. Retailers who adopt such technologies can expect not only higher conversion rates and customer satisfaction but also an increased willingness among consumers to pay premium prices (Chavan et al., 2025). Furthermore, the reduction in bounce rates and improvements in session completion highlight the potential for RTB personalization to optimize platform efficiency and reduce customer acquisition costs (Raneet al., 2023). For fashion retailers operating in competitive digital markets, these capabilities can serve as a differentiating factor that strengthens brand loyalty and long-term customer lifetime value (Chandra et al., 2025).

Ethical and technological considerations

While the findings point to substantial benefits, they also raise important ethical and technological considerations. The use of AI and RTB mechanisms involves extensive data collection and real-time decision-making, which may heighten concerns around privacy, transparency, and algorithmic fairness (Economy, 2025). Although this study maintained ethical safeguards, broader deployment in the industry must address these challenges to ensure consumer trust is not undermined. Additionally, technological scalability and cost considerations must be carefully evaluated, as implementing RTB-driven personalization requires substantial computational resources and continuous monitoring.

Limitations and directions for future research

This study has several limitations that provide opportunities for future inquiry. First, the simulated e-commerce platform, while robust, may not fully replicate the complexities of real-world fashion retail environments where multi-brand competition, logistics, and promotions influence consumer decisions. Second, the participant sample, although diverse, was limited in size compared to the scale of global e-commerce users. Third, the study focused on apparel; future research should test whether these findings generalize to other product categories such as luxury goods or fast fashion. Future studies should also investigate the long-term impact of AI + RTB personalization on customer retention, as well as the ethical implications of dynamic pricing and competitive bidding in personalization.

CONCLUSION

This study demonstrates that integrating artificial intelligence with real-time bidding mechanisms can significantly transform fashion commerce by delivering highly personalized apparel experiences that enhance consumer engagement, trust, and purchase intent. The findings reveal that while AI-driven personalization alone improves recommendation accuracy and customer satisfaction, the addition of RTB amplifies these benefits by ensuring contextual relevance and timeliness. Together, these technologies reduce bounce rates, increase session completion, and even raise consumers' willingness to pay a premium, offering retailers both competitive and financial advantages. However, the adoption of such systems must be accompanied by careful consideration of ethical issues related to data privacy, transparency, and algorithmic fairness. By bridging personalization with competitive bidding, this research not only advances theoretical understanding of consumer–technology interaction but also provides actionable insights for fashion retailers seeking to thrive in an increasingly dynamic and data-driven marketplace.

REFERENCES

1. Alkudah, N. M., & Almomani, T. O. (2024). The Integration of Artificial Intelligence Techniques in E-Commerce: Enhancing Online Shopping Experience and Personalization. *Global Journal of Economics & Business*, *14*(6).
2. Bansal, N., & Gupta, R. K. (2024, March). Unlocking Personalized Shopping: How Artificial Intelligence Crafts Your Perfect E-commerce Experience. In *International Conference on Information Technology* (pp. 511-527). Singapore: Springer Nature Singapore.
3. Campbell, C., Sands, S., Ferraro, C., Tsao, H. Y. J., & Mavrommatis, A. (2020). From data to action: How marketers can leverage AI. *Business horizons*, *63*(2), 227-243.
4. Casciani, D., Chkanikova, O., & Pal, R. (2022). Exploring the nature of digital transformation in the fashion industry: opportunities for supply chains, business models, and sustainability-oriented innovations. *Sustainability: Science, Practice and Policy*, *18*(1), 773-795.
5. Chandra, S., Ghule, G., Bilfaqih, S. M., Thiyagarajan, A., Sharmila, J., & Boopathi, S. (2025). Adaptive Strategies in Online Marketing Using Machine Learning Techniques. In *Digital Transformation Initiatives for Agile Marketing* (pp. 67-100). IGI Global.
6. Chavan, S., Bhosale, A., Ghodke, A., Shitole, D., & Magar, H. (2025, January). Optimizing E-Auction Systems with Cosine Similarity for Personalized Bidding. In *2025 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS)* (pp. 1-7). IEEE.
7. Dobreva, A. (2024). Impact of new technologies and artificial intelligence in brand management. *Годишник Телекомуникации*, (11), 107-117.
8. Economy, S. (2025). Edge Computing and Marketing in the. *Dynamic and Safe Economy in the Age of Smart Technologies*, 191.
9. Gao, Y., & Liang, J. (2025). The Impact of AI-Powered Try-On Technology on Online Consumers' Impulsive Buying Intention: The Moderating Role of Brand Trust. *Sustainability*, *17*(7), 2789.
10. Hasan, M., Chowdhury, K. Z., & Zubayer, M. (2025). The AI Advantage: Revolutionizing Personalization in Digital Marketing. *Business & Social Sciences*, *3*(1), 1-9.
11. Julian, S. (2025). AI-Driven Digital Optimization: Shaping the Next Era of Customer Experience. *Journal of Future Digital Optimization*, *1*(2), 30-36.
12. Kesavan, V., & Polisetty, A. (2025). A Comprehensive Overview of the Evolving Fashion Industry Landscape Through the Embracing of AI and Generative Artificial Intelligence Technologies. *Sustainable Practices in the Fashion and Retail Industry*, 33-60.
13. Kundu, N., Mustafa, F., & Chola, C. (2023). Artificial intelligence in retail marketing. In *Artificial Intelligence for Business* (pp. 86-107). Productivity Press.
14. Macharla, S. L., & Raghavendra, G. S. (2025). Leveraging AI for E-Business Transformation. In *Business Transformation in the Era of Digital Disruption* (pp. 29-58). IGI Global.
15. Nozari, H., Abdi, H., & Rafiei, K. (2025). Edge Computing and Marketing in the Smart Economy: Processing Consumer Data in Real-Time. In *Dynamic and Safe Economy in the Age of Smart Technologies* (pp. 191-208). IGI Global Scientific Publishing.
16. Ntumba, C., Aguayo, S., & Maina, K. (2023). Revolutionizing retail: a mini review of e-commerce evolution. *Journal of Digital Marketing and Communication*, *3*(2), 100-110.
17. Prajapat, R. (2024). Merchandising for Ecommerce Marketplace. In *AI-Powered Ecommerce: How Machine Learning Is Transforming Online Shopping* (pp. 63-80). Berkeley, CA: Apress.
18. Rainy, T. A. (2025). AI-driven marketing analytics for retail strategy: a systematic review of data-backed campaign optimization. *International Journal of Scientific Interdisciplinary Research*, *6*(1), 28-59.
19. Rane, N., Choudhary, S., & Rane, J. (2023). Metaverse for enhancing customer loyalty: effective strategies to improve customer relationship, service, engagement, satisfaction, and experience. *Service, Engagement, Satisfaction, and Experience (November 1, 2023)*.
20. Roy, A. (2024). Fashion Innovation Driven by AI: Transforming Design, Manufacturing, and Customer Experience. *Applied IT & Engineering*, *2*(1), 1-8.
21. Singh, S. (2024). Artificial intelligence in the fashion and apparel industry. *Tekstilec*, *67*(3), 225-240.