The impact of AI-powered personalisation on consumer purchase decisions in the textile sector

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ABSTRACT – REZUMAT

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In the context of accelerated digital transformation and shifting consumer expectations regarding online shopping experiences, digital marketing in the textile industry faces both significant challenges and emerging opportunities. This study investigates how artificial intelligence (AI) contributes to shaping consumer preferences by personalising commercial communication, generating relevant product recommendations, and automating interactions between brands and users.

By combining a literature review with primary data collected through a survey of 358 Romanian consumers active in digital environments, the research explores their perceptions of AI-driven online marketing. The results indicate that 61% of respondents view artificial intelligence as a helpful factor in their decision-making process, while 55% consider personalised recommendations to be relevant in selecting clothing products. At the same time, a substantial segment of users expresses concerns related to algorithmic transparency and the level of control offered.

The article proposes a conceptual model for integrating AI into digital marketing strategies, with a focus on personalising the shopping experience and influencing purchase intention. The findings support the need for data-driven, consumer-centred approaches that leverage automation to deliver added value in the textile industry through the use of advanced technologies.

Keywords: *consumer decision-making, algorithmic personalisation, digital user experience, data-driven marketing, customer trust in AI, textile retail innovation*

Impactul personalizării bazate pe inteligența artificială asupra deciziilor de cumpărare ale consumatorilor din sectorul textil

În contextul transformării digitale accelerate și al schimbării așteptărilor consumatorilor în ceea ce privește experiențele de cumpărături online, marketingul digital în industria textilă se confruntă atât cu provocări semnificative, cât și cu oportunități emergente. Acest studiu investighează modul în care inteligența artificială (IA) contribuie la modelarea preferințelor consumatorilor prin personalizarea comunicării comerciale, generarea de recomandări relevante de produse și automatizarea interacțiunilor dintre mărci și utilizatori.

Combinând o analiză a literaturii de specialitate cu date primare colectate printr-un sondaj realizat pe un eșantion de 358 de consumatori români activi în mediul digital, cercetarea explorează percepțiile acestora asupra marketingului online bazat pe IA. Rezultatele indică faptul că 61% dintre respondenți consideră inteligența artificială un factor util în procesul lor de luare a deciziilor, în timp ce 55% consideră recomandările personalizate relevante în selectarea produselor vestimentare. În același timp, un segment substanțial de utilizatori își exprimă îngrijorarea cu privire la transparența algoritmică și la nivelul de control oferit.

Articolul propune un model conceptual pentru integrarea IA în strategiile de marketing digital, cu accent pe personalizarea experienței de cumpărare și influențarea intenției de cumpărare. Rezultatele susțin necesitatea unor abordări bazate pe date și centrate pe consumator, care să utilizeze automatizarea pentru a oferi valoare adăugată în industria textilă prin utilizarea tehnologiilor avansate.

Cuvinte-cheie*: procesul decizional al consumatorilor, personalizarea algoritmică, experiența digitală a utilizatorilor, marketingul bazat pe date, încrederea clienților în IA, inovarea în comerțul cu amănuntul de textile*

INTRODUCTION

Online marketing has undergone an accelerated evolution over the past two decades, marking a clear transition from traditional "one-to-many" communication to personalised and adaptive approaches based on data analysis and machine learning. This shift has been enabled by the massive digitalisation of communication channels and the exponential growth of available data regarding user behaviour in digital environments [1]. In this context, content personalisation has become a central pillar of digital marketing strategies, particularly in industries such as textiles, where style preferences, aesthetics, and identity directly influence purchasing decisions.

Personalisation in digital marketing is defined as the process by which content, products, or services are adapted in real time to the behaviours, interests, or individual traits of a consumer [2]. Unlike classical segmentation, which involves grouping consumers into broad categories, personalisation enables a unique, user-specific approach based on historical data and the current interaction context [3]. This granular orientation increases consumer engagement, the perceived relevance of the message, and ultimately, the conversion rate [4].

In the textile industry specifically, personalisation has a high potential to influence consumer buying decisions. The selection of clothing items is often driven by emotional, aesthetic, and symbolic factors; consumers express their identity, status, and sense of belonging through fashion choices [5]. In this regard, an online shopping experience capable of recommending products based on past style preferences, colour, fit, or brand becomes a significant competitive advantage. Brands that invest in personalised recommendation engines, collaborative filtering algorithms, and tailored visual content are more likely to foster customer loyalty and improve conversion performance.

Technology enables personalisation at scale through the integration of CRM tools, intelligent e-commerce platforms, and AI systems. According to recent studies, online content personalisation can contribute to revenue increases of up to 20% in e-commerce compared to standard approaches [6]. Additionally, consumers who interact with personalised content spend more time on the site, have a higher likelihood of completing purchases, and are more likely to return.

In the fashion domain, personalisation extends beyond product suggestions to encompass the entire digital experience. For example, modern e-commerce platforms can adapt visual interfaces to user preferences, display models based on estimated customer morphology, or integrate intelligent filters that prioritise items aligned with a user's personal style. Furthermore, the use of augmented reality and virtual try-ons, customised to the consumer's digital avatar, represents the next frontier of personalisation in textile retail [7].

Despite its clear advantages, personalisation also raises challenges related to data privacy and technological acceptance. Research indicates that over-personalisation, perceived as intrusive, may lead to the opposite effect, diminished trust and even brand avoidance [8]. Therefore, personalisation strategies must be transparent, offer users control, and rely on informed consent.

GENERAL INFORMATION

Artificial Intelligence in digital marketing

Artificial Intelligence (AI) is one of the most transformative technologies of the 21st century, having a major impact on digital marketing practices. Through its capacity to process large volumes of data in real time, learn from behaviours, and automatically adapt strategies, AI is redefining how companies interact with the public, personalise content, and optimise commercial performance [9].

In marketing, AI is implemented through various applications targeting different stages of the customer relationship. Among the most common are personalised recommendation systems, which suggest products or services based on a user's past behaviour or similar customers. These algorithms, widely used on e-commerce and online retail platforms, contribute significantly to increasing average basket value and customer retention [10]. Typical examples include prompts such as "customers who bought this item also purchased…", generated by machine learning models based on frequent associations.

Another essential application of AI is content delivery automation. Through marketing automation systems, companies can send personalised emails, notifications, or banners based on user activity. For example, if a customer adds a product to their cart without completing the purchase, the system may automatically generate a limited-time discount offer to stimulate conversion. This contextual communication helps reduce cart abandonment and increases engagement [11].

Conversational chatbots based on natural language processing (NLP) are another prominent manifestation of AI in marketing. These tools interact with users in real time, answering frequently asked questions, offering recommendations, or assisting with the ordering process. Unlike early, basic versions, modern chatbots can understand user intent and generate coherent and natural responses [12]. In fashion retail, digital agents can be integrated into product pages to provide stock availability, sizing guides, or alternatives based on expressed preferences.

International fashion leaders such as Zara, H&M, and ASOS have already integrated advanced AI systems for automated styling, visual search, and micro-personalised recommendations at scale, demonstrating strong performance improvements across European markets. Similar trends are emerging globally, suggesting the universal relevance of AI-driven personalisation strategies in textile retail.

Sentiment analysis is also increasingly used in digital marketing campaigns. Through AI algorithms, brands can analyse user comments, reviews, and social media reactions to gauge overall attitudes toward a product or service. Based on this insight, advertising messages can be dynamically adjusted to reflect the appropriate tone, respond to criticism, or amplify positive feedback [13].

Empirical studies show that users are generally receptive to AI in digital environments as long as it offers tangible benefits, such as time savings, simplicity of the shopping experience, or access to more relevant products. According to Puntoni et al. [14], AI is perceived positively when it supports user autonomy and is not seen as invasive or manipulative.

However, the acceptance of AI is not universal. Some users express resistance, especially when they perceive a lack of transparency or a high level of automation that limits human control. Trust in technology becomes a key factor in the success of

AI-based marketing strategies. Brands must clearly communicate the role of these systems, offer customisation options, and avoid hyper-automation [15].

Consumer behaviour and AI

Consumer behaviour has always been shaped by a complex interplay of cognitive, emotional, social, and contextual factors. In the digital era, these traditional factors are now joined by interactions with intelligent systems, particularly those powered by artificial intelligence (AI), which directly influence decision-making processes and brand relationships [16].

Online consumers are exposed to an overwhelming number of options, often resulting in information saturation. In this environment, AI functions as a cognitive filter that reduces complexity by offering suggestions, anticipating needs, and personalising interactions based on a user's history and behaviours [9]. This process can lead to more efficient decision-making, time savings, and a smoother shopping experience.

However, the relationship between consumers and AI is mediated by a critical factor: trust in technology. Research indicates that consumers form a positive relationship with AI systems when the benefits are clear, and interactions are transparent, controllable, and predictable [14]. In contrast, a lack of transparency, excessive automation, or misuse of personal data can lead to resistance, anxiety, or even brand rejection [15].

In the textile industry specifically, purchasing decisions are often emotional and symbolic. Clothing fulfils not only a functional need but also contributes to self-expression, aesthetic preferences, and social integration [5]. Therefore, the integration of AI into fashion retail must be not only technological but also empathetic. Algorithms that can interpret stylistic preferences and offer recommendations aligned with a user's taste can strengthen brand trust and increase loyalty [17].

Another important element is the perception of control. When AI offers suggestions without limiting choices, consumers feel a sense of autonomy. On the other hand, when systems appear to "steer" decisions, psychological resistance may arise. Recent studies suggest that AI is more effective when it functions as a digital assistant rather than an invisible decision-maker [18].

Moreover, consumers vary in their willingness to accept AI. Digitally savvy younger users tend to adopt AI-based interactions more easily, while traditional users exhibit more scepticism, especially in the absence of clear explanations about system functionality [4]. Thus, the success of AI in influencing behaviour also depends on digital literacy and user familiarity with technology.

In the textile industry, where purchasing cycles are frequent yet impulsive, AI plays a key role in anticipating recurring needs. For example, by analysing purchase history and seasonal preferences, intelligent systems can recommend new collections or personalised discounts, increasing the likelihood of conversion. Additionally, in remarketing campaigns, AI enables message recalibration based on customer reactions, crucial in a sector driven by fast-changing trends and styles [13].

AI also contributes to the experiential aspect of shopping, an increasingly relevant factor for newer generations of consumers. Through augmented reality, friendly chatbots, or interactive video recommendations, AI transforms shopping from a simple transaction into an immersive experience, positively influencing brand perception [12].

In conclusion, consumer behaviour in the digital era is increasingly shaped by interactions with AI systems. In the textile industry, where decisions are emotional, visual, and taste-driven, AI has the potential to significantly enhance the decision-making process, provided it is implemented in a transparent, empathetic, and user-centred manner.

The proposed conceptual framework

Based on the relevant literature, we propose an integrated conceptual framework that describes how consumer perception of artificial intelligence (AI) indirectly influences the intention to purchase textile products through the perceived personalisation of marketing communication. Additionally, the model considers the role of trust in AI as a moderating variable in the relationship between personalisation and purchasing behaviour.

H1: Positive perception of AI (PAI) positively influences the perceived usefulness of AI (PU).

Consumer perception of AI is foundational to its acceptance. According to the Technology Acceptance Model (TAM), a positive attitude toward a system directly influences its perceived usefulness. In digital marketing, if AI is perceived as friendly, easy to use, and naturally integrated into the online experience, users are more likely to find it useful in decision-making [9]. In fashion retail, where choice overload is common, a favourable perception of AI leads to greater expectations for its value-added role.

H2: Perceived usefulness of AI (PU) positively influences perceived personalisation (PP).

The literature emphasises a strong link between perceived system usefulness and the level of personalisation users experience [2]. In e-commerce, AI is often valued for its ability to deliver content and recommendations tailored to individual needs. The more capable AI is of simplifying, filtering, or predicting consumer preferences, the greater the sense of personalisation [3]. In fashion retail, this relationship is magnified by expectations of stylistic fit, size guidance, and adaptive cross-selling.

H3: Perceived usefulness of AI (PU) positively influences trust in AI (TAI).

Trust in AI is largely shaped by consumer experience and assessment of system performance. When AI is perceived as helpful, saving time, reducing cognitive effort, and delivering relevant outcomes, consumers are more inclined to trust it [15]. Marketing research confirms that perceived usefulness not only boosts adoption but also functional trust, especially when AI recommendations and predictions are validated over time [14].

H4: Perceived personalisation (PP) positively influences brand engagement (BE).

Personalised marketing enhances the relevance and depth of the brand–consumer relationship. When content, offers, and communication align with individual needs and preferences, consumers feel understood, increasing satisfaction and involvement [1], [4]. In the textile industry, where style choices are deeply personal, personalisation becomes a key driver of brand loyalty.

H5: Trust in AI (TAI) positively influences brand engagement (BE).

In digital environments, trust extends not only to the brand but also to the technologies it employs. When AI is perceived as trustworthy, delivering accurate recommendations, respecting privacy, and avoiding intrusiveness, it positively impacts consumer perceptions of the associated brand [15]. Research shows that brands that transparently communicate how AI is used and offer users control over data create stronger emotional and attitudinal engagement [17].

H6: Brand engagement (BE) positively influences purchase intention (PI).

Brand engagement is a strong predictor of purchasing behaviour, according to brand attachment theory [19]. A consumer who feels emotionally connected or personally identified with a brand is more likely to make repeat purchases and express favourable intentions. In the fashion sector, this is amplified by the expressive nature of clothing, linking consumption choices with personal identity.

H7: Perceived personalisation (PP) positively influences purchase intention (PI).

Personalisation is often positively correlated with conversion and purchase intention. Consumers are more likely to buy when they feel the offer is tailored to them and the options meet their expectations [8]. In fashion retail, personalisation boosts confidence in the buying decision, especially when uncertainty exists around fit, aesthetics, or style.

H8: Trust in AI (TAI) moderates the relationship between perceived personalisation (PP) and purchase intention (PI).

Even if personalisation is perceived positively, its effectiveness in generating purchase intent depends on the level of trust in the technology behind it. When AI is seen as unreliable, invasive, or inaccurate, consumers may dismiss even highly relevant recommendations [18]. Thus, trust in AI acts as an amplifying or dampening factor, reinforcing the causal link between personalisation and purchase behaviour.

MATERIALS AND METHODS

The primary objective of this study is to analyse how artificial intelligence (AI), when applied in digital marketing, influences consumer purchasing behaviour in the textile industry. The research focuses specifically on the relationships between consumers' perceptions of AI, perceived personalisation, trust in technology, brand engagement, and purchase intention. To address the stated objectives and test the proposed hypotheses, a quantitative approach was employed, based on primary data collected through an online questionnaire.

This study adopts a quantitative, descriptive, and explanatory research design, aimed at identifying and quantifying the relationships among the variables under investigation. The descriptive dimension allows for the characterisation of digital consumer profiles who interact with AI technologies in the context of online shopping, while the explanatory dimension aims to test the direct, mediated, and moderated effects among the variables in the conceptual model.

The research follows a cross-sectional design, with data collected over a clearly defined period. No experimental manipulation was involved; instead, the study relied on passive observation of respondents' self-reported perceptions.

Research instrument

The Data collection was conducted through a self-administered online questionnaire, distributed via social media platforms, consumer forums, and communities interested in fashion and e-commerce. The data collection period spanned from April to June 2025.

The questionnaire was structured into six main sections, each corresponding to one of the key constructs analysed in the model:

- Demographics: gender, age, education level, frequency of online purchases;
- Familiarity with AI: previous interactions with AI technologies in e-commerce (e.g., chatbots, intelligent recommendations, personalised ads);
- Perception of AI: measured through items evaluating perceived usefulness, clarity, adaptability, and contribution to the shopping experience (5 items, 5-point Likert scale);
- Perceived personalisation: extent to which messages, offers, and products are tailored to individual preferences (4 items, 5-point Likert scale);
- Trust in AI: measured through trust in automated recommendations, perceived control, and transparency (4 items);
- Brand engagement: assessed through willingness to continue interaction with the brand, loyalty, and emotional attachment (3 items);
- Purchase intention: self-reported willingness to purchase textile products based on personalised AI recommendations (3 items).

A pilot test was conducted on a sample of 30 respondents to validate the structure and wording of the questionnaire. Feedback from the pilot was used to clarify certain terms and optimise the overall length and clarity of the instrument. To ensure the authenticity and quality of responses, two attention-check items were included, and responses exhibiting inconsistent patterns or extremely short completion times were removed. The survey platform also restricted multiple submissions from the same device/IP address. A pilot pre-test (N=30) confirmed respondent understanding of item wording and structure, ensuring content validity.

Sample characteristics

A non-probability, convenience sampling method was employed, resulting in a final sample of 358 Romanian respondents, selected based on the following two criteria:
- Participants had made at least one online clothing purchase in the past six months;
- Participants had interacted with at least one AI functionality (e.g., automated recommendation or chatbot).

Key demographic characteristics of the sample include:
- Gender: 63% female, 37% male;
- Age: 58% between 25 and 44 years old;
- Education: 81% with higher education;
- Frequency of online purchases: 66% reported shopping for clothing online at least once a month.

These demographic indicators reflect an urban, digitally engaged consumer base, well-aligned with the study's focus on emerging technologies in retail. Detailed descriptive statistics are presented in table 1, reflecting the diversity of respondents in terms of demographic and behavioural purchasing characteristics.
The distribution confirms the relevance of the sample for digital textile commerce research.

Data analysis methods

To test the proposed conceptual model, the WarpPLS 8.0 software was employed, which is specifically designed for Partial Least Squares Structural Equation Modelling (PLS-SEM). This methodological approach was chosen for its ability to handle complex models involving multiple causal relationships, latent variables, and both mediating and moderating effects [20].
Moreover, PLS-SEM is particularly suited for exploratory studies with moderately sized samples and non-normal data distributions, conditions that are met in the current research context.
The quality of the structural relationships is confirmed by the value of the Average Path Coefficient (APC), which is 0.389 with a high level of statistical significance ($p<0.001$). This value, exceeding the recommended threshold of 0.30, indicates a consistent connection between the model variables and supports the validity of the theoretical causal relationships. Additionally, the Average R-squared (ARS = 0.342) and Average Adjusted R-squared (AARS = 0.340) coefficients demonstrate that the model explains, on average, over 34% of the variance in the dependent constructs. This level of explanatory power is considered moderate to high in consumer behaviour studies [20], suggesting satisfactory predictive capability.
With respect to the global validity of the model, the Tenenhaus Goodness-of-Fit (GoF) index is 0.418, surpassing the threshold of 0.36, which is regarded as "large" according to the relevant literature [21]. This value indicates a strong alignment between the theoretical model structure and the empirical data collected, thus offering solid evidence for the robustness of the proposed framework.

Table 1

DEMOGRAPHIC AND SHOPPING BEHAVIOUR DISTRIBUTION OF RESPONDENTS		
Variable	**Categories**	**Percentage (%)**
Gender	Female / Male	63% / 37%
Age	18–24 / 25–34 / 35–44 / 45+	22% / 34% / 24% / 20%
Geographic area	Urban / Rural	78% / 22%
Monthly income	<600€ / 600–1000€ / >1000€	32% / 45% / 23%
Online clothing purchase frequency	Monthly / Quarterly / Rarely	66% / 22% / 12%
Clothing categories purchased	Casual / Sportswear / Business / Luxury	72% / 41% / 28% / 9%

Average path coefficient (APC)=0.389, P<0.001
Average R-squared (ARS)=0.342, P<0.001
Average adjusted R-squared (AARS)=0.340, P<0.001
Average block VIF (AVIF)=1.292, acceptable if <= 5, ideally <= 3.3
Average full collinearity VIF (AFVIF)=1.804, acceptable if <= 5, ideally <= 3.3
Tenenhaus GoF (GoF)=0.418, small >= 0.1, medium >= 0.25, large >= 0.36
Simpson's paradox ratio (SPR)=1.000, acceptable if >= 0.7, ideally = 1
R-squared contribution ratio (RSCR)=1.000, acceptable if >= 0.9, ideally = 1
Statistical suppression ratio (SSR)=1.000, acceptable if >= 0.7
Nonlinear bivariate causality direction ratio (NLBCDR)=1.000, acceptable if >= 0.7

Fig. 1. Global Model Fit and PLS-SEM quality indicators

Regarding collinearity and internal consistency, the very low values of the Average Variance Inflation Factor (AVIF = 1.292) and the Average Full Collinearity VIF (AFVIF = 1.804) confirm the absence of significant multicollinearity among latent constructs. These values fall well below the critical threshold of 3.3, indicating good independence between variables and reliability in the estimation of regression coefficients.

The stability and coherence of the model are further supported by four additional indicators, each achieving the ideal value of 1.000: the Simpson's Paradox Ratio (SPR), R-squared Contribution Ratio (RSCR), Statistical Suppression Ratio (SSR), and the Nonlinear Bivariate Causality Direction Ratio (NLBCDR). These results show that the model is not affected by statistical paradoxes or suppressor effects and that the identified causal relationships are coherent, directional, and robust. Each variable contributes in a positive and theoretically consistent manner to explaining the analysed consumer behaviour.

Overall, the set of statistical indicators confirms that the proposed model is appropriate for investigating the studied phenomenon, both in terms of the quality of internal relationships and its explanatory power and structural coherence.

RESULTS

The structural model analysis conducted using WarpPLS 8.0 aimed to test the eight hypotheses formulated in the conceptual framework by evaluating the strength and statistical significance of the relationships between latent variables. The results confirm the internal consistency of the theoretical model and offer empirical support for the assumed causal relationships.

R2 – Model's explanatory power

The R^2 coefficients reflect the proportion of variance in the dependent variables explained by their predictors:

- Perceived Usefulness of AI (UP): $R^2 = 0.17 \rightarrow 17\%$ of the variation in perceived usefulness is explained by the consumer's perception of AI.
- Perceived Personalisation (PP): $R^2 = 0.46 \rightarrow 46\%$ of the variation in perceived personalisation is explained by perceived usefulness.
- Trust in AI (IAI): $R^2 = 0.15 \rightarrow 15\%$ of the variation in trust is explained by perceived usefulness.
- Brand Engagement (AB): $R^2 = 0.49 \rightarrow$ Nearly half of the variation in brand engagement is explained by personalisation and trust.
- Purchase Intention (IC): $R^2 = 0.44 \rightarrow 44\%$ of the variation in purchase intention is explained by personalisation, trust, and engagement.

These values indicate good explanatory power, particularly in the context of digital marketing research [20].

Path coefficients interpretation (β)

- H1: PAI → UP ($\beta=0.41$, $p<0.01$) A positive perception of AI has a significant and moderate effect on perceived usefulness, confirming that a favourable image of AI leads to more functional evaluations.
- H2: UP → PP ($\beta=0.40$, $p<0.01$) Perceived usefulness has a strong positive effect on perceived personalisation. Users who find AI useful tend to perceive the marketing communication as more tailored.
- H3: UP → IAI ($\beta=0.39$, $p<0.01$) When AI is considered useful, it fosters consumer trust, supporting the hypothesis that functional perceptions enhance cognitive attachment.
- H4: PP → AB ($\beta=0.57$, $p<0.01$) The relationship between perceived personalisation and brand engagement is very strong and statistically significant – one of the most important in the model.
- H5: IAI → AB ($\beta=0.24$, $p<0.01$). Trust in AI has a significant positive impact on brand engagement, though weaker than personalisation. It still supports H5.
- H6: AB → IC ($\beta=0.18$, $p<0.01$) Brand engagement has a direct but relatively weak influence on purchase intention, suggesting a mediated effect.
- H7: PP → IC ($\beta=0.30$, $p<0.01$) Perceived personalisation has a significant positive impact on purchase intention, highlighting the importance of tailored content in driving e-commerce conversion.
- H8: IAI → IC ($\beta=0.56$, $p<0.01$) Trust in AI is the strongest direct predictor of purchase intention, emphasising the critical role of technology in shaping buying behaviour.

Hypothesis validation

All eight hypotheses (H1–H8) were statistically confirmed at the $p<0.01$ level. The path coefficients (β) indicate both the direction and intensity of the proposed theoretical relationships. Notably, H4 (PP → AB)

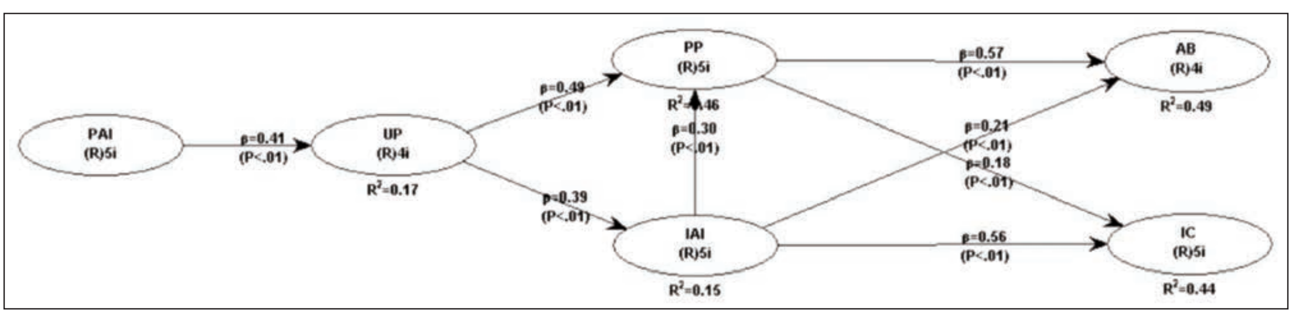

Fig. 2. The proposed conceptual model

and H8 (IAI → IC) recorded the highest effect sizes, suggesting that personalisation and trust in AI are essential drivers of consumer behaviour in the textile e-commerce context.

Construct reliability and validity

To build the latent variables included in the research model, defining items were derived from the questionnaire administered to respondents. Data analysis and interpretation were conducted using WarpPLS 8.0, a software specialised in estimating Partial Least Squares Structural Equation Models (PLS-SEM). WarpPLS is particularly recommended for empirical studies involving complex relationships between latent constructs, and it excels in handling non-normal data distributions and moderate to small samples [22].

The quality of measurement was assessed using standard reliability and convergent validity indicators: Composite Reliability (CR), Cronbach's Alpha, and Average Variance Extracted (AVE).

As shown in table 2, all constructs demonstrate composite reliability values above the 0.70 threshold (ranging from 0.777 to 0.896), indicating satisfactory internal consistency. Cronbach's Alpha values also fall within acceptable limits, ranging from 0.618 (UP) to 0.855 (IC), reflecting good internal coherence of the measurement items.

Average Variance Extracted (AVE) values range from 0.467 to 0.634. Most constructs exceed the 0.50 threshold, which is considered acceptable for convergent validity [20]. These results confirm that the latent variables adequately explain the variance of their respective indicators.

Discriminant validity was tested using the Fornell-Larcker criterion, which requires that the square root of each construct's AVE exceeds the inter-construct correlations. As shown in table 3, all diagonal values (in parentheses) are higher than the corresponding correlations, confirming discriminant validity.

These results validate both the measurement reliability and the theoretical distinctiveness of the constructs. Following Kock (2020) [22], the use of AVE and inter-construct correlations confirms that there are no 1:1 relationships between the analysed variables and that the items used reliably reflect the theoretical concepts proposed in the model.

In summary, the measurement instrument used in this study is both reliable and valid, enabling a rigorous and coherent interpretation of the relationships among the variables in the proposed model.

CONCLUSIONS

This study aimed to explore how artificial intelligence (AI), when applied to digital marketing, influences consumer purchase behaviour within the textile industry. Through an empirically validated conceptual model, the research identified significant relationships between positive perceptions of AI, perceived usefulness, online experience personalisation, trust in technology, brand engagement, and purchase intention.

The findings confirm that favourable perceptions of AI lead to an increase in perceived usefulness, which in turn positively influences both perceived personalisation and trust in AI technologies. Personalisation has a direct and substantial effect on brand engagement, while trust in AI emerges as the strongest direct predictor of purchase intention. Moreover, the effect of personalisation on purchase intention is further strengthened through the mediating role of engagement and the moderating effect of trust, illustrating a

Table 2

RELIABILITY AND VALIDITY OF LATENT CONSTRUCTS

Construct	Composite reliability	Cronbach's Alpha	AVE
PAI (Perception of AI)	0.833	0.749	0.503
UP (Perceived usefulness)	0.777	0.618	0.467
PP (Perceived personal)	0.825	0.732	0.493
AB (Brand engagement)	0.776	0.615	0.469
IC (Purchase intention)	0.896	0.855	0.634
IAI (Trust in AI)	0.834	0.750	0.504

Table 3

INTER-CONSTRUCT CORRELATIONS AND SQUARE ROOTS OF AVE

	PAI	UP	PP	AB	IC	IAI
PAI	(0.709)	0.372	0.316	0.323	0.271	0.314
UP	0.372	(0.684)	0.561	0.554	0.314	0.389
PP	0.316	0.561	(0.702)	0.665	0.447	0.479
AB	0.323	0.554	0.665	(0.685)	0.511	0.490
IC	0.271	0.314	0.447	0.511	(0.796)	0.620
IAI	0.314	0.389	0.479	0.490	0.620	(0.710)

complex and interdependent dynamic between the variables studied.

The model, tested using WarpPLS 8.0, demonstrated a good level of explanatory power (GoF = 0.418) and significant relationships between constructs (APC = 0.389, $p<0.001$), with all hypotheses statistically validated. These results provide strong empirical support for the digital marketing literature and highlight the importance of integrating AI into consumer-centred marketing strategies.

From a practical standpoint, the conclusions of this study can be utilised by textile industry brands seeking to develop personalised marketing strategies based on intelligent algorithms. Effective personalisation, supported by transparent and trustworthy AI technologies, can strengthen customer relationships and increase conversion rates in the digital environment.

On a theoretical level, the study contributes to a better understanding of the complex relationships between technology, psychological perceptions, and consumer behaviour, offering an integrated and empirically tested conceptual framework within the Romanian market context.

Managerial implications

The findings highlight several strategic priorities for textile brands:

- Ensure algorithmic transparency by clearly informing users how recommendations are generated;
- Provide users with control options (opt-in personalisation, adjustable preferences, privacy settings);
- Avoid intrusive or overly persistent personalisation to protect user trust;
- Adapt AI communication styles based on consumers' digital literacy and adoption readiness;
- Leverage trust signals (explainable AI, secure data handling, GDPR compliance) to strengthen credibility.

Given the strong relationship between trust in AI and purchase intention ($\beta = 0.56$), small increases in trustworthiness can generate meaningful improvements in conversion rates for online textile retailers.

Limitations and future research directions

While the findings make a valuable contribution to the understanding of how artificial intelligence influences consumer behaviour in the context of digital marketing within the textile industry, several limitations should be acknowledged, and they offer directions for future research.

The first limitation concerns the non-probabilistic, convenience-based sample, which restricts the generalizability of the findings to the broader population. Although the sample size (N = 358) is appropriate for PLS-SEM analysis, future studies could benefit from larger, probabilistic samples to produce more representative results at national or international levels.

Additionally, as the sample is restricted to Romanian consumers, cultural and market-specific factors may influence generalizability to other countries. Future comparative studies across different European and international markets would provide a broader understanding of how cultural context shapes consumer responses to AI personalisation.

Secondly, the cross-sectional design of the study prevents the establishment of robust causal relationships over time. Longitudinal research could provide deeper insights into how consumer perceptions of AI evolve and how purchasing intentions change in response to technological developments.

Thirdly, the reliance on self-reported data introduces potential cognitive biases (e.g., social desirability, overestimation of AI familiarity). Future research should consider incorporating behavioural data (such as clickstream analytics, engagement metrics, or conversion funnels) to enhance objectivity and accuracy.

Another limitation is that the proposed model was tested exclusively within the textile sector. While this industry is highly relevant for the study of AI-driven personalisation, the findings may differ across other sectors such as FMCG, financial services, or digital tourism. Cross-industry comparisons could reveal important consumer differences in their receptiveness to intelligent technologies.

Future research directions include:

- Extending the conceptual model by incorporating new variables, such as privacy attitudes, information overload, perceived brand equity, or user experience (UX).
- Conducting cross-national comparisons of AI's effects in digital marketing to explore cultural differences in technology adoption.
- Integrating qualitative methods (e.g., in-depth interviews, discourse analysis) to gain a more nuanced understanding of trust and resistance toward AI.
- Experimentally testing different types of AI-driven personalisation (visual, textual, behavioural) to isolate their specific impact on purchasing decisions.

By addressing these avenues, future studies can deepen our understanding of the human–technology interaction in digital marketing and provide more effective strategies for brands aiming to optimise consumer engagement in online environments.

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