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Keywords: AI-powered personalized recommendations; competence trust; benevolence trust; product trust; purchase intention; online clothing e-commerce.

AI-Powered Personalized Recommendations and Purchase Intention in Online Clothing E-commerce: A Serial Trust-Transfer Mechanism

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ABSTRACT

AI-powered personalized recommendation systems are increasingly used in online retail, but their influence on purchase intention may depend on how consumers interpret recommendations and form trust. Drawing on the Stimulus–Organism–Response model, multidimensional trust, and Trust Transfer Theory, this study examines how perceived personalization (PP), perceived accuracy (PA), and perceived usefulness (PU) relate to purchase intention through competence trust (CT), benevolence trust (BT), and trust in recommended clothing products (TRP). A structured cross-sectional online survey of Chinese consumers with recent online clothing-purchase and personalized-recommendation experience yielded 500 valid responses from 512 collected questionnaires. Data were analyzed using SPSS 27.0 and AMOS 26.0. All six hypothesized direct paths were positive and significant: PP was associated with BT; PA and PU with CT; CT and BT with TRP; and TRP with purchase intention. Bias-corrected bootstrapping with 5,000 resamples supported all three serial indirect pathways from PP, PA, and PU to purchase intention through the corresponding system-trust dimension and TRP. The findings conceptualize the Organism component of S-O-R as a staged trust process and extend Trust Transfer Theory from AI systems to recommended physical products. They also suggest that platforms should combine relevant recommendations with credible product information.

1. INTRODUCTION

Artificial intelligence has moved rapidly from a back-end analytical technology to a consumer-facing component of contemporary retail. In e-commerce, AI-powered recommendation systems

now participate directly in information search, product screening, service interaction, and purchase decision-making. This transformation is particularly important because recommendation agents can reduce consumers' search and evaluation burdens by filtering large product assortments and presenting options that appear more relevant to individual users (Blut et al., 2023). More broadly, AI has become integral to marketing activities involving customer insight, service innovation, customer relationships, and market performance (Mustak et al., 2021), while consumer evaluations of AI are shaped not only by efficiency and predictive accuracy but also by the cognitive, emotional, and social experiences that arise during human–AI interaction (Puntoni et al., 2021). In fashion retail, the use of AI-supported customer models and recommendation systems has likewise expanded as firms attempt to translate behavioral data, personal preferences, and prior shopping activity into more individualized product suggestions (Pereira et al., 2022).

The online clothing context provides a particularly useful setting for examining these developments because apparel purchases involve substantial pre-purchase uncertainty. Unlike many standardized products, clothing is evaluated through attributes such as fit, visual appeal, style compatibility, material characteristics, and expected wearing performance, many of which cannot be fully verified before purchase in an online environment. Consumers therefore depend on indirect information such as images, descriptions, size information, user reviews, and digital assistance tools. Prior research on fashion e-commerce shows that consumers engage in information search, comparison, order adjustment, and other risk-management activities when purchasing apparel online (Sutinen et al., 2022). Garment fit is especially salient because the inability to physically try on clothing makes fit-related information an important component of consumers' product judgments (Chrimes et al., 2022). Perceived risk also remains an important contextual factor in explaining attitudes and purchase intentions in online apparel shopping (Patel et al., 2023).

AI-powered personalized recommendations can help consumers manage some of this information burden by screening products and identifying items that are more likely to match their interests or needs. However, technical sophistication does not guarantee consumer acceptance. A user-centered evaluation perspective on recommender systems emphasizes that objective algorithmic accuracy explains only part of users' experiences; subjective perceptions of recommendation quality, effectiveness, and the interaction process are also important for understanding acceptance (Knijnenburg et al., 2012). Research on trustworthy recommender

systems similarly indicates that inaccurate recommendations and insufficient explanations may weaken users' trust (Dong et al., 2022). Thus, the consumer's experience of whether a recommendation feels personalized, appears accurate, and is practically useful may be as important as the underlying algorithm itself.

Trust is especially central in this process because AI-powered recommendation environments involve at least two distinct objects of evaluation. The first is the AI recommendation system itself: consumers may judge whether the system is capable of performing recommendation tasks and whether it appears to take their interests into account. The second is the specific clothing product recommended by that system. Consumers do not ultimately purchase the algorithm; they purchase the recommended item. Accordingly, trust in the AI system and trust in the recommended product should not automatically be treated as the same psychological judgment. Multidimensional trust research shows that consumers can form different trusting beliefs, including competence and benevolence judgments (McKnight et al., 2002), and research on online recommendation agents suggests that consumers may extend these socially oriented trust judgments to technological agents (Wang & Benbasat, 2005).

This distinction becomes theoretically important when Trust Transfer Theory is considered. Trust Transfer Theory proposes that trust toward one source can shape trust judgments toward another target when consumers perceive a meaningful connection between the two (Stewart, 2003). In an AI recommendation context, the recommendation system can be conceptualized as the trust source and the recommended clothing product as the trust target. Recent evidence in AI marketing supports a related logic: Keng et al. (2025) found that trust in an AI avatar was positively associated with product trust, which was subsequently associated with purchase intention. Nevertheless, that work treated trust in the AI entity relatively broadly and did not distinguish competence trust from benevolence trust, nor did it focus on the uncertainty-rich context of online clothing recommendations.

A second research gap concerns the differentiated formation of system trust. Previous studies have shown that personalization, recommendation accuracy, and usefulness matter for consumers' evaluations of recommendation agents (Komiak & Benbasat, 2006; Nilashi et al., 2016; Wang & Benbasat, 2005). Yet these perceptions are conceptually distinct and should not be treated as a single higher-order scale. Personalization concerns whether the recommendation appears tailored to an individual; accuracy concerns whether the results match the consumer's interests and needs; usefulness concerns whether the system helps the consumer complete the

shopping task efficiently. These distinct experiences may provide different informational cues for trust. A personalized recommendation may signal that the system attends to the user's individual needs, whereas accurate and useful recommendations may provide evidence of the system's task-performing competence.

A third gap lies in the integration of these relationships into a continuous psychological mechanism. Existing research provides support for several separate stages: recommendation perceptions may be associated with trust in recommendation agents; trust may transfer across connected objects; and product trust may be associated with purchase intention. However, less is known about whether these stages form a complete serial process in which consumer perceptions of AI-powered recommendations are associated with system-level trust, then with trust in the recommended product, and finally with purchase intention. This issue is especially relevant to online clothing e-commerce, where consumers must evaluate both the technology that selects the product and the product itself under conditions of incomplete pre-purchase information.

To address these gaps, the present study integrates the Stimulus–Organism–Response (S-O-R) model, a multidimensional trust perspective, and Trust Transfer Theory. Perceived personalization (PP), perceived accuracy (PA), and perceived usefulness (PU) are positioned as three distinct technological stimuli. Competence trust (CT) and benevolence trust (BT) in the AI recommendation system represent the first layer of internal cognitive evaluation, while trust in recommended clothing products (TRP) represents a second trust layer directed toward a different object. Purchase intention (PI) is conceptualized as the behavioral intention response. The proposed mechanism therefore moves from a general S → O → R structure to a more specific S → O1 → O2 → R structure: AI recommendation perceptions → system trust → product trust → purchase intention.

The study contributes in three ways. First, it refines the S-O-R framework by distinguishing sequential trust judgments within the Organism component rather than treating internal trust as a single undifferentiated state. Second, it contributes to multidimensional trust research by linking different recommendation experiences to theoretically targeted dimensions of system trust: perceived personalization to benevolence trust, and perceived accuracy and usefulness to competence trust. Third, it extends Trust Transfer Theory to a consumer decision process in which trust may extend from an AI recommendation system as a technological source to a physical clothing product as the trust target, and then be embedded in purchase intention. These

contributions are tested using survey data from 500 Chinese consumers with actual experience of AI-powered personalized clothing recommendations.

2. Literature Review and Hypothesis Development

2.1 Theoretical background: S-O-R, multidimensional trust, and trust transfer

The theoretical integration is particularly relevant to online clothing e-commerce because the consumption context contains uncertainty at both the system and product levels. Consumers have incomplete information about how an AI recommendation system processes behavioral data and why particular products are selected, while they also face uncertainty about whether the recommended apparel will fit, look, and perform as expected. Fashion e-commerce research shows that consumers actively manage these uncertainties through information search, comparison, order adjustment, and other compensatory behaviors (Sutinen et al., 2022). Fit information is especially consequential because the consumer cannot physically try on an item before purchase (Chrimes et al., 2022). These contextual characteristics make it possible for trust in the technological intermediary and trust in the physical product to develop as related but distinct judgments.

The distinction also reflects a broader shift in recommender-system research from purely technical evaluation toward user-centered evaluation. Earlier work often emphasized objective prediction performance, but consumer acceptance is shaped by the way recommendation outputs are experienced and interpreted. Knijnenburg et al. (2012) argue that objective system characteristics and subjective user experience should be analytically distinguished because users respond to the recommendation experience available to them, not to technical metrics that they cannot directly observe. This distinction is important for the present study. Perceived personalization, perceived accuracy, and perceived usefulness are not measures of the algorithm itself; they are consumer-level interpretations of what the system does during a real shopping episode. Positioning these perceptions at the Stimulus level therefore keeps the model focused on observable and reportable experiences rather than on inaccessible technical properties.

Applications of the S-O-R framework in digitally mediated retail also support the use of trust as an internal state. Zhu et al. (2023) show that AI-based services can operate as technological stimuli whose effects on consumer responses depend on intervening evaluations of the digital environment. Shahzad et al. (2024), in a luxury-fashion chatbot context, similarly position AI service quality as an external stimulus and trust-related evaluations as important internal states associated with subsequent brand outcomes. Silva et al. (2023) further demonstrate that trust and

risk perceptions are closely involved in consumer responses to e-retailing chatbots. Together, these studies suggest that AI-related technological experiences can be meaningfully conceptualized as stimuli while trust-related judgments function as mechanisms that connect those experiences with later behavioral intentions.

At the same time, the multidimensional trust perspective prevents the Organism component from becoming overly broad. Competence and benevolence represent different reasons for trusting a system. A consumer may believe that a recommendation system is highly capable of processing information but question whether it prioritizes the user's interests; conversely, a system may appear user-oriented without being perceived as sufficiently capable. The present model therefore avoids collapsing system trust into a single score. Integrity trust, although included in the broader typology of McKnight et al. (2002), is not included in the final model because the study focuses on dimensions that consumers can more directly infer from front-end recommendation experiences and because a parsimonious structure is needed to test the differentiated antecedents. This exclusion should be understood as a contextual modeling decision rather than as evidence that integrity is unimportant in AI trust.

Trust Transfer Theory then clarifies why product trust is positioned as a second Organism state rather than as another indicator of system trust. The recommended item is a different evaluation target with different sources of uncertainty. Consumers can use the system's recommendation as a cue when forming product judgments, yet they must still decide whether the item itself is likely to satisfy their needs. In this sense, trust transfer is not conceptualized as a complete substitution of one judgment for another. Instead, the system-level judgment becomes one input into product-level evaluation. This theoretical separation is essential for online clothing because the product remains materially uncertain even after the consumer accepts the recommendation process. The S-O-R model, multidimensional trust, and Trust Transfer Theory therefore address complementary parts of the same decision process: what consumer's experience, how they evaluate the system, how that evaluation extends to the product, and how product trust is associated with purchase intention.

The S-O-R model originates from environmental psychology and proposes that environmental stimuli influence behavioral responses through internal cognitive or affective states (Mehrabian & Russell, 1974). In consumer and digital-service research, the model provides a flexible structure for explaining how technological characteristics are translated into subsequent behavioral intentions through consumers' internal evaluations. In AI-enabled retail, this logic is

especially useful because consumers are exposed to observable system outputs rather than the underlying algorithmic process. AI service characteristics can therefore function as external stimuli, while trust and related cognitive judgments can be conceptualized as Organism states that connect technological experiences with behavioral responses (Shahzad et al., 2024; Silva et al., 2023; Zhu et al., 2023).

In the present study, perceived personalization, perceived accuracy, and perceived usefulness are treated as independent S-level perceptions because they reflect different consumer judgments about the recommendation experience. Competence trust and benevolence trust are positioned as system-level O1 states, while trust in recommended clothing products forms a second O2 state directed toward a distinct object. Purchase intention represents the R-level behavioral intention. This specification retains the overall logic of S-O-R while allowing the Organism component to contain an internal sequence of trust judgments.

The multidimensional trust perspective provides the basis for separating competence trust from benevolence trust. McKnight et al. (2002) conceptualized trusting beliefs in e-commerce as multidimensional, including competence, benevolence, and integrity. Competence refers to the belief that the trustee possesses the ability and expertise required to perform relevant tasks, whereas benevolence refers to the belief that the trustee cares about the user's interests and is willing to act in a user-oriented manner. Wang and Benbasat (2005) further showed that consumers can form comparable trust judgments toward online recommendation agents. In the present context, competence trust reflects whether consumers believe that an AI recommendation system is capable and professional in carrying out clothing recommendation tasks, while benevolence trust reflects whether consumers believe the system considers their genuine needs and interests.

Trust Transfer Theory adds a cross-object mechanism to this structure. Stewart (2003) argues that trust toward a relatively unfamiliar target can be influenced by pre-existing trust in a connected source. In the current setting, the AI recommendation system functions as the trust source because it identifies, screens, and presents products, while the recommended clothing item functions as the trust target because it is the object consumers may ultimately purchase. This distinction is important because consumers may trust the system's capabilities without necessarily believing that every product it recommends will satisfy their needs. Trust transfer therefore provides a theoretical explanation for how system-level trust may become associated with product-level trust.

2.2 AI recommendation perceptions and system trust

2.2.1 Perceived personalization and benevolence trust

Perceived personalization refers to the extent to which consumers believe that a recommendation system understands and responds to their individual needs, interests, and preferences. In recommendation-agent research, personalization increases the degree to which consumers perceive recommendations as tailored to them and can strengthen trust-related responses (Komiak & Benbasat, 2006). In online clothing shopping, personalization is experienced through recommendations that appear to reflect a consumer's browsing history, style interests, purchase records, or current needs rather than providing identical content to all users.

The connection between personalization and benevolence trust is grounded in the meaning of benevolence. Benevolence trust concerns whether the system is perceived as taking the user's interests into account (McKnight et al., 2002). When recommendations appear closely tailored to the consumer's actual clothing preferences and shopping needs, consumers may interpret this experience not only as evidence that the system has access to relevant information but also as an indication that the system is responding to them as an individual. This can reduce the perception that recommendations are merely generic promotional messages and may strengthen the belief that the system is oriented toward helping the user make an appropriate choice. Although Komiak and Benbasat (2006) did not directly test the specific PP → BT path used here, their findings provide a foundation for linking personalization to trust in recommendation agents. Accordingly, the present study proposes a theoretically targeted relationship between perceived personalization and benevolence trust.

H1. Perceived personalization is positively associated with consumers' benevolence trust in AI recommendation systems.

2.2.2 Perceived accuracy and competence trust

Perceived accuracy reflects the consumer's subjective judgment that recommendation results match personal interests, preferences, and current needs. It is distinct from objective algorithmic accuracy because consumers evaluate only the recommendations they actually encounter. For recommendation systems, producing relevant results is a core task; consequently, perceived match quality provides directly observable evidence from which consumers can infer whether the system is capable of identifying needs and screening appropriate products.

Nilashi et al. (2016) identified recommendation accuracy as an important component of recommendation quality and linked recommendation quality to trust in recommendation agents.

More recent work on AI digital agents similarly shows that quality and capability evaluations can be related to cognitive trust (Pathak & Bansal, 2024). In online clothing shopping, when recommended items consistently match consumers' style preferences, interests, and current needs, consumers may attribute this performance to the system's ability to process information and perform recommendation tasks effectively. Perceived accuracy should therefore provide a basis for competence-oriented trust judgments.

H2. Perceived accuracy is positively associated with consumers' competence trust in AI recommendation systems.

2.2.3 Perceived usefulness and competence trust

Perceived usefulness refers to the extent to which consumers believe that using a recommendation system improves shopping-task performance. In this study, usefulness concerns whether the AI recommendation system helps consumers find suitable clothing more quickly, screen and evaluate product information more efficiently, and complete product-search tasks with less effort. This construct therefore emphasizes functional decision support rather than recommendation-match quality alone.

Perceived usefulness is a central construct in technology-adoption research and has also been examined in recommendation-agent settings. Wang and Benbasat (2005) identified perceived usefulness and trust as important cognitive factors in consumers' acceptance of online recommendation agents, while Acharya et al. (2023) incorporated usefulness into a framework explaining trust and reuse intentions toward recommender systems. Nevertheless, the specific relationship between perceived usefulness and competence trust has received less direct examination. From a theoretical standpoint, competence trust concerns whether a system possesses the practical capability needed to perform the recommendation task. If consumers experience the system as reducing search time, improving screening efficiency, and helping them evaluate clothing alternatives, these outcomes provide experiential cues that the system is capable of performing its task effectively.

H3. Perceived usefulness is positively associated with consumers' competence trust in AI recommendation systems.

2.3 System trust and trust in recommended clothing products

Trust Transfer Theory suggests that trust can extend across connected objects when the relationship between the source and target is salient (Stewart, 2003). In AI-powered personalized shopping, the relationship is explicit: the recommendation system screens and presents products,

while the consumer evaluates those products partly because the system selected them. This creates a plausible basis for system-level trust to be associated with product-level trust.

Competence trust should be especially relevant because consumers may rely on the perceived capability of the system when evaluating whether a recommended product is suitable. If the recommendation system is viewed as professional and effective in identifying needs and filtering products, its recommendations may carry greater informational credibility. Under the uncertainty of online clothing shopping, where fit and actual product performance cannot be fully verified before purchase, confidence in the system's task competence may therefore be associated with stronger trust in the specific product it recommends. Keng et al. (2025) provide general empirical support for this logic by showing that trust in an AI entity can be associated with product trust.

H4a. Consumers' competence trust in AI recommendation systems is positively associated with their trust in recommended clothing products.

Benevolence trust may also extend to product-level evaluations. When consumers believe that the recommendation system genuinely considers their needs rather than simply serving the platform's short-term sales objectives, they may be more willing to regard the system's product selections as user-oriented. A recommendation from a system perceived as benevolent may therefore reduce uncertainty about the motive behind the recommendation and strengthen consumers' belief that the recommended product is appropriate for them. This logic is consistent with the general trust-transfer principle that trust in a source can shape judgments of a connected target (Stewart, 2003).

H4b. Consumers' benevolence trust in AI recommendation systems is positively associated with their trust in recommended clothing products.

2.4 Trust in recommended clothing products and purchase intention

Trust in recommended clothing products refers to the consumer's confidence that a specific recommended item can meet actual needs and deliver reliable product performance. This construct is deliberately separated from system trust. A consumer may believe that an AI recommendation system performs well while still being uncertain about the fit, quality, or suitability of a particular item. The product-level trust judgment is therefore closer to the final purchase decision.

Product trust should be especially important in online clothing e-commerce because consumers cannot fully verify fit, appearance, and performance before purchase. Keng et al. (2025) found a significant positive relationship between product trust and purchase intention in an AI marketing

context. More generally, trust reduces perceived uncertainty and supports transaction-related decisions in e-commerce (McKnight et al., 2002). When consumers believe that a recommended clothing item can satisfy their needs and has the attributes necessary to perform as expected, purchase-related hesitation should be reduced and purchase intention should be stronger.

H5. Consumers' trust in recommended clothing products is positively associated with their purchase intention.

2.5 Serial indirect relationships

The direct hypotheses together form a progressive mechanism that integrates the S-O-R model with Trust Transfer Theory. Consumers first interpret observable recommendation experiences as technological stimuli. These perceptions are associated with system-level trust judgments, which are then associated with trust in the specific products selected by the system. Product trust, in turn, is associated with purchase intention. Prior studies support individual stages of this chain: personalization is related to trust in recommendation agents (Komiak & Benbasat, 2006); recommendation accuracy and quality are linked to trust (Nilashi et al., 2016); usefulness is associated with trust and continued use of recommender systems (Acharya et al., 2023; Wang & Benbasat, 2005); trust can transfer between connected objects (Stewart, 2003); and trust in an AI entity can be associated with product trust and purchase intention (Keng et al., 2025).

However, the three complete serial pathways proposed here have not been directly tested in the same model and context. The present study therefore treats the serial effects as a theoretical integration of previously supported relationships rather than as a replication of an established serial model. For perceived personalization, a tailored recommendation should strengthen benevolence trust, which should be associated with trust in the recommended product and ultimately with purchase intention. For perceived accuracy and perceived usefulness, the recommendation experience should strengthen competence trust, which should likewise be associated with product trust and purchase intention.

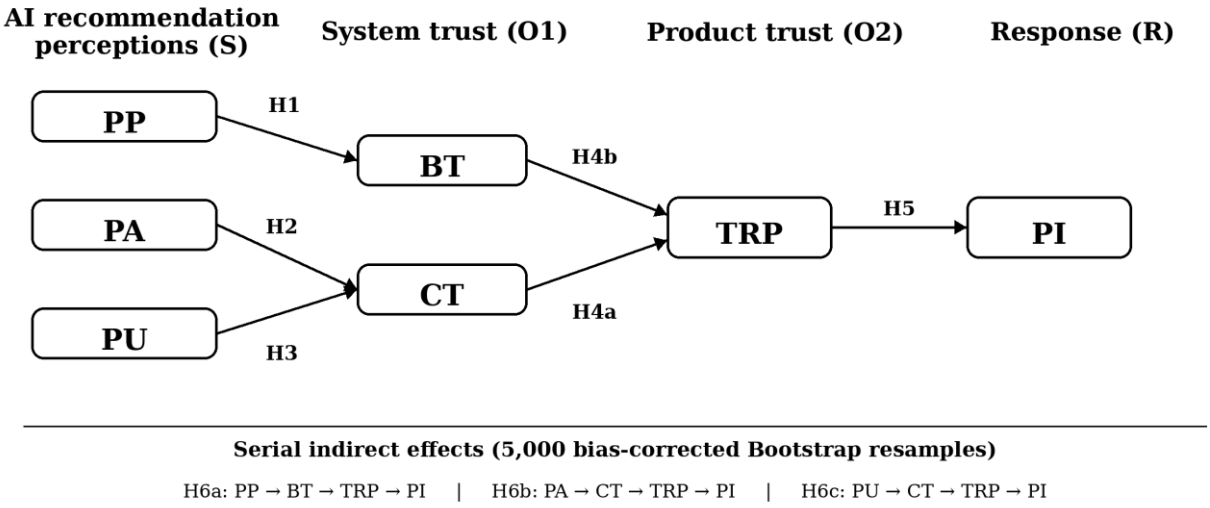
H6a. Perceived personalization has a significant serial indirect relationship with purchase intention through benevolence trust and trust in recommended clothing products (PP → BT → TRP → PI).

H6b. Perceived accuracy has a significant serial indirect relationship with purchase intention through competence trust and trust in recommended clothing products (PA → CT → TRP → PI).

H6c. Perceived usefulness has a significant serial indirect relationship with purchase intention through competence trust and trust in recommended clothing products (PU → CT → TRP → PI).

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Figure 1. Proposed research model



Note. PP = perceived personalization; PA = perceived accuracy; PU = perceived usefulness; BT = benevolence trust; CT = competence trust; TRP = trust in recommended clothing products; PI = purchase intention. Direct paths: PP → BT (H1), PA → CT (H2), PU → CT (H3), CT → TRP (H4a), BT → TRP (H4b), and TRP → PI (H5). H6a–H6c denotes the three serial indirect pathways.

3. Research Methodology

3.1 Research design and target population

The study adopted a positivist, quantitative, cross-sectional explanatory design. A structured self-administered online questionnaire was used to examine the theoretically specified relationships among the seven latent constructs. Because cross-sectional self-report data do not establish strict temporal precedence, the structural paths are interpreted as theoretically specified statistical associations and serial indirect relationships rather than definitive causal effects.

The target population comprised consumers aged 18 years or older who had purchased clothing through major e-commerce platforms in China within the previous six months and who had actual experience with AI-powered personalized clothing recommendations during their most recent online clothing shopping experience. Respondents were also required to recall one specific clothing product from the personalized recommendation that they had actually clicked to view or seriously considered purchasing. These screening criteria were used to ensure that the evaluations of the AI recommendation system and the recommended product were based on a concrete and recent consumption experience rather than general attitudes toward AI.

3.2 Questionnaire design, contextual anchoring, and measures

The final measurement model consisted of seven first-order latent variables: perceived personalization, perceived accuracy, perceived usefulness, competence trust, benevolence trust, trust in recommended clothing products, and purchase intention. A total of 22 core measurement items were measured on seven-point Likert scales ranging from 1 (strongly disagree) to 7 (strongly agree), together with one attention-check item used exclusively for data-quality control. The attention-check item was not included in latent-variable scoring or SEM analysis.

Established scales were prioritized and adapted to the context of AI-powered personalized clothing recommendations. Perceived personalization was adapted primarily from Komiak and Benbasat (2006), perceived accuracy from Nilashi et al. (2016), and perceived usefulness from Wang and Benbasat (2005). Competence trust and benevolence trust were adapted from the multidimensional trust measures of McKnight et al. (2002). Trust in recommended clothing products was adapted from Jeon et al. (2021), and purchase intention was adapted from the willingness-to-buy measures developed by Dodds et al. (1991). The semantic object of each item was modified to fit the online clothing recommendation context while retaining the conceptual meaning of the original scale.

A two-stage contextual anchoring procedure was used to reduce ambiguity in the evaluation object. In the first stage, respondents recalled their most recent online clothing shopping experience within the previous six months and identified one e-commerce platform and one AI-powered personalized clothing recommendation they had actually browsed or clicked. Perceived personalization, accuracy, usefulness, competence trust, and benevolence trust were all evaluated with reference to this same recommendation experience. In the second stage, before answering the product-trust and purchase-intention items, respondents identified one specific clothing product from the recommendation that they had actually clicked to view or seriously considered purchasing. All TRP and PI items referred to this same product. This design ensured that system-level trust and product-level trust were directed toward clearly defined and distinct objects, while product trust and purchase intention shared the same product target.

The questionnaire defined AI-powered personalized recommendations as clothing-product recommendations generated and presented by an e-commerce platform on the basis of individual information such as browsing, search, click, favorite, shopping-cart, purchase-history, or interest-preference data. General best-seller a ranking, a standardized promotional recommendation visible to all users, and general similar-product or cross-selling displays that did not reflect

individual behavioral or preference information was excluded from the definition. The formal questionnaire also avoided displaying theoretical construct labels to respondents in order to reduce potential cueing effects.

Because the original scales were drawn primarily from English-language studies, the measurement development process also emphasized semantic traceability. Original English items and construct definitions were checked against their direct literature sources before translation and contextual adaptation. The wording was then adjusted to refer explicitly to AI-powered clothing recommendations while preserving the core conceptual meaning of each construct. Supervisor feedback and cognitive feedback from pilot respondents were used to further examine clarity and contextual appropriateness. This procedure was intended to reduce the risk that translation or contextual adaptation would change the underlying meaning of the constructs.

The survey also incorporated procedural safeguards relevant to research ethics and response quality. Participation was voluntary and anonymous, and respondents were informed that the data would be used only for academic analysis. No personally identifying information was required. Screening questions ensured that respondents were adults and met the relevant shopping-experience criteria before proceeding to the core items. The use of a recent, concrete shopping episode and a specific recommended product also reduced the likelihood that participants would answer on the basis of generalized attitudes toward AI. These design choices were important because the model depends on maintaining clear distinctions between perceptions of the recommendation experience, trust in the AI system, and trust in the product selected by that system.

Table 1. Measurement constructs and primary sources

Construct	Items	Primary source
Perceived personalization (PP)	3	Komiak & Benbasat (2006)
Perceived accuracy (PA)	3	Nilashi et al. (2016)
Perceived usefulness (PU)	3	Wang & Benbasat (2005)
Competence trust (CT)	3	McKnight et al. (2002)
Benevolence trust (BT)	3	McKnight et al. (2002)
Trust in recommended clothing products (TRP)	4	Jeon et al. (2021)
Purchase intention (PI)	3	Dodds et al. (1991)

3.3 Pilot study and data collection

Before formal data collection, a pilot study was conducted to assess item comprehensibility, internal consistency, and potentially problematic items. The pilot analysis included 57 valid questionnaires. Cronbach's alpha coefficients for the seven constructs ranged from 0.843 to

0.907, and corrected item–total correlations ranged from 0.684 to 0.832. No core item was removed on the basis of the pilot results, and the final questionnaire retained the seven constructs and 22 core measurement items.

The questionnaire was created using an online questionnaire platform and distributed through the researcher's existing online channels. Because a complete sampling frame of Chinese online clothing consumers was unavailable, convenience sampling, a non-probability sampling method, was adopted. Screening questions were used to identify eligible respondents. Duplicate-response prevention mechanisms were activated, and response quality was assessed using eligibility, attention-check performance, response time, patterned or straight-line responding, duplicate-response indicators, and other signs of abnormal response behavior.

A total of 512 questionnaires were collected in the formal survey. After data-quality screening, 500 valid responses were retained for analysis. The final sample exceeded the study's prior planning target and provided an adequate basis for CFA, SEM, and bootstrap testing of the serial indirect effects.

Sample-size planning followed the respondent-to-item ratio as an empirical guideline. Following Hair et al. (2010), this study adopted a 20:1 ratio for the 22 core measurement items, resulting in a planned minimum of 440 valid responses. The attention-check item was excluded because it was used solely for data-quality screening and did not measure a latent construct. The final sample of 500 valid responses exceeded the planned target and was used for descriptive analysis, confirmatory factor analysis (CFA), structural equation modeling (SEM), and Bootstrap testing of the serial indirect effects.

Data-quality screening was designed to ensure that the retained responses reflected genuine engagement with the questionnaire. Eligibility conditions were applied at the beginning of the survey so that respondents who were under 18, had not purchased clothing online within the preceding six months, or could not confirm actual exposure to personalized clothing recommendations did not proceed to the core measurement section. In addition, the questionnaire included an explicit attention-check item, and the data-cleaning stage considered response time, patterned responding, straight-lining, and other abnormal response behaviors. The attention-check item was used only as a screening device and was excluded from construct scoring and the measurement and structural models. These procedures were intended to strengthen the credibility of the final analytical sample without altering the substantive constructs being tested.

3.4 Data analysis

SPSS 27.0 and AMOS 26.0 were used for data analysis. First, descriptive statistics were used to examine sample characteristics and the distribution of the observed items. Internal consistency was assessed using Cronbach's alpha. A seven-factor first-order confirmatory factor analysis was then estimated in AMOS to examine measurement-model fit. Convergent validity was evaluated using standardized factor loadings, composite reliability (CR), and average variance extracted (AVE), while discriminant validity was assessed using the Fornell–Larcker criterion (Fornell & Larcker, 1981).

Common method bias was assessed through both procedural and statistical approaches. Procedurally, anonymity, neutral wording, contextual anchoring, and moderate item-order adjustment were used to reduce method-related response tendencies. Statistically, Harman's single-factor test was used as a preliminary diagnostic, followed by a Common Latent Factor (CLF) sensitivity analysis in AMOS in line with broader recommendations on method-bias assessment (Podsakoff et al., 2003, 2012).

After establishing acceptable measurement quality, the structural equation model was estimated in AMOS. Model fit was evaluated using multiple indices, including chi-square/degrees of freedom (χ^2/df), RMSEA, SRMR, CFI, TLI, and IFI, supplemented by GFI, AGFI, NFI, and RFI. Direct paths were evaluated using standardized coefficients, critical ratios, and p-values. The three serial indirect effects were tested using 5,000 bias-corrected bootstrap resamples; an indirect effect was considered statistically significant when its 95% bias-corrected confidence interval excluded zero.

4. Results

4.1 Sample profile and descriptive results

The final sample comprised 500 valid respondents. The gender distribution was nearly balanced, with 246 males (49.2%) and 254 females (50.8%). Respondents aged 26–35 constituted the largest age group (36.4%), followed by those aged 36–45 (27.4%), 18–25 (19.8%), and 46 or older (16.4%). Nearly half of the respondents held a bachelor's degree (46.2%), while 24.8% held a junior college qualification, 18.4% had a high-school/technical-secondary education or below, and 10.6% held a master's degree or above. The largest monthly disposable-income group was RMB 2,001–5,000 (32.6%), followed by RMB 5,001–8,000 (27.2%). Regarding online clothing purchase frequency, 46.2% reported purchasing once or less and 32.0% reported purchasing two to three times. The sample therefore showed diversity across age, education,

income, and purchase-frequency categories, although the use of non-probability sampling means that these proportions should not be interpreted as representative of all Chinese online clothing consumers.

Across the 22 core measurement items, all 500 cases were valid and no missing values were observed. Item means ranged from 4.00 to 4.31 on the seven-point scale, and standard deviations ranged from 1.472 to 1.600. Skewness values ranged from −0.268 to −0.022 and kurtosis values from −0.701 to −0.383, indicating no evidence of severe univariate skewness or kurtosis.

Table 2. Demographic profile of the formal sample (N = 500)

Variable	Category	n	%
Age	18–25	99	19.8
Age	26–35	182	36.4
Age	36–45	137	27.4
Age	46 or above	82	16.4
Gender	Male	246	49.2
Gender	Female	254	50.8
Education	High school/technical or below	92	18.4
Education	Junior college	124	24.8
Education	Bachelor's degree	231	46.2
Education	Master's degree or above	53	10.6
Monthly disposable income	≤ RMB 2,000	61	12.2
Monthly disposable income	RMB 2,001–5,000	163	32.6
Monthly disposable income	RMB 5,001–8,000	136	27.2
Monthly disposable income	RMB 8,001–12,000	100	20.0
Monthly disposable income	> RMB 12,000	40	8.0
Purchase frequency	Once or less	231	46.2
Purchase frequency	2–3 times	160	32.0
Purchase frequency	4–5 times	75	15.0
Purchase frequency	6 times or more	34	6.8

4.2 Reliability, measurement model, and construct validity

Cronbach's alpha coefficients for all seven constructs exceeded 0.80: PP = 0.840, PA = 0.860, PU = 0.850, CT = 0.850, BT = 0.848, TRP = 0.880 and PI = 0.862. These results indicate satisfactory internal consistency.

The seven-factor CFA model also demonstrated satisfactory overall fit: $\chi^2 = 196.596$, df = 188, p = .319, $\chi^2/df = 1.046$, GFI = 0.965, AGFI = 0.953, NFI = 0.965, RFI = 0.958, IFI = 0.998, TLI =

0.998, CFI = 0.998, and RMSEA = 0.010 (90% CI [0.000, 0.022], PCLOSE = 1.000). Standardized factor loadings ranged from 0.760 to 0.875. Composite reliability values ranged from 0.840 to 0.881, and AVE values ranged from 0.637 to 0.677. These results support convergent validity.

Discriminant validity was assessed using the Fornell–Larcker criterion. The square roots of AVE for PP, PA, PU, CT, BT, TRP, and PI were 0.798, 0.820, 0.809, 0.811, 0.809, 0.806, and 0.823, respectively. Each value exceeded the corresponding inter-construct correlations. The highest observed correlation was between TRP and PI (r = 0.606), which remained below the square roots of AVE for both constructs. The seven constructs were therefore empirically distinguishable from one another.

Table 3. Reliability and convergent validity

Construct	Cronbach's α	CR	AVE	Loading range
PP	0.840	0.840	0.637	0.770–0.825
PA	0.860	0.860	0.673	0.804–0.847
PU	0.850	0.851	0.655	0.790–0.836
CT	0.850	0.852	0.658	0.760–0.875
BT	0.848	0.850	0.654	0.776–0.871
TRP	0.880	0.881	0.650	0.785–0.843
PI	0.862	0.863	0.677	0.787–0.841

4.3 Common method bias

Harman's single-factor test extracted seven factors with eigenvalues greater than 1, explaining 76.868% of total variance. The first unrotated factor explained 26.219%. Because Harman's test alone cannot establish the absence of method bias, a CLF sensitivity analysis was also conducted. The baseline CFA model produced $\chi^2/df = 1.046$, CFI = 0.998, TLI = 0.998, IFI = 0.998, and RMSEA = 0.010, while the CLF model produced $\chi^2/df = 1.051$, CFI = 0.998, TLI = 0.998, IFI = 0.998, and RMSEA = 0.010. The CLF variance was 0.004 and non-significant (p = .982), and standardized CLF loadings were approximately 0.040–0.043. Taken together, the analyses provided no evidence that severe common method bias exerted a substantive influence on the results.

4.4 Structural model and direct hypothesis tests

The main structural model demonstrated a satisfactory fit to the formal sample: $\chi^2 = 210.831$, df = 200, p = .286, $\chi^2/df = 1.054$, GFI = 0.963, AGFI = 0.953, NFI = 0.963, RFI = 0.957, IFI = 0.998, TLI = 0.998, CFI = 0.998, RMSEA = 0.010 (90% CI [0.000, 0.022]), and SRMR = 0.0328. These indices supported examination of the structural paths.

All six direct paths were positive and statistically significant. Perceived personalization was positively associated with benevolence trust (β = 0.365, p < .001), supporting H1. Perceived accuracy was positively associated with competence trust (β = 0.274, p < .001), supporting H2, and perceived usefulness was positively associated with competence trust (β = 0.265, p < .001), supporting H3. Competence trust was positively associated with trust in recommended clothing products (β = 0.407, p < .001), supporting H4a, while benevolence trust was also positively associated with product trust (β = 0.395, p < .001), supporting H4b. Finally, trust in recommended clothing products was positively associated with purchase intention (β = 0.611, p < .001), supporting H5. This final path had the largest standardized coefficient among the six direct relationships.

The structural model explained 13.3% of the variance in benevolence trust (R^2 = 0.133), 18.7% of the variance in competence trust (R^2 = 0.187), 33.4% of the variance in trust in recommended clothing products (R^2 = 0.334), and 37.3% of the variance in purchase intention (R^2 = 0.373). Thus, the model accounted for approximately one-third of the variance in product trust and more than one-third of the variance in purchase intention.

Table 4. Direct structural paths and hypothesis tests

Hyp.	Path	B	S.E.	β	C.R.	p	Result
H1	PP → BT	0.371	0.055	0.365	6.794	< .001	Supported
H2	PA → CT	0.261	0.050	0.274	5.235	< .001	Supported
H3	PU → CT	0.266	0.053	0.265	5.025	< .001	Supported
H4a	CT → TRP	0.442	0.052	0.407	8.546	< .001	Supported
H4b	BT → TRP	0.428	0.052	0.395	8.272	< .001	Supported
H5	TRP → PI	0.629	0.051	0.611	12.337	< .001	Supported

4.5 Serial indirect effects

The three serial indirect effects were tested using 5,000 bias-corrected bootstrap resamples. The PP → BT → TRP → PI pathway was significant (B = 0.100, bootstrap S.E. = 0.019, standardized indirect effect = 0.088, 95% BC CI [0.065, 0.143], p < .001), supporting H6a. The PA → CT → TRP → PI pathway was also significant (B = 0.072, bootstrap S.E. = 0.018, standardized indirect effect = 0.068, 95% BC CI [0.041, 0.112], p < .001), supporting H6b. The PU → CT → TRP → PI pathway was significant as well (B = 0.074, bootstrap S.E. = 0.018, standardized indirect effect = 0.066, 95% BC CI [0.043, 0.112], p < .001), supporting H6c. None of the three confidence intervals included zero.

Table 5. Serial indirect effects

Hyp.	Serial path	B	Boot SE	Std. indirect	95% BC CI	p	Result
H6a	PP → BT → TRP → PI	0.100	0.019	0.088	[0.065, 0.143]	< .001	Supported
H6b	PA → CT → TRP → PI	0.072	0.018	0.068	[0.041, 0.112]	< .001	Supported
H6c	PU → CT → TRP → PI	0.074	0.018	0.066	[0.043, 0.112]	< .001	Supported

5. Discussion

5.1 Formation of system trust from AI recommendation perceptions

The first set of findings shows that the three recommendation perceptions were positively associated with the theoretically targeted dimensions of system trust. Perceived personalization was associated with benevolence trust, while perceived accuracy and perceived usefulness were associated with competence trust. These findings support the proposition that consumers' trust in AI recommendation systems is not necessarily a single homogeneous judgment. Instead, different recommendation experiences appear to provide different cues for evaluating the system.

The positive relationship between perceived personalization and benevolence trust is broadly consistent with the direction of prior research showing that personalization can strengthen trust-related responses toward recommendation agents (Komiak & Benbasat, 2006). The present study adds specificity by linking personalization to a benevolence-oriented trust judgment. When consumers feel that clothing recommendations are tailored to their individual preferences and needs, they may interpret the system as being more attentive to their interests. This is conceptually different from simply believing that the system is technically capable. The finding therefore provides a more fine-grained account of how personalization may be psychologically interpreted in AI-assisted shopping.

The positive association between perceived accuracy and competence trust is likewise consistent with Nilashi et al. (2016), who identified recommendation accuracy as an important component of recommendation quality related to trust formation. In the present context, a recommendation that matches consumers' interests and current needs provides observable evidence of the system's capability to identify needs and screen products. The result therefore supports the idea that perceived match quality is not only an outcome evaluation but also a cue for judging system competence.

Perceived usefulness was also positively associated with competence trust. This finding is broadly consistent with work emphasizing the joint importance of usefulness and trust in

recommendation-agent adoption (Wang & Benbasat, 2005) and with more recent evidence connecting usefulness, trust, and reuse intentions in recommender systems (Acharya et al., 2023). However, the specific PU → CT relationship has received less direct attention. The present result suggests that usefulness can function as experiential evidence of task-performing capability: when the AI system helps consumers search, screen, and evaluate clothing more efficiently, consumers are more likely to regard it as competent.

5.2 Trust transfer from the AI system to recommended products

The second set of findings concerns cross-object trust. Both competence trust and benevolence trust were positively associated with trust in the recommended clothing products. This pattern is consistent with Trust Transfer Theory, which proposes that trust in one source can shape trust judgments toward a connected target (Stewart, 2003). It is also compatible with prior e-commerce research that incorporates product trust into broader trust structures (Jeon et al., 2021) and with evidence that trust in an AI entity can be associated with product trust (Keng et al., 2025).

The present study extends this literature in two important respects. First, it differentiates the source-side trust judgment into competence trust and benevolence trust rather than relying on a general measure of AI trust. The significant CT → TRP path indicates that consumers who believe the recommendation system is capable and professional are more likely to trust the products it selects. The significant BT → TRP path indicates that believing the system takes users' interests into account is also associated with stronger product trust. Thus, both capability-based and intention-based trust judgments may participate in the extension of trust from the recommendation system to the recommended product.

Second, the study focuses on online clothing, where cross-object trust is especially salient. Consumers cannot fully verify fit, material feel, or actual product performance before purchase. Consequently, the system's recommendation becomes part of the informational environment through which product suitability is judged. This does not mean that trusting the system automatically guarantees trust in every recommended item. Rather, the findings indicate a statistically significant association between the two levels of trust while maintaining their conceptual distinction.

5.3 Product trust and purchase intention

Trust in recommended clothing products showed the strongest direct association in the model, with a standardized coefficient of 0.611 for TRP → PI. This result is consistent with Keng et al.

(2025), who found that product trust was positively associated with purchase intention in an AI-related marketing setting. It also reinforces the practical importance of distinguishing system trust from product trust. Consumers ultimately purchase the clothing item rather than the AI system, so the final trust judgment closest to the purchase decision concerns whether the specific recommended product can meet their needs and perform reliably.

The magnitude of the TRP → PI relationship suggests that system-level trust alone does not fully explain purchase intention. Even a highly trusted recommendation system must still help consumers reach a positive judgment about the recommended product itself. In online apparel, this transition is especially consequential because uncertainty about size, fit, style compatibility, and material performance persists even after the system has selected an item. Product trust therefore appears to be an important psychological bridge between trust in the technology and purchase-related intention.

5.4 Serial trust mechanism

The three significant serial indirect effects provide the clearest evidence for the integrated mechanism proposed in this study. Perceived personalization was indirectly associated with purchase intention through benevolence trust and product trust, while perceived accuracy and perceived usefulness were indirectly associated with purchase intention through competence trust and product trust. These results connect relationships that prior studies have often examined separately into one continuous process: recommendation perceptions → system trust → product trust → purchase intention.

This mechanism is broadly consistent with the evidence available at different stages of the process. Komiak and Benbasat (2006), Nilashi et al. (2016), and Wang and Benbasat (2005) provide foundations for linking recommendation perceptions with trust and acceptance of recommendation agents. Stewart (2003) provides the theoretical basis for trust transfer, while Keng et al. (2025) provide relatively direct evidence for the sequence from AI trust to product trust and purchase intention. The present study does not claim that personalization, accuracy, usefulness, trust, or purchase intention is novel constructs. Its contribution lies instead in integrating these previously separated relationships into three theoretically differentiated serial pathways and testing them in the online clothing recommendation context.

The results also offer a mechanism-based interpretation of AI recommendations. Consumers do not appear to respond only to the presence of AI or to an abstract evaluation of algorithm quality. Rather, they evaluate specific recommendation experiences, form trust judgments about the

system, extend those judgments to the recommended product, and then form purchase intention. This layered process helps explain why AI recommendation performance can be commercially ineffective when consumers do not trust either the system or the product it presents.

5.5 Theoretical implications

The first theoretical implication concerns the S-O-R model. The findings support a more differentiated conceptualization of the Organism component. Instead of representing Organism as a single trust state, the present model distinguishes system trust (O1) from product trust (O2). This produces a progressive S → O1 → O2 → R structure. Such a specification is useful in consumption settings where consumers interact with a technological intermediary that selects or recommends a separate physical product. In these settings, the consumer's internal evaluation may evolve through multiple trust objects rather than remaining focused on one target.

This internal sequencing matters because AI-assisted shopping contains an intermediary–object structure that is not present in many conventional S-O-R applications. The consumer first encounters a technological system that filters information and makes suggestions; only after that interaction does the consumer evaluate a separate market object that may be purchased. Treating all trust-related judgments as a single Organism variable would obscure the fact that the target of evaluation changes over the course of the decision process. By distinguishing O1 from O2, the model can represent a psychologically plausible progression without altering the basic logic of S-O-R. This may also be useful in other AI-mediated consumption settings in which algorithmic agents recommend products, services, destinations, or content that remain separate from the recommending technology itself.

The model also offers a boundary-oriented interpretation of trust transfer. Trust in the AI system is not assumed to transfer automatically or completely to the product. The structural model instead estimates whether stronger system trust is statistically associated with stronger product trust, while the product remains an independent construct with its own measurement items and explanatory role. This distinction is important for avoiding an overly deterministic interpretation of trust transfer. Consumers may still reject a recommended product because of price, style, fit, reviews, or other product-specific information even when they trust the system. The empirical contribution is therefore the identification of a significant cross-object association and serial mechanism, not a claim that system trust guarantees product acceptance.

The second implication concerns multidimensional trust. The results show that different AI recommendation experiences can be associated with different trust dimensions. Perceived

personalization was associated with benevolence trust, whereas accuracy and usefulness were associated with competence trust. This does not imply that other cross-dimensional relationships are impossible; the model tested theoretically targeted paths specified a priori. Nevertheless, the results show that differentiated trust antecedents can be empirically meaningful. They therefore extend multidimensional trust research beyond the question of whether trust has multiple dimensions toward the question of how different consumer experiences may contribute to the formation of those dimensions.

The third implication concerns Trust Transfer Theory. The findings extend the theory to a relationship between a technological system and the physical products it recommends. The AI recommendation system serves as the trust source, and the specific recommended clothing product serves as the trust target. Both competence trust and benevolence trust were associated with product trust, and product trust was further embedded in the formation of purchase intention. This suggests that trust transfer in AI-assisted consumption can be conceptualized not merely as a relationship between actors or channels, but also as a process through which consumers extend trust from an algorithmic decision-support system to the material object that the system selects for them.

Taken together, these implications show how the three theoretical perspectives complement one another. S-O-R provides the overall structure linking external recommendation experiences with internal states and behavioral intention. The multidimensional trust perspective explains why system trust should be differentiated into competence and benevolence judgments. Trust Transfer Theory explains how trust can move from the system to the product within the Organism process. Their integration therefore opens the ‘black box’ between AI recommendation perceptions and purchase intention by specifying both the type of system trust formed and the object to which trust subsequently extends.

5.6 Practical implications

For e-commerce managers, the findings suggest that AI recommendation performance should be evaluated from the consumer’s perspective rather than only through back-end indicators such as algorithmic accuracy, exposure, or click-through rates. A system may be technically sophisticated yet fail to generate trust if consumers do not experience its outputs as personally relevant, accurate, or useful. Platforms should therefore monitor whether users actually perceive that recommendations reflect their preferences, match current needs, and reduce the burden of product search and evaluation.

First, platforms should enhance the perceptibility of personalization. Recommendations can be dynamically adjusted using recent browsing, search, favorite, shopping-cart, and purchase data so that the output remains relevant to current shopping tasks. Where appropriate, interfaces can provide light-touch cues explaining why a product is being recommended, for example by connecting it to recently viewed styles or similar preferences. The managerial goal should not simply be to demonstrate that personal data are being used, but to create an experience in which consumers feel that the recommendation genuinely understands their needs. Such an experience is likely to support benevolence-oriented trust.

Second, accuracy and usefulness should be managed jointly as cues of system competence. Accurate recommendations require more than repeatedly showing products that are superficially similar to items previously clicked. Apparel recommendations should reflect current context, style preferences, size requirements, price ranges, and recent behavior. Usefulness can be strengthened by integrating recommendations with decision-support tools such as size information, style tags, product comparison, usage scenarios, personalized filters, and other functions that reduce search and evaluation effort. A competent recommendation system is therefore one that not only predicts what the consumer might like but also helps the consumer make a better decision more efficiently.

Third, platforms should distinguish the management of system trust from the management of product trust. A consumer can believe that the AI system is competent without being certain that a particular recommended item will fit or perform as expected. Recommended product pages should therefore provide accurate and verifiable information on size, material, fit characteristics, realistic product presentation, user reviews, and return or exchange conditions. Where feasible, supporting technologies such as size recommendation or virtual try-on tools can further help consumers evaluate the recommended item. Strengthening system trust without strengthening product information may leave an important part of the decision process unresolved.

Finally, the strong TRP → PI relationship suggests that product trust should be treated as a key managerial link between AI recommendations and purchase-related outcomes. Platforms may therefore benefit from viewing recommendation, product verification, and purchase support as one continuous journey. The recommendation stage should establish relevance; the product-detail stage should help verify suitability; and the purchase stage should reduce residual uncertainty. This approach shifts the managerial objective from ‘recommending more’ toward

'recommending more appropriately, creating a trustworthy system experience, and giving consumers stronger reasons to trust the products ultimately recommended to them.'

5.7 Limitations and future research

Several limitations should be considered when interpreting the findings. First, the study used a cross-sectional self-administered survey, which is appropriate for examining structural associations and indirect effects but does not establish strict temporal causality. Future studies could use longitudinal, multi-wave, or experimental designs to examine whether manipulated changes in personalization, accuracy, or usefulness lead to subsequent changes in system trust and product trust.

Second, convenience sampling was used because a complete sampling frame of Chinese online clothing consumers was unavailable. Although the final sample included 500 valid responses and showed diversity across demographic groups, the probability of inclusion could not be controlled. Future studies could employ quota, stratified, or other more representative sampling approaches and could test the model across regions or countries.

Third, all core variables were self-reported. Procedural safeguards and statistical diagnostics provided no evidence that severe common method bias exerted a substantive influence, but self-report and recall biases cannot be fully eliminated. Combining survey data with behavioral indicators such as clicks, favorites, shopping-cart additions, purchases, returns, or repeat purchases would provide a stronger basis for examining the relationship between psychological trust and actual behavior.

Fourth, purchase intention rather than actual purchase behavior was used as the final outcome. Actual transactions may also be affected by price, promotions, inventory, budget constraints, competing products, and temporary changes in consumer needs. Future research should therefore extend the model to actual behavioral outcomes.

Fifth, the study focuses on online clothing e-commerce. Apparel products involve strong fit, style, and experiential uncertainty, which makes the context especially suitable for examining system-to-product trust transfer. However, the strength and form of the mechanism may differ for more standardized goods, cosmetics, food products, tourism services, or digital content. Cross-category comparisons could clarify the boundary conditions of trust transfer.

Finally, the model focuses on competence and benevolence trust and does not include integrity trust. Future research could incorporate integrity and related concerns such as transparency, explainability, privacy, fairness, and perceived risk. Moderators such as prior AI experience,

technological familiarity, privacy sensitivity, product involvement, or brand familiarity may also determine when system trust is more or less likely to extend to recommended products.

6. Conclusion

This study develops and tests a progressive trust mechanism linking AI-powered personalized recommendation perceptions with purchase intention in online clothing e-commerce. By distinguishing perceived personalization, perceived accuracy, and perceived usefulness as separate technological stimuli; competence trust and benevolence trust as differentiated forms of system trust; trust in recommended clothing products as a product-level trust judgment; and purchase intention as the behavioral response, the study provides a more detailed explanation of how consumers move from evaluating an AI recommendation experience to forming a purchase-related intention.

Using 500 valid survey responses and SEM, the study found that perceived personalization was positively associated with benevolence trust, while perceived accuracy and perceived usefulness were positively associated with competence trust. Both system-trust dimensions were positively associated with trust in recommended clothing products, and product trust was strongly associated with purchase intention. The three serial indirect pathways were also significant, supporting the proposed sequence of AI recommendation perceptions → system trust → product trust → purchase intention.

The central conclusion is that consumer responses to AI-powered recommendations are not determined by algorithmic performance alone. Consumers evaluate whether recommendations feel tailored, accurate, and useful; they form trust judgments about the system's capability and user orientation; and they subsequently decide whether the recommended product itself is trustworthy. For theory, this layered process refines the Organism component of S-O-R and extends Trust Transfer Theory to a system-to-product relationship. For practice, it indicates that e-commerce platforms should optimize recommendation relevance and decision support while simultaneously building trust in the system and providing credible product information. Understanding AI-assisted consumption therefore requires attention not only to whether consumers accept the technology, but also to how trust moves across the technological and product objects involved in the purchase decision.

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The author(s) declare that it is not applicable.

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