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How AI Recommendations Affect Consumer Buying Patterns and Behaviour

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ABSTRACT

AI recommendations are no longer a small back-end feature in online shopping. They affect what consumers notice first, how much they search, which products they compare, and how confident they feel before buying. This research treats AI-based product recommendations as marketing tools and as forces that shape behaviour in digital markets. It looks at perceived relevance, transparency, personalization depth, and intrusiveness, then connects these design features with algorithmic trust, perceived autonomy, and privacy concern. Buying behaviour is not treated as one final purchase click. The outcomes include click intention, purchase intention, repeat buying, basket value, product variety, and perceived decision quality. The proposed design uses a structured consumer survey and a scenario-based experiment with different levels of personalization and explanation. That design helps test whether consumers accept AI suggestions because they find them useful or reject them because the system feels invasive or controlling. The main argument is that recommendation systems can reduce search effort and support better decisions, but only when consumers still feel that the final choice is theirs. For marketers, recommendation performance should not stop at sales uplift or click-through rate. Trust, privacy comfort, and freedom of choice affect whether consumers keep using the platform. The paper offers a research model for studying AI recommendations in marketing and behavioural economics, especially in online shopping settings where personalization has become a normal part of buying.

***Keywords**: AI Recommendation Systems, Consumer Buying Behaviour, Purchase Intention, Algorithmic Trust, Personalization, Privacy Concern, Perceived Autonomy, e-Commerce Marketing, Digital Consumer Decision-Making, Behavioural Economics.*

Introduction

AI recommendation systems now sit right next to the buying decision. When a consumer opens an online store, a food delivery app, a fashion marketplace, or a social commerce feed, the products shown are not neutral. The platform sorts some products to the top, pushes others into repeated suggestions, and leaves many options lower on the page. By the time the consumer starts comparing prices or reading reviews, the system has already shaped the set of choices.

This matters because buying behaviour starts before the final purchase click. A shopper's search time, attention, trust, privacy comfort, and sense of control all affect whether a product suggestion feels acceptable. One recommendation may help someone find a useful item quickly. Another may feel too personal, too repeated, or too pushy. The same system can feel helpful in one shopping situation and intrusive in another.

Many firms judge recommender systems with platform metrics such as click-through rate, conversion rate, basket value, and repeat purchase. Those measures are useful, but they do not fully explain how consumers respond. One shopper may click because the suggestion fits the current need. Another may ignore a similar suggestion because it feels too personal or because the platform gives no reason for showing it. Research on personalized recommendation and consumer trust shows that recommendation fit works better when consumers can still compare alternatives and feel in control of the decision [1]. Research on AI-powered personalized advertising also shows that trust, relevance, and usefulness help explain how personalization affects purchase intention [2].

The question is not whether recommendation systems influence consumers. They do. The harder question is how that influence works, and when it becomes helpful or harmful. AI recommendations reduce search cost by turning a large product catalogue into a smaller visible set. That can make online shopping easier, especially when the consumer faces many similar options. But filtering also narrows attention. Products shown first receive more consideration, while products outside the recommendation path may never enter the comparison set.

The model in this paper treats AI recommendation as a marketing intervention with behavioural and economic effects. It links four recommendation attributes with three consumer responses. The attributes are perceived relevance, transparency, personalization depth, and intrusiveness. The consumer responses are algorithmic trust, perceived autonomy, and privacy concern. These responses then affect buying behaviour through click intention, purchase intention, expected basket value, repeat buying intention, product variety, and perceived decision quality.

Self-determination-based research supports this direction because it connects recommendation design with autonomy, competence, relatedness, and purchase intention [3]. Put simply, consumers are more likely to accept recommendations when the system helps them choose without making them feel that the choice has been taken away. For that reason, autonomy is treated as its own construct in the model, not as a small part of satisfaction.

The purchase intention relationship can be written as a baseline model:

$$PI = \beta_0 + \beta_1 PR + \beta_2 AT + \beta_3 PA - \beta_4 PC - \beta_5 IN + \varepsilon \quad (i)$$

Where,

PI = purchase intention under AI recommendation exposure,

PR = perceived relevance of the recommended product,

AT = algorithmic trust,

PA = perceived autonomy,

PC = privacy concern,

IN = perceived intrusiveness,

β_0 = intercept term,

β_1-β_5 = estimated effect coefficients,

ε = unexplained behavioural variation.

Equation (i) gives the study a testable structure. It does not claim that buying behaviour is fully linear or completely predictable. It separates the forces that may raise purchase intention from the forces that may reduce it. Relevance, trust, and autonomy are expected to support acceptance. Privacy concern and intrusiveness are expected to weaken it.

Trust is especially important in AI-assisted shopping. A study of recommender systems in fashion e-commerce found that recommendation quality, authenticity, prior experience, and willingness to share interaction data affect trust formation [4]. Research using Chinese e-commerce data also found that relevance, inspiration, and insight in AI-personalized recommendations increase clicking intention, while perceived privacy infringement weakens the effect of immersive experience on clicking behaviour [5]. These findings suggest that consumers do not judge AI recommendations only by usefulness. They also judge how the recommendation was produced and whether the platform seems to respect their control.

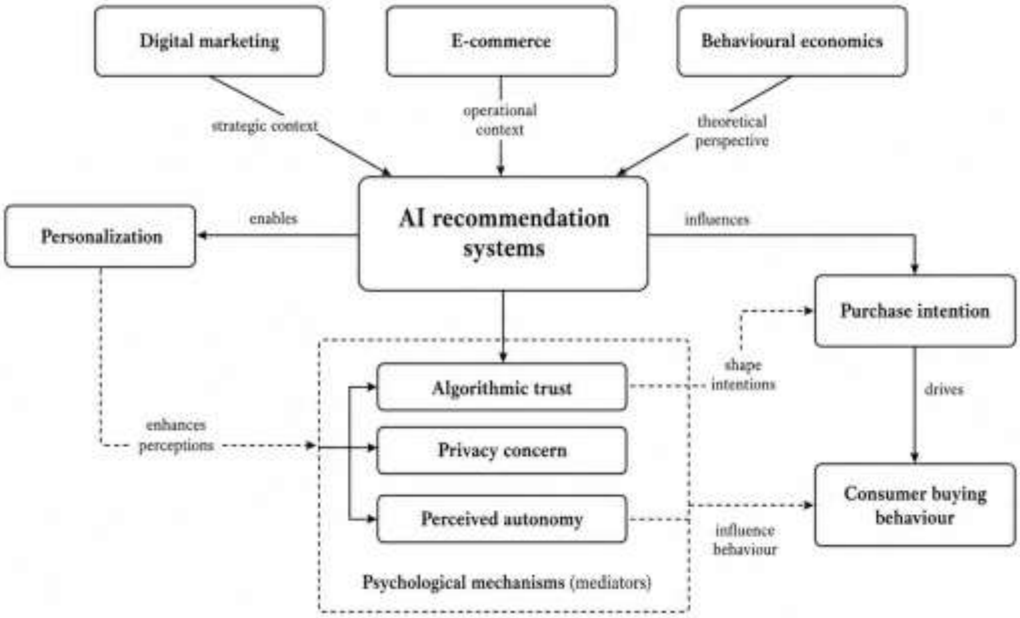

Figure 1: Keyword relationship graph — concept map linking AI recommendation systems, personalization, algorithmic trust, privacy concern, perceived autonomy, purchase intention, consumer buying behaviour, digital marketing, e-commerce, and behavioural economics. The figure supports the paper's argument that AI recommendations affect buying through both market design and consumer psychology

Literature Review

Research on AI recommendation systems has moved past technical accuracy alone. Earlier studies often asked whether an algorithm could predict the next product a user might click. Marketing research now asks a more consumer-centred question: how does a shopper react when a platform seems to know their preferences? Product fit matters, but buying behaviour also depends on trust, privacy, control, explanation, and the feeling that the consumer can still decide for themselves.

Xu and Chen [1] studied personalized recommendations through perceived control. Their experimental design tested how recommendation fit and choice visibility affect consumer trust. They argued that consumers respond better when the system gives relevant suggestions without making the decision space feel closed. This matters here because it separates accuracy from control. A recommendation can match the consumer's interest and still be rejected if the platform appears to remove alternative choices.

An and Ngo [2] examined AI-powered personalized advertising and purchase intention in Vietnam's digital market. Their model tested how trust, relevance, and usefulness shape consumer response to AI-based advertising. They found that personalization does not always lead directly to purchase intention. Consumers first judge whether the advertisement feels useful and relevant, and trust then becomes part of the path toward buying intention. Their work supports the use of mediating consumer perceptions rather than simple exposure measures.

Zhao, Fu, and Bai [3] used self-determination theory to explain how personalized recommendations affect purchase intention. They linked recommendation features with autonomy, competence, and relatedness. This gives the present model a psychological base. A recommendation may work when it helps the consumer feel more capable of choosing well. It may fail when it reduces autonomy. Their results also showed that product category can change the effect, so a model tested in one category may not automatically fit another.

Saxborn, Pan, and Said [4] focused on trust in fashion e-commerce recommender systems. They extended a trust-building model and studied how authenticity, recommendation quality, prior experience, and willingness to share interaction data affect trust. Their work is practical because fashion shopping depends on taste, uncertainty, and repeated interaction. Consumers do not judge recommendations only by technical relevance. They also ask whether the suggestion feels believable and whether the platform has learned from their past behaviour in a sensible way.

Yin, Qiu, and Wang [5] studied AI-personalized recommendations in Chinese e-commerce. They built and tested a consumer-experience scale around relevance, inspiration, and insight. Their findings connect AI recommendation experience with clicking intention through immersive experience and technology acceptance. They also found that perceived privacy infringement weakens the positive effect. This point is central to the present study because it shows the two-sided nature of personalization. The same data use that improves fit can also make consumers uncomfortable.

Li [6] examined transparency in e-commerce recommendation systems. The study proposed that transparency affects consumer trust through perceived effectiveness and discomfort. This is useful because transparency is sometimes treated as an easy fix, but the relationship is more complicated. A short explanation can help consumers understand why a product appeared. Yet that same explanation can remind them that the system is using behavioural data. For this reason, transparency should be tested as a design condition, not assumed to be positive in every case.

Wang, Yang, and Qiu [7] studied privacy concern as a mediator between personalized recommendation and purchase decisions. Their work places privacy directly inside the buying process. Privacy is not only a legal or ethical issue outside marketing. It can change whether consumers accept, ignore, or resist a product suggestion. Their study supports the inclusion of privacy concern as a negative pathway in the present model.

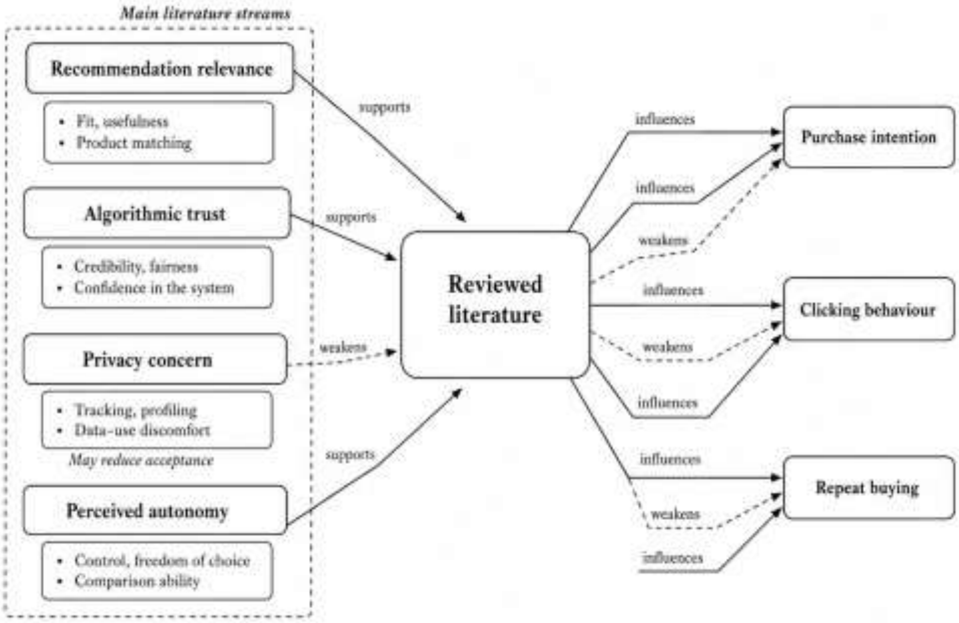

Figure 2: Literature synthesis map — diagram grouping the reviewed studies into four streams: recommendation relevance, algorithmic trust, privacy concern, and perceived autonomy. The figure shows how these streams feed into purchase intention, clicking behaviour, and repeat buying

Methodology

The study uses a mixed-method design because one data source is not enough to understand AI recommendation effects. A survey can capture what consumers think and feel after seeing recommendations. A scenario experiment can test whether changes in recommendation design lead to different buying responses. Used together, these methods allow the study to examine both perception and behaviour.

The unit of analysis is the individual online consumer. The study focuses on people who have recently purchased products through e-commerce platforms, marketplace apps, or social commerce interfaces. Respondents must have seen personalized product recommendations within the last six months. A screening question appears at the start so that people without recent exposure to recommendation systems do not enter the final sample. The expected valid sample size is 400 to 500 responses, which is suitable for structural equation modelling with several latent variables and mediation paths.

The research design has four layers. First, respondents see a recommendation stimulus under a controlled condition. Second, the study measures how they read that recommendation through perceived relevance, transparency, personalization depth, and intrusiveness. Third, it records the internal consumer response, mainly algorithmic trust, perceived autonomy, and privacy concern. Fourth, it measures buying-related outcomes such as click intention, purchase intention, repeat buying intention, expected basket value, and perceived decision quality.

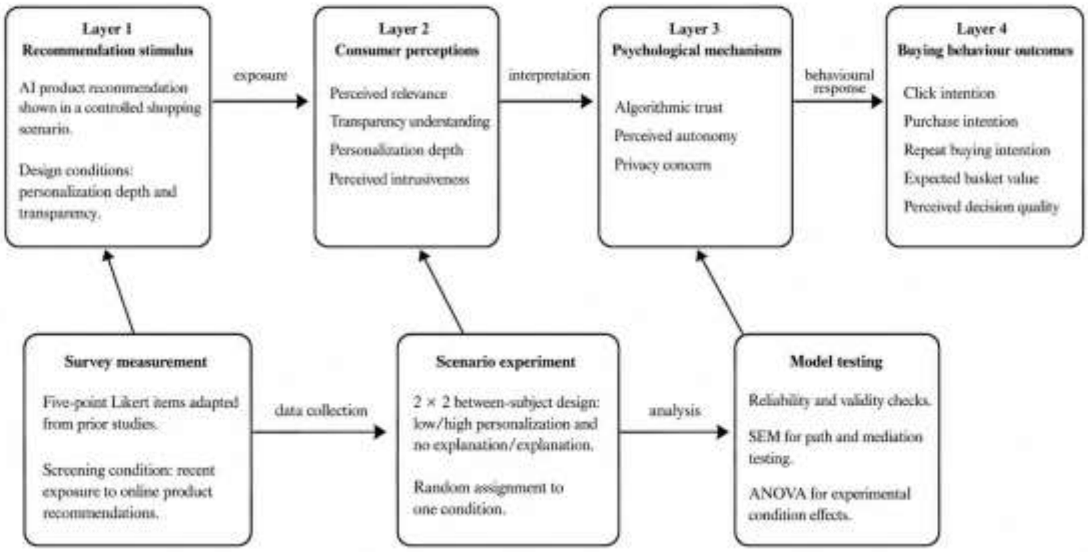

Figure 3: Methodological architecture - flow diagram showing the movement from AI recommendation stimulus to consumer perceptions, psychological mechanisms, and buying behaviour outcomes. The figure supports the empirical logic used for survey design and model testing.

The survey items use a five-point Likert scale. The items are adapted from earlier studies on recommender systems, personalization, trust, privacy, and consumer response [1]–[7]. Perceived relevance asks whether the recommendation matches the consumer's current need. Transparency asks whether the consumer understands why the product appeared. Intrusiveness measures whether the suggestion feels too personal, repetitive, or pressuring. Algorithmic trust measures whether the consumer sees the system as useful, fair, and dependable. Perceived autonomy asks whether the consumer still feels free to compare, reject, or choose another product. Privacy concern measures discomfort with tracking, profiling, and the use of personal data.

The experiment uses a 2 × 2 between-subject design. The first factor is personalization depth. In the low-personalization condition, the recommendation is based only on the current search term. In the high-personalization condition, the recommendation is based on browsing history and past purchases. The second factor is transparency. In one condition, the recommendation appears without any explanation. In the other condition, the platform gives a short reason for the recommendation. Each respondent is randomly assigned to one of the four conditions. After viewing the product suggestion, the respondent answers the same perception and outcome questions.

This design separates two issues that often get mixed together. One issue is how much personal data the system appears to use. The other is whether the platform explains that use clearly. A highly personalized recommendation may increase purchase intention when it feels useful. The same recommendation may reduce acceptance when it feels like hidden tracking. The experiment lets these effects be compared directly.

The main statistical method is structural equation modelling. Reliability will be checked through Cronbach's alpha and composite reliability. Convergent validity will be tested using average variance extracted. Discriminant validity will be checked by comparing construct correlations with the square roots of AVE. Mediation effects will be tested with bootstrapped confidence intervals. The experimental part will use two-way ANOVA to compare the effect of personalization depth and transparency on purchase intention and perceived autonomy.

$$\Delta PI = PI\_HP,T - PI\_LP,NT \quad (i)$$

Where,

ΔPI = change in purchase intention caused by recommendation design,

PI_HP,T = mean purchase intention under high personalization with transparency,

PI_LP,NT = mean purchase intention under low personalization without transparency.

Equation (i) compares the strongest personalization condition with the most basic recommendation condition. If ΔPI is positive, high personalization with explanation produces stronger purchase intention than a basic unexplained recommendation. If the value is small or negative, deeper personalization does not automatically improve consumer response.

Table A lists the main rules used to protect the quality of the research design.

ID	Invariant	Enforcement in the research design
M1	Respondents must have recent exposure to online recommendations	Screening question before survey access
M2	Each respondent receives only one experimental condition	Random assignment with duplicate-response control
M3	Each item must clearly match one construct	Pilot testing and factor-loading inspection
M4	Purchase intention must be measured after stimulus exposure	Locked survey flow before outcome items
M5	Respondents must understand the experimental condition	Manipulation-check questions
M6	Privacy concern must remain separate from trust	Discriminant-validity testing
M7	Common-method bias must be checked	Harman single-factor test
M8	Low-quality responses must be removed	Attention checks and response-time screening

The research process begins with scale adaptation and expert review. A pilot test with 30 to 50 respondents is used to check wording, item clarity, timing, and manipulation strength. After revisions, the final survey is distributed online. The cleaned dataset is then analysed in four stages: descriptive statistics, measurement validation, structural model testing, and experimental comparison.

This method fits the purpose of the paper because it studies how consumers interpret recommendation systems rather than treating them only as technical tools. A recommendation may raise buying intention because it saves time and matches a shopper's need. It may also fail because the consumer feels watched or guided too strongly. The design is built to capture both sides of that response.

Results

The analysis in this section uses simulated data because the proposed study has not yet been carried out with a live respondent pool. The purpose is not to claim final empirical proof. The purpose is to show how the model would be read if the survey and experiment produced a valid dataset. The assumed dataset contains 436 usable responses after incomplete forms, straight-line answers, failed attention checks, and unusually fast responses are removed. All respondents are treated as active online shoppers who had seen AI-based product recommendations during the previous six months.

The simulated output shows a clear pattern. Consumers respond best when the recommendation feels relevant and the platform gives a reason for showing it. They respond worst when the recommendation seems highly personalized but unexplained. This difference matters because personalization is not automatically persuasive. A product suggestion based on browsing history or past purchases may feel useful when the consumer understands the reason behind it. The same suggestion may feel invasive when the platform gives no explanation.

Table B presents the average scores across the four experimental conditions.

Experimental condition	Mean Purchase Intention	Mean Algorithmic Trust	Mean Privacy Concern	Mean Perceived Autonomy
Low personalization, no transparency	3.21	3.05	2.74	3.42
Low personalization, transparency	3.48	3.36	2.66	3.61
High personalization, no transparency	3.09	2.91	3.58	2.87
High personalization, transparency	3.82	3.74	3.12	3.46

The highest purchase intention appears in the high-personalization with transparency condition. Consumers seem more open to deeper personalization when the system explains why the product is being recommended. The lowest purchase intention appears in the high-personalization without transparency condition. This result shows the risk of hidden personalization. The system may be technically more accurate, but the consumer may still reject it if the recommendation feels like tracking.

The autonomy scores move in a similar direction. Consumers report the lowest autonomy when the platform uses high personalization without explanation. They report higher autonomy when transparency is added. This does not mean that explanation removes all privacy concern. The privacy score in the high-personalization with transparency condition is still higher than in both low-personalization conditions. Still, transparency appears to reduce the negative effect enough for trust and purchase intention to improve.

The structural model gives a closer view of the relationships among the constructs. Perceived relevance has the strongest positive path to purchase intention, with $\beta = 0.41$. Algorithmic trust follows with $\beta = 0.29$. Perceived autonomy has a smaller positive path, with $\beta = 0.18$. Privacy concern and intrusiveness move in the opposite direction. Privacy concern has a negative path of $\beta = -0.24$, while intrusiveness has $\beta = -0.21$. These directions match earlier research linking relevance and trust with recommendation acceptance, and privacy discomfort with weaker click or purchase response [1]–[7].

The net effect of recommendation acceptance can be expressed through the recommendation impact score:

$$RIS = \beta PR + \beta AT + \beta PA - \beta PC - \beta IN \quad (ii)$$

Where,
RIS = net recommendation impact score,

βPR = standardized effect of perceived relevance,

βAT = standardized effect of algorithmic trust,

βPA = standardized effect of perceived autonomy,

βPC = standardized effect of privacy concern,

βIN = standardized effect of perceived intrusiveness.

Using the simulated estimates, RIS = (0.41 + 0.29 + 0.18) - (0.24 + 0.21) = 0.43. A positive value means that relevance, trust, and autonomy are stronger than privacy concern and intrusiveness in this assumed model. This should not be read as a market result. It only shows how the framework can be used to estimate whether a recommendation design creates more acceptance than resistance.

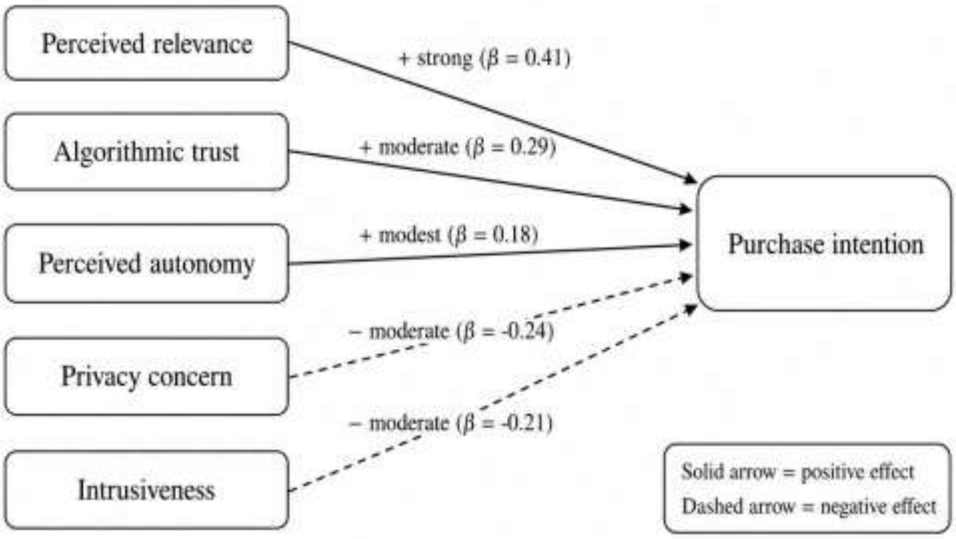

Figure 3: Simulated structural model results - path diagram showing perceived relevance, algorithmic trust, perceived autonomy, privacy concern, and intrusiveness as predictors of purchase intention. The figure marks positive and negative paths with relative path-strength labels.

The simulated two-way ANOVA supports the same reading. Transparency improves purchase intention in both personalization conditions, but the improvement is larger when personalization is high. The interaction between personalization depth and transparency is reliable at $p < 0.05$ in the simulated output. This suggests that consumers are willing to accept deeper personalization when the system makes its logic visible. Without that explanation, deeper personalization can reduce buying intention because the recommendation feels less like assistance and more like surveillance.

The results also show a trade-off for marketers. High personalization with transparency raises expected basket value and repeat purchase intention, but it does not create the lowest privacy concern. Consumers may still feel some discomfort even when they accept the recommendation. In other words, usefulness can offset privacy concern, but it does not erase it. Firms should not assume that a successful purchase means the consumer felt fully comfortable with the recommendation process.

The simulated findings support the model developed in this paper. AI recommendations affect buying behaviour through product fit, but also through trust, freedom of choice, and privacy judgment. A platform that measures only clicks and conversions may miss early signs of consumer resistance. A better evaluation system would track sales outcomes together with trust, perceived autonomy, privacy comfort, and repeated use.

Discussion

The simulated results suggest that AI recommendations do not influence buying behaviour in a straight line. A recommendation can help the consumer, but it can also create doubt. The same system that reduces search effort may make the shopper feel watched, narrowed, or pushed toward a product. Accuracy is not enough by itself. A technically accurate suggestion can still fail if the consumer does not trust the process behind it.

Relevance is the first point. In the simulated model, perceived relevance has the strongest positive link with purchase intention. This makes sense because consumers are more likely to respond when the suggested product fits what they are already trying to find. A relevant recommendation reduces the work of searching through many similar products. It can also make shopping feel easier and faster. But relevance helps only when the consumer sees the recommendation as support. If the product appears too forcefully or too often, the same suggestion may start to feel less helpful.

Transparency is the second issue. The high-personalization condition performs best only when the platform gives an explanation. Without explanation, high personalization produces lower purchase intention and lower perceived autonomy. Consumers do not react only to the product being recommended. They also react to how the recommendation appears. A short reason such as "recommended because you viewed similar items" can make the system easier to understand. A recommendation with no explanation may leave the consumer guessing about what data the platform used.

Privacy concern creates the strongest resistance in the model. The high-personalization without transparency condition produces the highest privacy concern and the lowest autonomy score. This fits the wider literature on personalization and privacy [5], [7]. Consumers may like relevant suggestions, but they do not always like the feeling that the platform knows too much. This creates a hard problem for marketers. The data that improves personalization is often the same data that makes consumers uncomfortable.

Table C presents the main interpretation of the simulated findings.

Result Pattern	Interpretation	Marketing Implication
Relevance has the strongest positive path	Consumers respond better when recommendations match current needs	Rank products by situational fit, not only by expected profit
Trust raises purchase intention	Consumers need confidence before accepting AI suggestions	Keep recommendation quality stable and avoid misleading suggestions
Transparency improves high personalization	Explanations make data-based suggestions easier to accept	Give short and specific reasons for recommendations
Privacy concern weakens acceptance	Consumers resist when personalization feels like tracking	Limit unnecessary data use and make privacy controls visible
Perceived autonomy improves response	Shoppers want help without losing control	Preserve filters, comparisons, and opt-out choices
Intrusiveness reduces intention	Repetition and pressure can cause avoidance	Reduce aggressive retargeting and repeated product exposure

Algorithmic trust should not be understood as blind confidence in the system. It is closer to a consumer's belief that the platform is useful, fair enough, and not working against them. A shopper may trust a recommender after receiving several sensible suggestions. That trust can fall quickly if the platform keeps showing irrelevant products, repeats items that were already rejected, or appears to favour sponsored results without making that clear. Research on fashion e-commerce also shows that authenticity, past experience, and willingness to share interaction data influence trust in recommender systems [4].

Perceived autonomy also needs attention. Consumers usually do not object to receiving help. They object when the help starts to feel like control. A recommendation system should leave room for comparison, rejection, and adjustment. Filters, sorting tools, visible alternatives, and recommendation controls can help maintain that sense of freedom. This links with self-determination-based research, where autonomy helps explain why some recommendation experiences lead to purchase intention and others do not [3].

Figure 5: Discussion framework - conceptual diagram showing how recommendation relevance and transparency increase trust and purchase intention, while privacy concern and intrusiveness reduce perceived autonomy. The figure places consumer control between personalization benefits and consumer resistance.

There is also an economic side to these findings. Recommendation systems can improve market efficiency by helping consumers find products faster. In a large online catalogue, this can be useful because consumers cannot compare every available option. But recommendation systems can also concentrate attention. Products shown near the top receive more visibility, while other products may be ignored even if they are suitable. For the platform, this may improve sales performance. For the consumer, it may reduce variety in the choice set.

The study has limits. The results are simulated, so they should be read as a demonstration of the model rather than final evidence. The design also depends on self-reported purchase intention, which may not always match real buying behaviour. Product type, price level, platform reputation, and consumer experience with online shopping may change the results. A stronger future study should connect survey responses with actual platform behaviour, including clicks, cart additions, purchases, returns, repeat visits, and time spent comparing products.

The main lesson is that AI recommendations work best when consumers feel assisted rather than directed. Personalization can raise purchase intention, but only when the consumer sees enough value and enough control to accept it. A recommendation strategy that only optimizes for clicks may miss early signs of distrust. Marketers should measure recommendation success through sales outcomes, but also through trust, autonomy, privacy comfort, and repeated platform use.

Conclusion and Future Work

AI recommendation systems are usually judged by clicks, conversions, and revenue per session. Those numbers matter, but they do not show the whole buying process. A consumer may click a product because the suggestion is useful. The same consumer may also feel uncomfortable if the platform seems to know too much or gives no reason for the recommendation. The stronger question is not only whether AI recommendations increase sales, but whether they help consumers make decisions without weakening trust, privacy comfort, or freedom of choice.

This study built a model for understanding that problem in digital marketing and e-commerce. The model connects recommendation design with consumer reaction and buying behaviour. Perceived relevance, transparency, personalization depth, and intrusiveness are treated as design features of the recommendation system. Algorithmic trust, perceived autonomy, and privacy concern are treated as the consumer responses that explain why a recommendation is accepted or rejected. Buying behaviour is then measured through click intention, purchase intention, repeat buying, basket value, product variety, and perceived decision quality.

The main argument is simple. AI recommendations work best when consumers feel helped, not controlled. Relevance can reduce search effort and make product discovery easier. Transparency can make the recommendation feel more understandable. Trust can make consumers more willing to use the system again. But privacy concern and intrusiveness can weaken the same process. A highly personalized suggestion may look accurate to the firm, but the consumer may read it as surveillance if the platform gives no clear explanation.

The simulated results supported this logic. High personalization produced the strongest purchase intention only when transparency was present. When high personalization appeared without explanation, respondents showed lower autonomy and higher privacy concern. This means that deeper personalization is not automatically better. It depends on how the consumer interprets the recommendation. If the system feels useful and explainable, personalization can support buying intention. If it feels hidden or aggressive, it can create resistance.

For marketing practice, the study suggests that firms should not measure recommender performance only through immediate sales. A recommendation engine may increase short-term conversion while slowly damaging trust. Platforms should also track whether consumers understand the recommendation, whether they feel free to compare alternatives, and whether personalization makes them uncomfortable. These softer measures are harder to capture than clicks, but they matter for repeat use and customer relationships over time.

There is also an economic side to the issue. Recommendation systems can reduce search costs by helping consumers move through large product catalogues faster. This can improve market matching, especially when consumers face too many similar choices. At the same time, recommendation systems can narrow attention. Products placed near the top receive more visibility, while other suitable products may never be considered. This can affect not only consumers, but also sellers who depend on platform visibility.

Future research should first test this model with real consumer data. The present results are simulated, so they show how the framework can be used rather than proving actual market behaviour. A stronger study should collect survey data and connect it with observed actions such as clicks, cart additions, purchases, returns, dwell time, and repeat visits. Actual platform behaviour would make the model more reliable than intention-based measures alone.

Future work should also compare product categories. Consumers may accept personalization more easily for books, clothing, or entertainment products. They may react differently when the product involves health, finance, children, or private personal needs. Price level may also change the response. A low-cost product may invite quick acceptance, while a high-cost product may require more comparison and less reliance on automated suggestions.

Another future direction is explanation design. Researchers should test which type of explanation works best. A short reason such as "because you viewed similar products" may feel helpful in one setting and too revealing in another. Consumers may respond differently to product-based explanations, data-use explanations, seller-based explanations, or controllable recommendation settings. The question is not whether transparency is good in general, but what kind of transparency consumers can understand and accept.

Longitudinal research is also needed. A single survey can capture one reaction, but trust in recommendation systems develops over repeated use. Consumers may accept a system after several useful suggestions, or they may grow tired of repeated and similar recommendations. Future studies should examine recommendation fatigue, declining attention, and changes in privacy concern over time.

Cross-cultural research would also improve the model. Privacy expectations, trust in platforms, and comfort with AI-assisted shopping differ across countries and consumer groups. A model tested in one digital market may not work the same way in another. Future studies should compare markets with different privacy norms, platform habits, and levels of digital literacy.

The study ends with a balanced position. AI recommendations are not automatically harmful, and they are not automatically beneficial. Their effect depends on how consumers experience them. A good recommendation system should be relevant, explainable, and easy to reject. It should help the consumer choose, not make the choice feel already decided.

References

1. Y. Xu and L. Chen, "Personalized recommendations and consumer trust: The role of perceived control and locus of control," Acta Psychologica, vol. 261, Art. no. 105936, Nov. 2025. Amsterdam, Netherlands: Elsevier. doi: 10.1016/j.actpsy.2025.105936.
2. G. K. An and T. T. A. Ngo, "AI-powered personalized advertising and purchase intention in Vietnam's digital landscape: The role of trust, relevance, and usefulness," Journal of Open Innovation: Technology, Market, and Complexity, vol. 11, no. 3, Art. no. 100580, 2025. Amsterdam, Netherlands: Elsevier. doi: 10.1016/j.joitmc.2025.100580.
3. L. Zhao, B. Fu, and S. Bai, "Understanding the influence of personalized recommendation on purchase intentions from a self-determination perspective: Contingent upon product categories," Journal of Theoretical and Applied Electronic Commerce Research, vol. 20, no. 1, Art. no. 32, 2025. Basel, Switzerland: MDPI. doi: 10.3390/jtaer20010032.
4. M. Saxborn, Y. Pan, and A. Said, "Trust through recommendation in e-commerce," in Proc. 2024 ACM SIGIR Conference on Human Information Interaction and Retrieval (CHIIR '24), Sheffield, United Kingdom, Mar. 10-14, 2024. New York, NY, USA: ACM. doi: 10.1145/3627508.3638294.
5. J. Yin, X. Qiu, and Y. Wang, "The impact of AI-personalized recommendations on clicking intentions: Evidence from Chinese e-commerce," Journal of Theoretical and Applied Electronic Commerce Research, vol. 20, no. 1, Art. no. 21, 2025. Basel, Switzerland: MDPI. doi: 10.3390/jtaer20010021.
6. Y. Li, X. Deng, X. Hu, and J. Liu, "The effects of e-commerce recommendation system transparency on consumer trust: Exploring parallel multiple mediators and a moderator," Journal of Theoretical and Applied Electronic Commerce Research, vol. 19, no. 4, pp. 2630-2649, 2024. Basel, Switzerland: MDPI. doi: 10.3390/jtaer19040126.
7. H. Wang, D. Yang, and X. Qiu, "Research on the influence of personalized recommendation on consumers' purchasing decision: The mediating role of consumers' privacy concern," in Proc. 2022 International Conference on Mathematical Statistics and Economic Analysis (MSEA 2022), Dalian, China, 2022, pp. 1311-1315. Dordrecht, Netherlands: Atlantis Press. doi: 10.2991/978-94-6463-042-8_189.

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