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Generative AI to Generative Commerce: An Integrated Model of AI Personalization, Consumer Trust, Privacy and Purchase Intention

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Abstract:
Generative artificial intelligence (GenAI) is starting to shape how people look for, compare and choose products online. The traditional recommendation systems focus mainly on the suggestions from existing patterns from customer data. AI can also take it one step further, such as having a conversation, providing explanations, generating product-related content, and tailoring responses to the shopper's queries. This change has led to the emergence of what has been termed as Generative Commerce. Meanwhile, the value of extremely personalized AI relies on consumer trust in the AI system, and a sense of comfort with how their information is being used. This study thus proposes an integrated model that connects the AI personalization, transparency, privacy assurance, privacy concern, consumer trust and purchase intention construct. The proposed framework is a synthesis of existing views on personalization research, privacy calculus, relationship trust and technology acceptance. The synthetic data set of 400 hypothetical respondents is just an example of the empirical analysis that can be performed. The illustrative results indicate the direction of the relationships as well as give a template for a future investigation that could employ real primary survey data. Finally, the paper highlights the need for the commercial potential of Generative AI to be analyzed in conjunction with consumer trust and responsible data management.
Important Data Note: This draft contains synthetic data for methodological purposes only and has been generated from the empirical data for illustrative purposes only and the variables and coefficients labelled "illustrative" in this draft are not intended to represent real data. These need to be changed for real primary survey answers before submission as an empirical research article.

Keywords: Generative AI; Generative Commerce; AI personalization; Consumer trust; Privacy concern; Privacy assurance; Purchase intention; E-commerce

1. Introduction

AI has come from the shadows to become a part of everyday life for consumers. AI is already a key technology in digital commerce, providing product recommendations, customization of ads, forecasting

customer behaviors, and automating customer service. These applications may speed up and ease shopping, but they also alter the way consumers engage with online platforms.

Generative AI brings a new layer to this interplay. Rather than responding to a query from a pre-established list, a generative system can answer a shopper's query using natural language, make comparisons, summarize reviews, offer alternatives, and modify its answer as the dialogue progresses. For instance, a consumer could say, "I have a budget of $1000, and here's a need I have, what are some good products I can buy? The system is incorporated into the shopping process instead of being a background feature.

This ease also brings a common friction into electronic transactions. The more information that's available about the consumer, the better the personalization can be. If they see value in the benefits and feel it is proportionate, they may be willing to share information. If the same data collection seems like too much, unclear or intrusive, privacy concerns can be enhanced. According to the research in privacy-calculus, this decision is a weighing of the potential outcomes and the perceived privacy costs [3,4].

The balance is crucial since the consumers may not be able to know how an AI system reaches a recommendation or what happens to their information. Trust has always been at the heart of a successful exchange relationship [6] and is therefore a key component of relationship-marketing research. Other more recent research on generative AI shopping assistive systems and generative AI chatbots also indicates that trust can influence the consumer's reactions to AI-aided shopping experiences [7,9,10].

With this background, the present study explores the possible interplay between AI personalization, transparency, privacy assurance, and privacy concern in relation to consumer trust and purchase intent in the context of Generative Commerce. The proposed model does not address personalization and privacy as separate problems, but considers them to be part of the same consumer decision making process.

The study has three primary contributions. First, it incorporates personalization, confidence and privacy in a single context for learning about Generative Commerce. Second, it sees consumer trust as a key connection between the consumer's experience of AI-personalization and their actual purchase. Third, it offers a practical survey tool and an analytical framework which can be applied to primary data in future empirical studies.

2. Literature Review

2.1 The shift to Generative Commerce and the potential of Generative

The initial use of AI for marketing was more around prediction, recommendation, classification, and automation. Generative AI takes this capability one step further by enabling content generation and natural language interaction. For instance, Huang and Rust [1] state that AI is becoming more and more relevant to personalization and customer connections. For the consumer, this translates to more than just selecting an item to display: AI can become a part of the conversation, helping the consumer to make a selection.

This evolving consumer journey has recently been the focus of some studies. Research on generative AI-driven shopping assistants shows that the quality of the interaction can impact consumer motivations, expectations, experience, and future actions [9]. AI-generated recommendations and shopping chatbots have also been the subject of research, highlighting the need for trust, perceived usefulness, and consumer willingness to trust AI in their product selection [7,8,10]. The results confirm that a model is needed that takes into account both the benefits and the concerns generated by generative shopping systems.

2.2 Transparency about technology that uses AI.2.4 AI tools and perceived value.

Personalization is beneficial when the recommendations are relevant to the consumer's needs. A recommendation that can save time, limit the number of products a shopper has to look at, or more

specifically, one that aligns with a shopper's stated preferences can save online shoppers a lot of effort. Previous studies on personalized advertising have shown that personalization can be effective, but there are several aspects to consider, such as when, where, and what information is delivered [13]. Relevance can be even more apparent in Generative Commerce, as users can explicitly specify their desired content and continue to adjust that input throughout the interaction with the AI.

But, personalization is not necessarily a good thing. There is the potential that consumers will be asking themselves why a system knows specific information about them and why specific products are being suggested. More recent work on AI-driven personalisation therefore calls for the governance, transparency, fairness, and personal-data management aspects to be taken into account, along with commercial performance [14]. Personalization is explored as a source of value, and trust and privacy are viewed as conditions that could impact the acceptance of that value by the consumer.

2.3 Consumer trust in AI-generated search results

Trust is essential because the consumer has to make choices without being able to see all the details of the AI system. The shopper might not be aware of what data was used for a particular recommendation, whether or not it's correct, or how the retailer will use the information in the future. Trust is considered to be an important factor in relationship marketing that helps to lessen uncertainty and aid the ongoing exchange [6]. Trust can also help overcome apprehension when using an online shopping system, which is also somewhat invisible.

As generative AI moves into the shopping space, this becomes increasingly a relevant issue. Chakraborty et al. [7] explored the trust consumers put in online grocery shopping using generative AI chatbots and Xie [9] looked at how generative AI shopping assistants influence consumer motivation and behaviour. With studies on buyer intent to purchase with AI-chatbots [10] these studies indicate that consumer response to AI will not only rely on its capabilities but also on consumer comfort with relying on AI.

2.4 Privacy, personalisation and privacy calculus

The following explanation of this trade-off is offered by privacy-calculus theory. Consumers can share information when the benefits that are anticipated increase the costs of privacy they perceive [3]. One of those benefits, in e-commerce, could be personalisation, as preferences can help to make more relevant recommendations. But issues of disclosures related to data collection, profiling, secondary use, or unauthorized access can elevate the perceived costs of disclosure [4,5].

In the context of Generative Commerce, it helps to differentiate between privacy concern and privacy assurance. Privacy concern is the consumers' sense of risk (e.g., they worry an AI system will gather too much data, or draw inferences beyond what they were looking for). Ensuring privacy is a sign of trust that the platform provides adequate security measures, has clear policies, and safeguards personal data. The two concepts are correlated, but are not identical to consumer perception.

2.5 Transparency and responsible GenAI

The concept of transparency has emerged as a fundamental attribute of trustworthy AI, and it is being highlighted as one of the essential qualities of AI systems. Transparency, accountability, explainability and enhancement of privacy are among the characteristics mentioned by NIST AI Risk Management Framework which may contribute to trustworthy AI [11]. The NIST Generative AI Profile also outlines specific risks specific to generative systems [12]. Transparency in a commerce context doesn't need to involve consumers' understanding of the technical intricacies of a large language model. Instead, it can mean making it clear to shoppers when AI is being used, explaining what the AI recommendations are in terms the shoppers can understand, and communicating the important limitations.

Transparency, in this study, means that the consumer feels the platform clearly communicates the fact and utility of AI, and gives them understandable information on the basis and limits of personalization. Transparency is not used as a technical metric of model interpretability, but rather as a signal of trust.

2.6 Research gap

There are robust foundations in the existing research that advance the study of personalization and privacy, trust, technology acceptance, and AI-assisted shopping. But these areas are usually looked at individually. It is not too late to get them together in a packaged model that not only illuminates how the benefits of AI personalization can co-exist with privacy concerns, but also how these perceptions can in turn affect trust and purchase intention. The proposed model overcomes this by positioning consumer trust between the core AI and privacy perception aspects and the consumer's purchase intention.

3. Materials and Methods

This study is built around the methodological approach that is evident in the literature review in the uploaded reference article, where it moves from the research objectives, literature review, data preparation, modelling, evaluation, analysis and conclusion. The present research takes that structure and applies it to a consumer-behaviour research question. The empirical results reported here are not from an actual population but rather are presented as a demonstration of the methodology.

3.1 Research objectives

To explore the connection between consumer trust in Generative Commerce and perceived AI personalisation.

To investigate if there is a positive relationship between transparency and assurance of privacy with consumer trust.

To investigate if there is a negative relationship between privacy concern and consumer trust.

To investigate the relationship between consumer trust and purchase intention is positive.

To see if consumer trust is a mediator between AI personalization and purchase intent.

To develop a survey instrument and analysis procedure that would be appropriate for a future primary-data study.

The conceptual model and hypotheses are developed.A conceptual model and hypotheses are formulated. The conceptual model is an S-O-R (stimulus–organism–response) model. The primary stimuli to consumers are AI personalization, transparency, privacy assurance, and privacy concern. Consumer trust is the subjective assessment that a consumer makes when evaluating the AI-powered shopping experience. The behavioural response is considered purchase intention. The model in turn explores whether personalization (via useful applications) and responsible AI can enhance the sense of trust, and whether privacy (via concern) can have the opposite effect.

H1: Perceived AI personalization positively influences consumer trust.

H2: Perceived transparency positively influences consumer trust.

H3: Privacy assurance positively influences consumer trust.

H4: Privacy concern negatively influences consumer trust.

H5: Consumer trust positively influences purchase intention.

H6: Perceived AI personalization positively influences purchase intention.

H7: Consumer trust mediates the relationship between AI personalization and purchase intention.

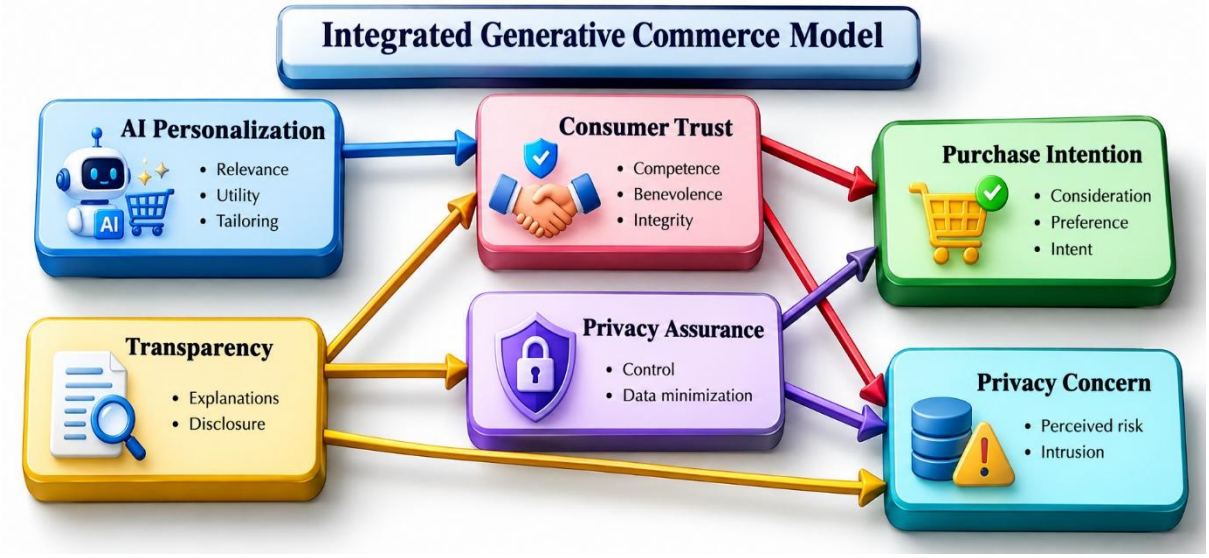

Fig. 1. Proposed integrated Generative Commerce model.

3.3 Research workflow

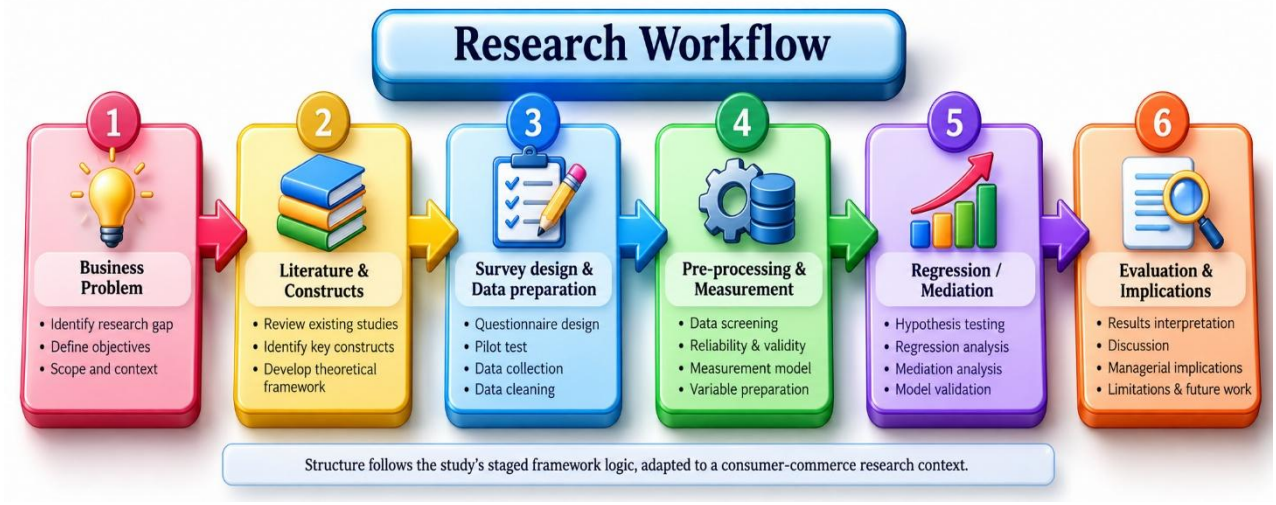

Fig. 2. Research workflow adapted to the Generative Commerce context.

3.4 Data source and ethical design

To conduct an empirical study in the future, adult participants who have shopped online in a specific time window in the past few months and have interacted with an AI-based shopping assistant or personalized recommendation should be recruited.Future empirical study should recruit adults who bought online in a specific time window in recent months, and interacted with an AI shopping assistant or a personalized recommendation. The respondent must be told what the study is about, and he or she must be free to refuse to be a part of the study, and identifying information should not be collected unless it is necessary. The ethics of the final study should be undertaken in accordance to the ethics requirement of the researchers' institution and the data protection requirement as appropriate.

The use of a synthetic dataset of 400 hypothetical respondent cases is only for the purpose of demonstration of the proposed analytical procedure for the present draft. The data consists of age group, gender, and standardized score data on the study constructs and shopping frequency. These are “observed” and not actual consumers. They should not be used as primary survey findings in a journal article.

3.5 Measurement instrument

Each construct will be assessed with several items that are measured on a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). The questions are designed to be easily understood by all respondents, regardless of their level of education or profession, and without any prior knowledge of AI terms. The items are conceptually based on existing research related to personalization, trust, privacy, and technology acceptance.

AI Personalization (AIP)

AIP1: The AI shopping system gives recommendations that match my preferences.
AIP2: The AI-generated suggestions are relevant to my current shopping needs.
AIP3: The system adapts recommendations based on my interaction or context.
AIP4: AI personalization reduces the effort required to find suitable products.

Transparency (TRN)

TRN1: The platform clearly tells me when I am interacting with AI.
TRN2: The platform explains why products are recommended to me.
TRN3: The platform communicates important limitations of AI-generated recommendations.
TRN4: Information about AI use is easy to understand.

Privacy Assurance (PRA)

PRA1: I believe the platform gives me meaningful control over my personal data.
PRA2: I believe the platform minimizes unnecessary data collection.
PRA3: I believe my data are protected when AI is used for personalization.
PRA4: The platform provides clear information about how my data are used.

Privacy Concern (PRC)

PRC1: I worry that AI personalization may collect more information than necessary.
PRC2: I am concerned that my shopping conversations could be used for other purposes.
PRC3: I worry about unauthorized access to data used by AI shopping systems.
PRC4: AI personalization makes me concerned about excessive profiling.

Consumer Trust (CT)

CT1: I trust the AI shopping system to provide dependable recommendations.
CT2: I believe the platform uses AI in my interests.
CT3: I believe the platform is honest about its AI capabilities.
CT4: I feel confident relying on the AI system during shopping.

Purchase Intention (PI)

PI1: I am likely to purchase a product recommended by the AI system.
PI2: I would consider completing a purchase after using the AI shopping assistant.
PI3: I would choose an AI-assisted shopping option when suitable products are available.
PI4: I intend to use AI-assisted recommendations in future purchases.

3.6 Synthetic-data demonstration and analysis procedure

To illustrate, the artificial data set has 400 hypothetical cases. The observations were produced around standardized construct scores such that the relationships suggested in the conceptual model could be drawn and normal variation between respondents was maintained. The estimation of the equations of trust and purchase-intention are demonstrated using ordinary least-squares regression as a way to estimate the equations in a real survey study.

The two demonstrations equations are: (1) Consumer Trust = 0 + 1(AI Personalization) + 0 + 2(Transparency) + 0 + 3(Privacy Assurance) + 0 + 4(Privacy Concern) + 0 + 1(Consumer Trust); and (2) Purchase Intention = 0 + 5(AI Personalization) + 0 + 6(Transparency) + 0 + 7(Privacy Assurance) + 0 + 8(Privacy Concern) + 0 + 9(Consumer Trust).

Mediation testing of the pathway between AI personalization and purchase intention via consumer trust is also demonstrated by a bootstrap procedure. Repeated resampling gives an approximation of the indirect effect and its confidence interval. Since the underlying data are simulated, this exercise demonstrates the approach and not that mediation is present in the broader consumer population.

3.7 Evaluation criteria

Stage	Suggested metric	Purpose
Measurement model	Cronbach's alpha / composite reliability	Internal consistency
Convergent validity	AVE	Construct convergence
Discriminant validity	HTMT / Fornell–Larcker	Construct distinctiveness
Collinearity	VIF	Predictor redundancy
Structural model	β, t, p, confidence interval	Hypothesis testing
Explained variance	R^2	Predictive explanatory power
Effect size	f^2	Relative contribution
Predictive relevance	Q^2 / PLSpredict	Out-of-sample relevance
Mediation	Bootstrapped indirect effect	Mechanism testing

4. Analysis and Results

The results presented in this section are illustrative only. They are based on the synthetic dataset of 400 hypothetical respondents prepared for methodological demonstration. The values should be replaced with results calculated from genuine primary survey responses before the manuscript is submitted as an empirical research article.

4.1 Illustrative sample profile

Age group	n	%
18–25	125	31.2%
26–35	110	27.5%
36–45	84	21.0%
46–55	54	13.5%
56+	27	6.8%

Table 1: Sample profile

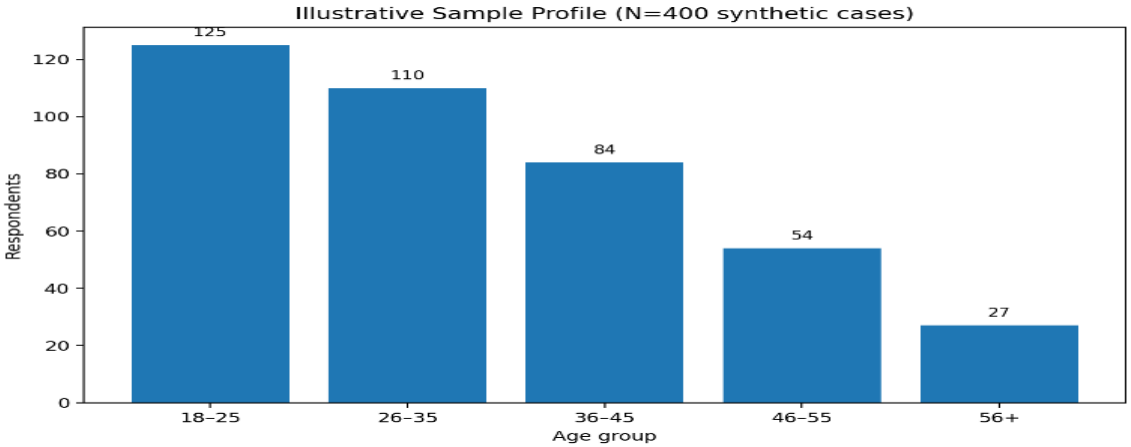

Fig. 3. Illustrative age profile of the synthetic dataset (N = 400).

The sample profile below is included to show how demographic information can be presented in the final paper. Since the respondents are simulated, the distribution should not be interpreted as a description of actual online shoppers.

4.2 Illustrative structural results

Table 2: Structural Result

Relationship	β (illustrative)	Direction	Interpretation for the model
AI Personalization → Consumer Trust	0.453	+	Higher-perceived personalization is associated with higher trust.
Transparency → Consumer Trust	0.323	+	Greater perceived transparency is associated with higher trust.
Privacy Assurance → Consumer Trust	0.270	+	Stronger assurance is associated with higher trust.
Privacy Concern → Consumer Trust	-0.238	–	Greater concern is associated with lower trust.
Consumer Trust → Purchase Intention	0.573	+	Higher trust is associated with higher purchase intention.
AI Personalization → Purchase Intention	0.189	+	Personalization retains a direct positive association.

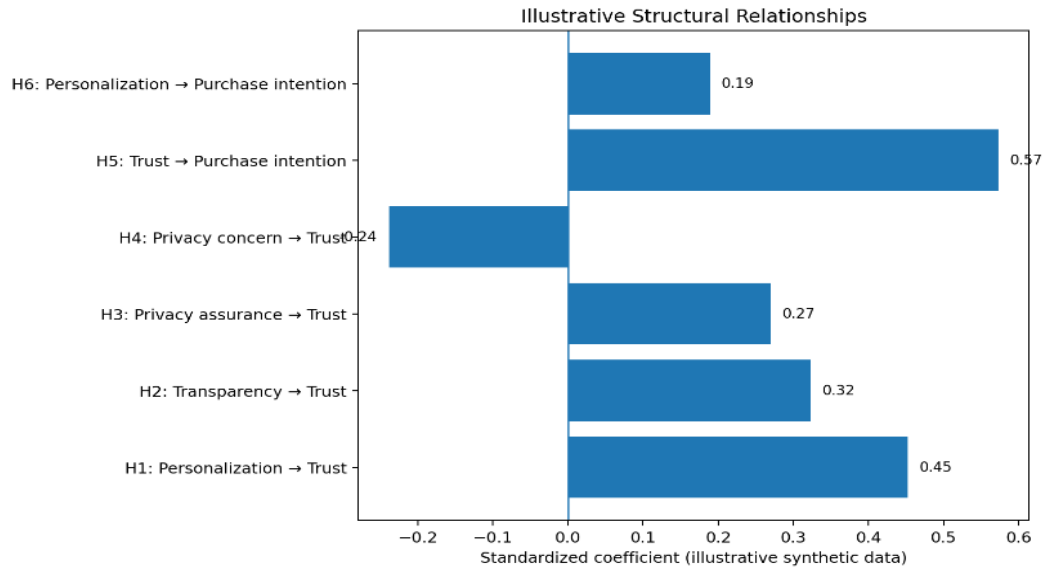

Fig. 4. Illustrative standardized path coefficients from the synthetic dataset.

In the synthetic analysis, the trust equation explains approximately 44.2% of the variance in consumer trust ($R^2 = 0.442$), while the purchase-intention equation explains approximately 56.5% ($R^2 = 0.565$). The estimated coefficients follow the directions proposed in the conceptual framework. These values are useful for demonstrating how the statistical results can be presented, but they should not be treated as evidence supporting the hypotheses until the model is tested with real respondents.

4.3 Illustrative mediation analysis

Indirect pathway	Indirect effect	Bootstrap 95% CI	Status in synthetic demonstration
AI Personalization → Consumer Trust → Purchase Intention	0.261	[0.203, 0.327]	Illustrative positive indirect association

Table 3: Mediation Analysis

The illustrative bootstrap interval does not include zero, showing how evidence for an indirect effect could be reported in an empirical study. In the final version, the researcher should calculate and report the indirect effect, direct effect, total effect, confidence interval, and relevant robustness checks using the actual respondent-level dataset.

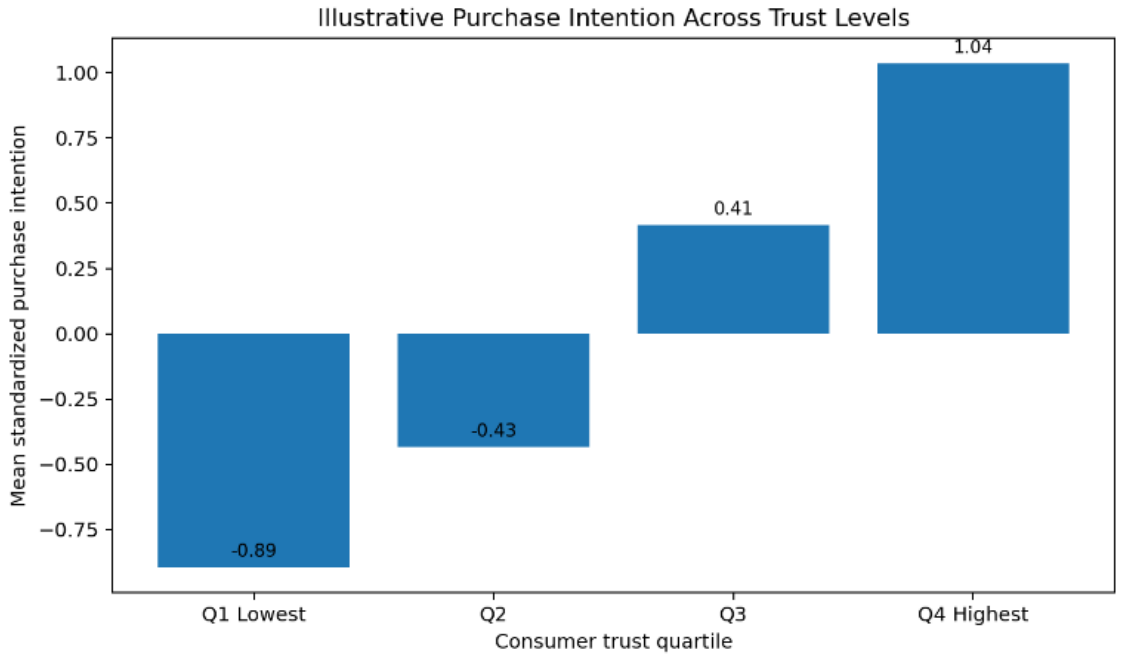

Fig. 5. Illustrative purchase intention across consumer-trust quartiles.

4.4 Hypothesis decision table for future empirical testing

Hypothesis	Proposed relationship	Synthetic demonstration	Decision rule for actual study
H1	AI Personalization → Trust	Positive	Support if β > 0 and p < .05 / CI excludes 0
H2	Transparency → Trust	Positive	Support if β > 0 and p < .05 / CI excludes 0
H3	Privacy Assurance → Trust	Positive	Support if β > 0 and p < .05 / CI excludes 0
H4	Privacy Concern → Trust	Negative	Support if β < 0 and p < .05 / CI excludes 0
H5	Trust → Purchase Intention	Positive	Support if β > 0 and p < .05 / CI excludes 0
H6	AI Personalization → Purchase Intention	Positive	Support if β > 0 and p < .05 / CI excludes 0
H7	AIP → Trust → PI	Mediation	Support if bootstrapped indirect CI excludes 0

Table 4: Hypothesis decision table for future empirical testing

5. Discussion

The proposed framework is more than just a technical upgrade to traditional e-commerce, as it considers Generative Commerce to be a strategic approach. It's an adjustment in consumer behavior with a retailer. Similar to previous studies on personalization [4,13], AI personalization can help simplify how users discover products by minimizing the need to search and make it more relevant. But a good recommendation is not sufficient to build confidence. Consumers may ask why the recommendation has

been issued, what information was used to make the recommendation, and what will happen to the information after it was used.

Transparency thus becomes a practical aspect of the model. Consumers must be informed if they are engaging with AI and be provided with sufficient information to understand what the AI is doing. It can help the interaction to be evaluated, if a short explanation of why a product was recommended, and a clear indication of important limitations can be included. The framework does not presume that additional explanation of the information is always beneficial—it focuses on information that is understandable and relevant to the consumer.

The issue of privacy assurance is related, but different. The retailer can state that the AI is used, but the consumer may not be aware of what data is being retained, shared or controlled. Privacy assurance is about consumers' perceptions that adequate protection is being offered and that they have meaningful control over their information. This distinction is consistent with the privacy-calculus-based research of consumers balancing the perceived costs of information sharing with its benefits to personalization [3–5].

The proposed framework puts consumer trust at its core, as buying is a behavioural and relational action. The shopper is not just assessing a technology, but the confidence that they can place in a technology and the retailer. The issue of generative AI shopping assistants and chatbots has become more apparent as research has emerged in this area [7,9,10]. The proposed model includes the role of trust as the connecting factor between perception of personalization, transparency and privacy and purchase intention.

For practitioners, the framework proposes a trust architecture, not just on the basis of recommendation accuracy, but also based on a trust architecture. Retailers can check if the recommendations are relevant, and they should also seek to learn if the customer doesn't understand the AI interaction, or if they don't feel their information is secure or if the AI is working on their behalf. These principles can be more conspicuous to consumers by using simple controls for personalization, conversation history and data use.

The framework provides a step-by-step reference for primary-data tests for researchers. There is potential for future research to explore differences in relationships by age, frequency of shopping, product category, and experience with AI prior to the study. Investigators can also perform a comparative analysis between the traditional recommender systems and generative shopping assistants, as well as explore transitions and shifts in the role of trust with consumers as they increasingly come to know the AI-powered shopping assistant.

6. Managerial and Theoretical Implications

6.1 Managerial implications

Align design personalisation with consumers' desire for value, which translates to relevance, time saving, comparison support and reduced decision effort.

Represent clear explanations for suggestions rather than dark expressing.

Provide to consumers visible controls to customize, short-term memory, dialogue history and data consumption.

Distinguish between mandatory and optional transaction information and personalization information.

Mark AI-generated content and specify key restrictions as necessary.

Track Conversion Metrics along with Trust, Privacy Concern, and Perceived Intrusiveness.

Avoid blindly following generative output in critical, or uncertain, product decisions; use human escalation for high-stakes decisions.

6.2 Theoretical implications

Extends personalization research by embedding AI personalization in a trust-and-privacy pathway.
Combines privacy calculus with commitment–trust logic to explain how benefits and risks can coexist.
Connects AI governance signals-transparency and privacy assurance to consumer-level behavioural outcomes.
Provides a measurable Generative Commerce construct architecture suitable for SEM and experimental designs.

7. Limitations and Future Research

The biggest drawback of the present draft is that the empirical section is synthetic data. The coefficients, sample profile and graphs are provided to illustrate the analytical workflow and not be interpreted as population level results. The next step of the research should be conducted using real primary responses, and should be conducted in accordance with the relevant ethics requirements and must include the sampling procedure, response rate and data quality checks.
The second one is the cross-sectional design of the principal study. One survey can only recognise the connection, but not the process of trust building over time. This could be explored through a longitudinal study to determine if interactions with AI affect levels of trust and privacy. Besides that, purchase intent does not necessarily lead to purchase behaviour. Future research could then include survey responses with the actual purchase behaviour or experimental data as applicable.

8. Conclusion

Generative Commerce is a transition to regarding AI as primarily intended to facilitate e-commerce to regarding it as active participants in product discovery and evaluation, recommendation, and customer interaction. It is a big opportunity, and the consumer experience is not solely reliant on the smartness of the underlying model. Shoppers must also be convinced that the system is easy to use, reliable and does not abuse their personal information.
The framework constructed within the framework of this paper combines the proven concepts of personalization, privacy calculus, relationship trust, and technology acceptance with the latest studies on generative AI in commerce. Its main claim is simple: personalization has the potential to generate value, however, this value is more significant when the consumers are also provided with clear information about AI application and experience that their privacy is respected. Consumer trust is then considered as a valuable mediator between the technical abilities of Generative AI and the intention to purchase.
The wider implication is that Generative Commerce can be considered as not only a technology system but also as a system of relationships with consumers. An incredibly competent AI can draw attention by making seemingly convenient suggestions, though the continued use by consumers will rely on trust in the manner in which the system operates. Careful personalization, transparent clarity and plausible protection of privacy can thus be significant components of the customer experience as commerce is mediated more by AI.

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