

Generative Artificial Intelligence Powered Hyper Personalization and Consumer Decision Making in Digital Marketing Ecosystems

Raden Roro Ayu Metarini^{1*} , Aswadi Jaya² , Herman Herman³ , Rizky Sebastian⁴ 

¹Faculty of Economics and Business, Pamulang University, Indonesia

²Master's Program in English Language Education, Universitas PGRI Palembang, Indonesia

³Department of English Education, HKBP Nommensen University of Pematangsiantar, Indonesia

⁴Department of Information Technology, Ilearning Incorporation, Estonia

¹dosen00945@unpam.ac.id, ²aswadijaya@univpgri-palembang.ac.id, ³herman@uhnp.ac.id ⁴kymyboy@ilearning.ee

*Corresponding Author

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ABSTRACT

Generative Artificial Intelligence (GenAI) is transforming digital marketing personalization from conventional retrieval- and recommendation-based approaches toward hyper-personalization characterized by real-time adaptivity, generative content synthesis, multimodality, and contextual relevance. However, the mechanisms linking GenAI-powered hyper-personalization to Consumer Decision Making (CDM) remain theoretically fragmented, particularly regarding perceived personalization, trust in AI, and privacy concern. **This study develops** a conceptual framework explaining how GenAI-powered hyper-personalization influences CDM through sequential psychological mechanisms and under privacy-related boundary conditions. **Grounded primarily** in the Stimulus-Organism-Response (S-O-R) paradigm and complemented by the Technology Acceptance Model and Privacy Calculus Theory, the study synthesizes literature from 2021 to 2026 and develops six research propositions. Empirical validation is proposed using PLS-SEM and a between-subjects scenario experiment comparing GenAI-generated and conventional algorithmic personalization. **The framework** conceptualizes GenAI-powered hyper-personalization as the stimulus, perceived personalization and trust in AI as sequential organismic mechanisms, privacy concern as a boundary condition, and CDM as the response. **The study contributes** by distinguishing generative hyper-personalization from conventional personalization, specifying a sequential perceived-personalization and trust mechanism, and incorporating privacy concern as a dual boundary condition. The framework also provides implications for technology innovation management, digital transformation, responsible AI governance, transparency, privacy protection, and consumer relationships.

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1. INTRODUCTION

Digital marketing ecosystems are undergoing a structural transformation through the increasing Adoption of Generative GenAI. Unlike conventional marketing technologies that primarily select or retrieve predefined content, GenAI can generate marketing content, dynamically adapt messages, and support individualized interactions across multiple digital touchpoints [1, 2]. In this study, GenAI-powered hyper-personalization refers to the use of generative AI to produce real-time, multimodal, and contextually adapted marketing content and interactions at the individual level. Although AI-enabled personalization can improve relevance and engagement, excessive or insufficiently transparent personalization may also raise concerns about privacy, intrusiveness, authenticity, and trust [3–5].

This study focuses on the consumer-level mechanism through which GenAI-powered hyper-personalization may influence CDM. The proposed framework suggests a sequential relationship in which GenAI-powered hyper-personalization increases perceived personalization, which contributes to trust in AI, and subsequently influences CDM. Privacy concern is positioned as a boundary condition that may attenuate these relationships. The framework also adopts the digital marketing ecosystem as its contextual setting, recognizing that consumers increasingly encounter cumulative personalization across e-commerce, social commerce, conversational commerce, and mobile applications [6]. Therefore, organizations need to coordinate AI capabilities, personalization, data governance, transparency, consumer control, and trust across interconnected digital channels [7].

Four research gaps motivate the proposed framework. First, a conceptual distinction gap exists between conventional algorithmic personalization and GenAI-powered personalization, which the framework addresses through four characteristics: real-time adaptivity, generative content synthesis, multimodality, and contextual relevance [8]. Second, a mechanism gap concerns how personalization capability is translated into consumer decision outcomes via sequential conversion. Third, a boundary-condition gap models privacy concern as a dual moderator. Fourth, a methodological distinction gap addresses how consumers respond differently to generative versus conventional personalization through scenario-based experimentation alongside PLS-SEM. Based on these gaps, the study addresses four research questions (RQ1–RQ4) regarding how GenAI influences decisions, the role of trust mediation, privacy moderation, and experimental distinction.

Accordingly, this paper aims to conceptualize GenAI hyper-personalization, develop an integrated behavioral framework, specify privacy boundaries, formulate propositions, and propose a mixed-method design [9]. The novelty lies in its mechanism and boundary-condition architecture specifically developed for generative personalization within digital marketing ecosystems. By treating generative personalization as a distinct stimulus and mapping its sequential path under privacy constraints, this framework provides conceptual and methodological contributions to guide responsible digital transformation through transparency, privacy protection, and sustainable consumer trust [10].

2. LITERATURE REVIEW

2.1. Stimulus-Organism-Response and Supporting Theoretical Perspectives

The proposed framework is primarily grounded in the (S-O-R) paradigm and supported by the Technology Acceptance Model (TAM), Privacy Calculus Theory, and the Consumer Decision-Making Process [11]. Each perspective serves a specific conceptual role. The S-O-R paradigm provides the overall theoretical architecture; TAM supports the explanation of consumers' evaluations of AI-enabled personalization; Privacy Calculus Theory explains the tension between personalization benefits and perceived privacy costs; and the Consumer Decision-Making Process provides the behavioral context for the proposed outcomes [12].

Within the proposed model, GenAI-powered hyper-personalization represents the Stimulus, while perceived personalization and trust in AI represent the Organism. Consumer decision-making outcomes represent the Response [13]. Privacy concern functions as a boundary condition that may alter the strength of the proposed relationships. TAM provides supporting logic for understanding how perceived relevance and interaction quality may shape consumer evaluations of AI-enabled experiences, whereas Privacy Calculus Theory explains why consumers may respond differently to similar levels of personalization depending on their perceptions of privacy costs. CDM is represented by purchase intention, decision satisfaction, and post-purchase behavioral intention [14]. This theoretical configuration integrates technological characteristics, consumer psychological evaluations, and behavioral responses within a single conceptual structure. It further clarifies how perceived personalization and trust in AI operate as sequential mechanisms between the technological stimulus and con-

sumer decision-making outcomes. Accordingly, the framework provides a basis for examining how the benefits of AI-enabled personalization may interact with privacy-related concerns in shaping consumer responses.

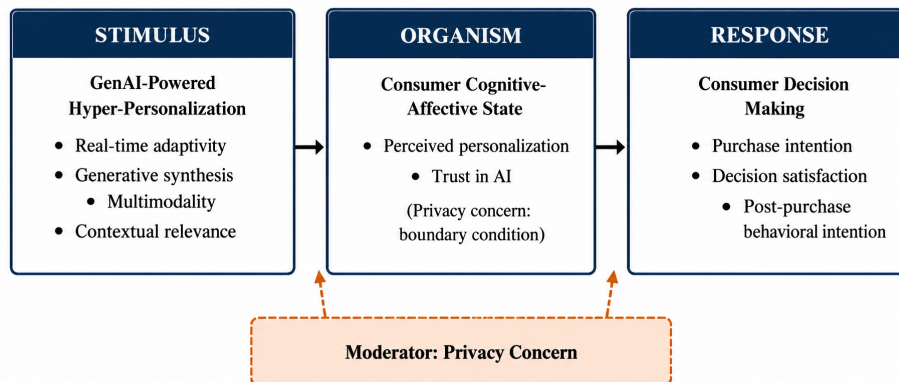


Figure 1. (S-O-R) overview of the proposed theoretical architecture, integrating TAM, Privacy Calculus Theory, and the classical consumer decision-making process

The theoretical contribution does not arise from simply combining established theories. Instead, as illustrated in Figure 1, these perspectives are integrated to explain how the generative characteristics of hyper-personalization may influence CDM through perceived personalization and trust under varying privacy conditions [15]. This integration highlights the sequential psychological mechanism through which consumers may interpret personalized AI experiences before forming trust and responding to decision-making outcomes. It also positions privacy concern as a boundary condition that may shape the strength of these relationships within the digital marketing ecosystem.

2.2. GenAI-Powered Hyper-Personalization Conceptualization

This paper conceptualizes GenAI-powered hyper-personalization as a multidimensional marketing capability through which generative AI dynamically produces or adapts content, recommendations, and interactions for individual consumers using behavioral, contextual, and multimodal information. Unlike conventional algorithmic personalization, which primarily selects, ranks, or retrieves existing content, GenAI can generate new textual, visual, conversational, and multimodal content according to changing consumer contexts [16]. The construct consists of four dimensions:

- **Real-Time Adaptivity** – the ability to modify content or recommendations as new behavioral or contextual signals become available.
- **Generative Content Synthesis** – the production of new marketing messages, recommendations, explanations, or creative content.
- **Multimodality** – the integration of text, images, voice, and conversational interaction.
- **Contextual Relevance** – the extent to which generated content corresponds to consumers' needs, preferences, situations, and decision contexts.

These dimensions distinguish GenAI-powered hyper-personalization from conventional personalization, which is primarily based on recommendation accuracy or content matching [17]. Accordingly, the contribution is not the introduction of personalization as a new construct, but the specification of GenAI-powered hyper-personalization as a distinct stimulus characterized by generation, real-time adaptation, multimodality, and contextual relevance [18]. This distinction emphasizes the generative capability of GenAI to create individualized content and interactions rather than merely select or retrieve existing content. It also provides a clearer basis for examining how these characteristics may shape perceived personalization and subsequently contribute to trust in AI. In this framework, the distinctive technological characteristics of GenAI-powered hyper-personalization therefore serve as the foundation for explaining consumer responses within the proposed digital marketing ecosystem.

Table 1. Constructs and Conceptual Operationalization

Construct	Working Definition	Role in Framework	Measurement Orientation
GenAI-Powered Hyper-Personalization	Generative AI produces real-time, multimodal, and contextually adapted marketing content and interactions for individual consumers.	Stimulus	Reflective higher-order construct
Perceived Personalization	Consumer perception that content is tailored to individual needs, preferences, and context.	Organism	Reflective
Trust in AI	Willingness to rely on AI-generated recommendations based on perceived competence, reliability, transparency, and integrity.	Organism / Mediator	Reflective
Privacy Concern	Concern regarding the collection, use, monitoring, and potential misuse of personal data.	Boundary Condition / Moderator	Reflective
CDM	Consumer responses resulting from evaluation and choice processes in digital purchasing contexts.	Response	Reflective multidimensional outcome

Table 1 outlines the working definitions, theoretical roles, and measurement orientations for each construct within the proposed framework. Specifically, it delineates the sequential transition from the technological stimulus to the cognitive and affective organismic states, accounting for privacy boundaries that condition consumer decision-making responses in digital marketing ecosystems.

2.3. CDM in the GenAI Era

AI-enabled personalization may influence consumer responses through perceived relevance, usefulness, trust, engagement, and purchase intention [19]. However, personalization does not necessarily produce uniform responses because consumers may evaluate both its potential benefits and associated privacy risks. In GenAI environments, this distinction becomes particularly relevant because AI can generate individualized recommendations, explanations, and content during the interaction itself [20]. Research comparing generative recommendations with conventional AI recommenders further suggests that generative systems may influence consumer consideration and choice differently.

Accordingly, this study does not assume that greater personalization automatically produces better consumer decisions. Instead, it proposes that consumers first evaluate whether an AI-generated experience is genuinely personalized. This perception may contribute to trust, which subsequently facilitates decision-making outcomes. Privacy concern is incorporated as a boundary condition because perceived personalization benefits may coexist with perceived costs associated with data use, monitoring, and surveillance [21].

2.4. Trust in AI as a Mediating Mechanism

Trust represents the principal psychological mechanism connecting AI-enabled personalization with consumer behavioral responses [22]. Recent research indicates that trust can mediate relationships between GenAI-generated communication and purchase-related intentions, while personalization may influence trust through perceptions of relevance and usefulness.

Accordingly, the proposed mechanism is:

- GenAI-Powered Hyper-Personalization
- Perceived Personalization
- Trust in AI
- CDM

Trust is positioned as a mediator because it reflects consumers' willingness to rely on AI-generated recommendations when uncertainty remains regarding their quality, reliability, and potential consequences [23]. Thus, trust is not treated merely as another positive perception but as the mechanism through which personalization may be translated into consumer decision outcomes.

2.5. Privacy Concern as a Boundary Condition

The relationship between personalization and consumer responses is constrained by the personalization–privacy tension [24]. Consumers may value highly relevant recommendations while simultaneously becoming concerned about the amount and use of personal information required to generate them. This issue is particularly relevant to GenAI-powered hyper-personalization because generative systems may combine information from multiple interaction points to produce highly individualized outputs [25].

The proposed framework therefore treats privacy concern as a boundary condition rather than as an independent competing explanation [26]. Higher privacy concern is expected to weaken the relationship between hyper-personalization and trust in AI and to attenuate the direct relationship between hyper-personalization and CDM [27]. Consistent with Privacy Calculus Theory, consumers are expected to evaluate the benefits of personalization together with perceived privacy costs.

2.6. Analytical Synthesis and Research Gap

Existing literature establishes the importance of AI personalization, trust, privacy, and consumer behavior; however, these elements remain conceptually fragmented [28]. Previous studies generally examine personalization as a broad technological capability, trust as a predictor or mediator, and privacy as an independent concern. Research comparing GenAI with conventional recommendation systems also suggests that generative mechanisms warrant separate examination [29].

The unresolved issues can be summarized into four gaps:

Table 2. Research Gaps and Proposed Advancements

Gap	Unresolved Issue	Proposed Advancement
Generative Distinction Gap	GenAI's generative characteristics are not consistently modeled as a distinct stimulus.	Defines hyper-personalization through real-time adaptivity, generative content synthesis, multimodality, and contextual relevance.
Mechanism Gap	The sequential process connecting personalization to consumer decisions remains insufficiently specified.	Proposes the sequence: hyper-personalization → perceived personalization → trust → CDM.
Boundary-Condition Gap	Privacy concern is often treated as an independent predictor rather than as a boundary condition.	Models privacy concern as a moderator of the relationships involving hyper-personalization, trust, and decision making.
Methodological Distinction Gap	Cross-sectional studies cannot clearly isolate the distinctive contribution of GenAI-generated personalization.	Proposes a scenario-based experiment comparing GenAI-generated and conventional algorithmic personalization, complemented by PLS-SEM.

The proposed contribution is therefore not the invention of the individual constructs or theories summarized in Table 2. Instead, it lies in specifying their operational relationships around a GenAI-specific stimulus and developing a future empirical strategy capable of distinguishing generative personalization from conventional personalization [30].

2.7. Conceptual Model

The proposed conceptual model follows the S-O-R architecture. GenAI-powered hyper-personalization constitutes the Stimulus and is represented by real-time adaptivity, generative content synthesis, multimodality, and contextual relevance [31]. Perceived personalization and trust in AI constitute the Organism and represent

the sequential psychological mechanism through which consumers may evaluate and respond to personalized AI experiences [32]. Privacy concern functions as a boundary condition that may weaken the proposed relationships. CDM represents the Response and is operationalized through purchase intention, decision satisfaction, and post-purchase behavioral intention.

AI literacy and product category involvement are retained as potential variables for future empirical extensions and are therefore excluded from the core conceptual model [33].

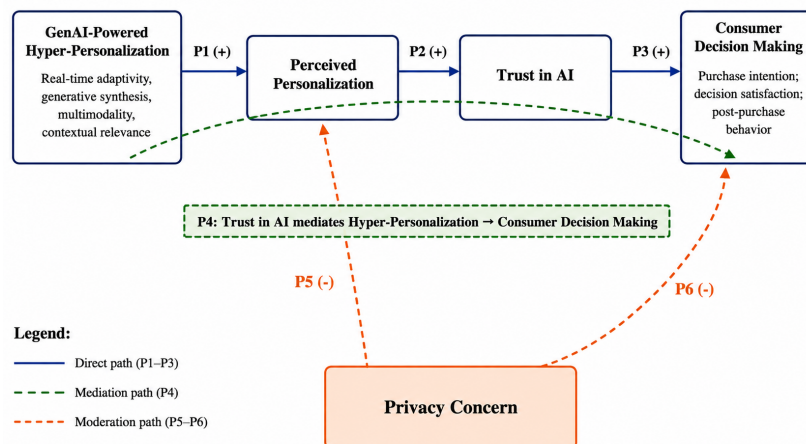


Figure 2. Proposed research model showing direct paths (P1–P3), the mediating path (P4), and the moderating paths (P5–P6).

Figure 2 illustrates the structural architecture of the proposed research model, delineating the interrelationships among the theoretical constructs. The diagram highlights the sequential conversion process from GenAI-powered hyper-personalization to consumer decision-making via perceived personalization and trust in AI (P1–P4), while depicting the dual moderating influence of privacy concern (P5–P6) that attenuates these relationships. The model positions GenAI-powered hyper-personalization as the primary stimulus that initiates the consumer response process within the digital marketing ecosystem. Perceived personalization represents the consumer’s cognitive evaluation of whether the generated content or recommendation is relevant to their individual preferences and circumstances. This perception is subsequently expected to strengthen trust in AI, which functions as an important psychological mechanism linking personalized interactions with consumer decision-making. The sequential relationship therefore emphasizes that personalization alone does not directly determine consumer responses, but may operate through consumers’ perceptions and trust toward AI-based interactions. Privacy concern is incorporated as a boundary condition to recognize that consumers may respond differently to personalized experiences depending on their concerns regarding data collection, processing, and use. Accordingly, the proposed model integrates personalization effectiveness with responsible data considerations to provide a more comprehensive explanation of consumer decision-making in GenAI-enabled digital marketing environments.

2.8. Research Propositions

This research framework formulates six core propositions explaining how Generative AI (GenAI) hyper-personalization influences consumer decision-making [34]. First (P1), GenAI-powered hyper-personalization is positively associated with perceived personalization, as the integration of its four dimensions real-time adaptivity, generative content synthesis, multimodality, and contextual relevance strengthens consumers’ perception that marketing content is uniquely tailored to their needs and situation [35].

Subsequently (P2), perceived personalization is positively associated with trust in AI, because relevant and tailored experiences reduce uncertainty, thereby increasing consumers’ willingness to rely on the system [36]. This trust then directly drives behavior (P3), where trust in AI is positively associated with CDM outcomes by easing evaluation processes and fostering purchase intention, decision satisfaction, and post purchase behavioral intentions [37]. Integrating these paths yields a sequential mediation pathway (P4), wherein perceived personalization and trust in AI sequentially mediate the relationship between GenAI hyper personalization and CDM outcomes, confirming that personalization does not directly dictate decisions but operates

through a step-by-step psychological conversion mechanism [38]. Conversely, privacy concern functions as a boundary condition that negatively moderates these relationships. Under the fifth proposition (P5), privacy concern negatively moderates the positive relationship between GenAI-powered hyper-personalization and trust in AI, as heightened anxiety over data collection and potential misuse triggers a privacy calculus that suppresses trust formation [39]. Finally (P6), privacy concern negatively moderates the direct relationship between GenAI hyper-personalization and consumer decision-making outcomes, indicating that when personalization is perceived as overly intrusive or insufficiently controlled, consumer responses deteriorate despite the content's contextual relevance.

Table 3. Proposed Research Propositions

Proposition	Proposed Relationship	Expected Direction
P1	GenAI-powered hyper-personalization → Perceived personalization	+
P2	Perceived personalization → Trust in AI	+
P3	Trust in AI → CDM	+
P4	GenAI-powered hyper-personalization → Perceived personalization → Trust in AI → CDM	+ indirect
P5	Privacy concern × GenAI-powered hyper-personalization → Trust in AI	– attenuation
P6	Privacy concern × GenAI-powered hyper-personalization → CDM	– attenuation

Table 3 synthesizes the core research propositions and their expected directional effects within the conceptual framework. The structural model delineates a positive sequential mechanism from GenAI-powered hyper-personalization to consumer decision-making through perceived personalization and trust in AI (P1–P4), while accounting for the attenuating influence of privacy concern as a critical boundary condition (P5–P6).

2.9. Conceptual Contribution

The framework makes three principal conceptual advances. First, it distinguishes GenAI-powered hyper-personalization from conventional algorithmic personalization through its generative, adaptive, multi-modal, and contextual characteristics. Second, it specifies a sequential psychological mechanism in which perceived personalization precedes trust, while trust connects personalization with CDM [40]. Third, it incorporates privacy concern as a boundary condition, recognizing that the potential benefits of personalization may depend on consumers' evaluation of associated privacy costs.

Overall, the framework provides a theoretical explanation of why, through what mechanism, and under what privacy conditions GenAI-powered hyper-personalization may influence CDM [41]. The proposed combination of PLS-SEM and scenario-based experimentation provides a future methodological basis for testing the framework and distinguishing GenAI-generated personalization from conventional algorithmic personalization.

3. RESEARCH METHODOLOGY

3.1. Research Design

A sequential mixed-method design is proposed, consisting of (a) an online survey analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) and (b) a between-subjects scenario-based experiment [42]. The survey is designed to examine the proposed relationships among GenAI-powered hyper-personalization, perceived personalization, trust in AI, privacy concern, and consumer decision-making outcomes. PLS-SEM is appropriate for assessing latent constructs and examining the proposed mediation and moderation relationships [43].

The experiment is designed to compare GenAI-generated personalization with conventional non-generative algorithmic personalization. Participants will be randomly assigned to one of two conditions using comparable products, consumer information, recommendation objectives, and information quantity [44]. The proposed experiment is intended to provide additional evidence regarding differences in perceived personalization, trust in AI, and consumer decision-making outcomes between the two conditions. Because the experiment

has not yet been conducted, no causal effects are claimed in the present study [45].

3.2. Population, Sample, and Sampling Technique

The target population comprises digital consumers who have interacted with AI-based personalization features within the previous three months [46]. Purposive non-probability sampling is proposed, with screening questions used to confirm participants' relevant experience with AI-enabled personalization.

The proposed survey sample is 200–300 respondents, while the experimental sample is 120–200 participants, approximately equally divided between the two conditions [47]. Final sample sizes should be determined through an a priori power analysis based on the anticipated effect size, $\alpha = .05$, and statistical power = .80. These figures represent planning targets rather than achieved sample sizes [48].

3.3. Measurement

Validated multi-item measurement scales should be adapted to the GenAI-powered hyper-personalization context using a 7-point Likert scale [49]. GenAI-powered hyper-personalization consists of four dimensions: real-time adaptivity, generative content synthesis, multimodality, and contextual relevance. Perceived personalization measures the extent to which consumers perceive content as tailored to their needs and situations, while trust in AI captures perceptions of reliability, competence, transparency, and integrity. Privacy concern addresses concerns regarding the collection, use, monitoring, and potential misuse of personal information. CDM is represented by purchase intention and decision satisfaction.

The measurement instrument should undergo expert review and a pilot test involving approximately 30 respondents before the main survey. Measurement quality should subsequently be assessed using indicator reliability, average variance extracted (AVE), heterotrait-monotrait ratio (HTMT), Cronbach's alpha, and composite reliability.

Table 4. Proposed Measurement Structure

Construct	Indicative Items	Scale	Orientation	Adapted From
GenAI-Powered Hyper-Personalization	12–16	7-point Likert	Multidimensional; four dimensions	[2, 8]
Perceived Personalization	3–4	7-point Likert	Reflective	[3]
Trust in AI	4–5	7-point Likert	Reflective	[50]
Privacy Concern	4–5	7-point Likert	Reflective	[51]; recent AI-privacy measures
Purchase Intention	3–4	7-point Likert	Reflective	[52]
Decision Satisfaction	3–4	7-point Likert	Reflective	Established consumer decision-making measures

Table 4 summarizes the proposed measurement specifications, indicating the distribution of items, measurement scales, theoretical orientations, and foundational literature sources for each construct. By adapting validated items onto a 7-point Likert scale, this measurement framework establishes a robust foundation for evaluating both reflective first-order constructs and the multidimensional higher-order structure of GenAI-powered hyper-personalization in empirical evaluations. The proposed measurement structure ensures that each construct is represented by indicators that correspond to its conceptual definition and theoretical role within the framework. For GenAI-powered hyper-personalization, the four dimensions provide a comprehensive representation of its real-time, generative, multimodal, and contextual characteristics. The reflective constructs are designed to capture consumers' perceptions of personalization, trust, privacy concern, and decision-related responses consistently across the proposed empirical setting. Before the main data collection, the measurement items should be reviewed for conceptual clarity and contextual relevance and subsequently assessed through

a pilot test. The resulting measurement model can then be evaluated for reliability, convergent validity, and discriminant validity before testing the structural relationships proposed in the framework.

3.4. Data Collection

Data collection is proposed through an online questionnaire distributed through e-commerce platforms, social-commerce channels, and relevant online consumer communities. Screening questions will be used to confirm participants' recent exposure to AI-enabled personalization. For the experimental component, participants will be randomly assigned to either a GenAI-generated personalized content condition or a conventional algorithmic recommendation condition. Comparable products and consumer profiles will be used across conditions to maintain consistency in the experimental stimuli. Following stimulus exposure, participants will evaluate perceived personalization, trust in AI, and consumer decision-making outcomes.

A manipulation check will assess whether participants recognize the distinction between the generative and conventional personalization conditions [53]. Predetermined attention and comprehension criteria should be established before the analysis is conducted.

3.5. Data Analysis Technique

Survey data should be analyzed using PLS-SEM, such as SmartPLS. The measurement model will assess indicator reliability, average variance extracted (AVE), heterotrait-monotrait ratio (HTMT), Cronbach's alpha, and composite reliability. The structural model will evaluate path coefficients, R^2 , effect sizes, confidence intervals, and bootstrapping based on approximately 5,000 resamples.

Mediation analysis will examine the proposed sequential pathway from GenAI-Powered Hyper-Personalization to Perceived Personalization, followed by Trust in AI and ultimately Consumer Decision-Making (CDM). This analysis corresponds to P4 and is intended to assess the proposed sequential mediating mechanism linking hyper-personalization to consumer decision-making outcomes. Moderation analysis will examine whether Privacy Concern attenuates the relationship between GenAI-Powered Hyper-Personalization and Trust in AI (P5), as well as the direct relationship between GenAI-Powered Hyper-Personalization and Consumer Decision-Making outcomes (P6).

Experimental data should be analyzed using ANOVA or ANCOVA, depending on the final experimental design and covariate requirements. Differences between the GenAI-generated and conventional algorithmic conditions will be examined for perceived personalization, trust in AI, and consumer decision-making outcomes. Effect sizes and confidence intervals should also be reported where appropriate. All procedures described in this section represent proposed analyses and should not be interpreted as empirical findings.

4. RESULTS AND DISCUSSION

4.1. Conceptual Results of GenAI-Powered Hyper-Personalization

The conceptual analysis identifies GenAI-powered hyper-personalization as distinct from conventional algorithmic personalization because of its ability to dynamically generate individualized content and interactions from behavioral and contextual signals. The proposed stimulus consists of four dimensions: real-time adaptivity, generative content synthesis, multimodality, and contextual relevance. These characteristics are theoretically expected to strengthen perceived personalization, corresponding to P1. However, the framework does not assume that GenAI-powered personalization is inherently more effective than conventional personalization.

The distinction is particularly relevant because conventional algorithmic personalization primarily selects, ranks, or retrieves existing content, whereas GenAI can generate new content and interactions according to changing consumer contexts. Therefore, the proposed framework treats the generative capability itself as an important characteristic of the stimulus rather than simply extending conventional personalization models.

4.2. Sequential Mechanism from Perceived Personalization to CDM

The framework proposes a sequential mechanism in which GenAI-powered hyper-personalization influences perceived personalization, perceived personalization contributes to trust in AI, and trust subsequently influences consumer decision-making outcomes. P1, P2, and P3 represent the individual relationships within this mechanism, while P4 integrates them into the proposed sequential mediation pathway:

GenAI-Powered Hyper-Personalization → Perceived Personalization → Trust in AI → CDM This mechanism suggests that the potential influence of GenAI-powered hyper-personalization is not conceptualized as a direct technological effect alone. Instead, the framework emphasizes the psychological process through

which consumers interpret personalized AI experiences and develop willingness to rely on AI-generated recommendations. Trust therefore functions as the proximate mechanism connecting perceived personalization with consumer decision-making outcomes.

Table 5. Proposed Conceptual Relationships and Expected Results

Proposition	Conceptual Relationship	Expected Relationship
P1	GenAI-powered hyper-personalization → Perceived personalization	Positive
P2	Perceived personalization → Trust in AI	Positive
P3	Trust in AI → CDM	Positive
P4	GenAI-powered hyper-personalization → Perceived personalization → Trust in AI → CDM	Positive indirect relationship
P5	Privacy concern × Hyper-personalization → Trust in AI	Negative attenuation
P6	Privacy concern × Hyper-personalization → CDM	Negative attenuation

Table 5 summarizes the expected conceptual relationships and directional outcomes corresponding to the formulated propositions. It highlights the positive direct and indirect structural pathways connecting GenAI hyper-personalization to consumer decision-making (P1–P4), while specifying the negative attenuating effects imposed by privacy concern as a moderating boundary condition (P5–P6).

4.3. Privacy Concern as a Boundary Condition

Privacy concern represents an important boundary condition within the proposed framework because GenAI-powered hyper-personalization may rely on behavioral, contextual, and cross-channel information. P5 proposes that higher privacy concern may weaken the relationship between hyper-personalization and trust in AI, while P6 proposes a similar attenuation of the direct relationship between hyper-personalization and consumer decision-making outcomes.

This relationship reflects the personalization–privacy tension. Consumers may perceive highly relevant recommendations as useful while simultaneously perceiving the underlying data practices as intrusive or insufficiently controlled. Accordingly, the potential benefits of personalization may depend on how consumers evaluate the privacy costs associated with data collection and use. Effective implementation should therefore incorporate transparent data practices, meaningful consumer control, and clear communication regarding AI-generated personalization.

4.4. Implications for Digital Transformation and Responsible AI Management

The proposed framework suggests that organizations should evaluate GenAI-powered hyper-personalization beyond conversion rates and recommendation performance. Consumer trust, perceived personalization, privacy concern, transparency, and consumer control should also be incorporated into the evaluation of AI-enabled marketing initiatives.

GenAI can integrate customer information, content generation, recommendations, conversational interfaces, and multiple digital channels, thereby supporting more interconnected digital customer experiences. However, greater integration of consumer data also increases the importance of governance mechanisms. Organizations should therefore prioritize AI transparency, privacy-aware personalization, meaningful consumer control, and trust-oriented performance evaluation when implementing GenAI-powered personalization.

From a technology innovation management perspective, the framework indicates that successful digital transformation involves more than adopting advanced AI capabilities. Organizations also need to align technological innovation with consumer-facing governance mechanisms. Such alignment may help organizations capture the potential value of hyper-personalization while addressing concerns related to privacy, transparency, and consumer autonomy.

5. MANAGERIAL IMPLICATIONS

For digital marketing practitioners, the proposed framework indicates that GenAI-powered hyper-personalization should be implemented as an organizational capability that integrates AI governance, transparency, privacy protection, personalization strategy, and trust-building mechanisms. Technological sophistication alone may not produce favorable CDM unless it is supported by appropriate psychological and governance mechanisms. From a technology innovation management and digital transformation perspective, organizations should provide transparent information about data collection, processing, and AI-generated recommendations while giving consumers meaningful control over personalization settings. Explainability should also be incorporated into personalized marketing systems to help consumers understand the rationale underlying AI-generated content and recommendations, thereby supporting the trust-formation mechanism proposed in P2.

Privacy and consent mechanisms should be embedded directly into the personalization experience rather than treated solely as compliance-oriented disclosures. This approach enables consumers to evaluate the perceived benefits and privacy costs of personalized interactions, consistent with the boundary conditions proposed in P5 and P6. Because privacy concern may vary across consumer segments, organizations should adopt adaptive personalization strategies that account for differences in consumer perceptions and responses rather than applying uniform personalization intensity to all users. Furthermore, because trust represents a proposed mechanism connecting GenAI-powered hyper-personalization with CDM in P3 and P4, managers should evaluate personalization strategies using broader indicators that include trust, transparency, privacy perceptions, consumer control, and responsible AI governance alongside conventional measures such as engagement, conversion, and recommendation performance.

An integrated management approach can therefore support digital transformation and technological innovation while maintaining responsible data practices, consumer autonomy, and sustainable long-term digital customer relationships. The proposed framework provides managers with a basis for aligning GenAI personalization capabilities with consumer-oriented governance rather than treating personalization solely as a technological or performance-optimization function.

6. CONCLUSION

Generative AI is reshaping digital marketing personalization from conventional retrieval- and recommendation-based approaches toward more generative, adaptive, multimodal, and context-sensitive interactions. This paper develops a conceptual framework that positions GenAI-powered hyper-personalization as a distinct technological stimulus within the Stimulus-Organism-Response perspective and explains its proposed relationship with CDM through a sequential mechanism involving perceived personalization and trust in AI. The framework also incorporates privacy concern as a boundary condition that may influence the relationships between hyper-personalization, trust, and consumer decision-making outcomes. Accordingly, the paper extends the emerging literature on GenAI personalization by integrating the technological characteristics of generative personalization with consumer psychological mechanisms and privacy-related conditions within a unified conceptual framework.

From a technology innovation management and digital transformation perspective, the framework emphasizes that the organizational value of GenAI-powered hyper-personalization depends not only on content-generation and personalization capabilities but also on how organizations manage trust, transparency, privacy, and consumer control. The framework provides a basis for integrating responsible AI governance into personalization strategies through transparent data practices, explainable AI-generated recommendations, meaningful consent, and consumer control mechanisms. These elements are relevant to sustainable digital management because long-term value creation from AI-enabled personalization requires a balance between technological innovation, customer relevance, responsible data use, and consumer autonomy. In this context, the framework contributes conceptually to digital transformation and sustainable management objectives related to SDG 8, SDG 9, and SDG 12.

As a conceptual study, the conclusions presented in this paper are theoretically derived and do not constitute empirical confirmation of the six proposed propositions. Future research should therefore implement the proposed sequential mixed-method methodology by testing the relationships through PLS-SEM and examining the distinction between GenAI-generated and conventional algorithmic personalization through controlled experimental scenarios. Subsequent research may extend the framework using longitudinal and cross-

cultural designs and examine additional boundary conditions, including AI literacy, product involvement, and regulatory context. Future empirical studies should also investigate potential adverse consequences of hyper-personalization, such as decision fatigue, perceived manipulation, privacy discomfort, and reduced consumer autonomy. Such validation can clarify the conditions under which GenAI-powered hyper-personalization may contribute to effective, trustworthy, and responsible CDM across evolving digital marketing ecosystems.

7. DECLARATIONS

7.1. About Authors

Raden Roro Ayu Metarini (AM)  <https://orcid.org/0009-0000-7196-2926>

Aswadi Jaya (AJ)  <https://orcid.org/0000-0001-5706-0977>

Herman (HH)  <https://orcid.org/0000-0001-6818-5142>

Rizky Sebastian (RS)  <https://orcid.org/0009-0008-5917-6664>

7.2. Author Contributions

Conceptualization: AM and AJ; Methodology: HH; Software: RS and AM; Validation: AJ and HH; Formal Analysis: RS and AM; Investigation: AJ; Resources: HH; Data Curation: RS; Writing Original Draft Preparation: AM and AJ; Writing Review and Editing: HH and RS; Visualization: AM. All authors, AM, AJ, HH and RS, have read and agreed to the published version of the manuscript.

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