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Algorithmic Performance Expectations and Impulsive Buying in E-Commerce: Trust in Algorithm-Generated Recommendations As a Mediator

Syahida Norviana[1*], Victoria Kusumaningtyas Priyambodo[2], Septiningdyah Arianisari[1], Willa Putri Malinda Buchori[1]

[1]Universitas Negeri Yogyakarta, Yogyakarta, Indonesia
[2]Universitas Mataram, Nusa Tenggara Barat, Indonesia
*Correspondence email : syahida.norviana@uny.ac.id

Abstract - This study investigates the impact of algorithmic performance expectations on impulsive buying behavior within e-commerce platforms, with trust in algorithm-generated recommendations serving as a mediating variable. A structured questionnaire was administered to 116 online shoppers in Yogyakarta, Indonesia. The hypothesized relationships were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The empirical findings indicate that algorithmic performance expectations significantly enhance consumer trust, which subsequently drives spontaneous purchasing decisions. These insights suggest that consumers' perceptions of the accuracy and transparency of AI recommendation systems are crucial factors for e-commerce businesses in building platform trust, reducing user skepticism, and effectively encouraging spontaneous consumption among digital shoppers.

Keywords: *algorithmic performance expectations, e-commerce, impulsive buying, persuasion knowledge theory, trust*

INTRODUCTION

The landscape of global e-commerce has witnessed an unprecedented metamorphosis over the last decade, catalyzed by the pervasive integration of digital technologies (Chen et al., 2024). This digital surge, however, has intensified market competition, forcing online retailers to grapple with the dual challenge of sustaining customer loyalty and managing logistical complexities, such as escalating product return rates and operational overheads (Gallin & Portes, 2024). Beyond mere survival, businesses are now compelled to innovate their engagement strategies to meet the burgeoning consumer demand for highly personalized shopping journeys (Ratchford et al., 2022) and to navigate the intricacies of multi-channel consumer behavior (Patten et al., 2020).

Current empirical evidence highlights the strategic importance of impulsive buying, noting that spontaneous shoppers often outspend planned shoppers by 20-50% (Redine et al., 2023). In fact, approximately 40% of online transactions occur without prior intent (Liu et al., 2020), positioning impulsive behavior as a vital engine for increasing both sales volume and average transaction value. In Indonesia, this phenomenon is particularly robust, fueled by high internet penetration and the dominance of platforms like Shopee, Tokopedia, and Lazada. While external stimuli such as discounts and persuasive advertisements play a role (Basu, 2021), the modern catalyst for such spontaneity lies in the sophisticated mechanics of AI-driven recommendation systems.

This algorithmic engine has become the "central nervous system" of e-commerce, leveraging big data to deliver hyper-personalized suggestions that can boost conversion rates by up to 30% (Kimiagari & Malafe, 2021). Yet, the technical prowess of an algorithm is only half the battle; its actual efficacy is deeply contingent upon how consumers perceive its performance and the subsequent trust they vest in those automated suggestions (Komiak & Benbasat, 2006). Despite the wealth of literature on impulsive buying, the specific nuance of "algorithmic performance expectations" remains an under-researched frontier (Ngo et al., 2024; Yuan et al., 2024). Furthermore, there is a distinct lack of comprehensive understanding regarding how trust functions as a mediating bridge in this relationship (Wang et al., 2023).

To address this theoretical lacuna, this study adopts the Persuasion Knowledge Model (PKM) as its primary analytical lens (Paz & Vargas, 2023). The PKM provides a sophisticated framework for understanding how consumers interpret and respond to the persuasive tactics embedded in AI systems (Fu et al., 2020). The theoretical novelty of this study extends beyond merely proposing a mediating role for trust. Specifically, this study introduces Trust in Algorithm-Generated Recommendations as a context-specific mediator. This variable captures consumers' confidence in the accuracy, benevolence, and integrity of AI-driven recommendations. This construct is distinct from general trust in platforms or vendors. Furthermore, this study differs from traditional PKM studies by positioning impulsive buying behavior as the outcome variable. Consequently, this study examines when and how persuasion knowledge leads to spontaneous purchases rather than skepticism. When consumers scrutinize whether an algorithm serves their best interests or merely acts as a manipulative tool for the seller (Chen et al., 2023), their Trust in Algorithm-Generated Recommendations becomes the decisive mediating mechanism in shaping impulsive responses. By integrating Trust in Algorithm-Generated Recommendations with the PKM in the context of Indonesia's mobile-based e-commerce, this study fills a critical gap in the literature on AI persuasion, algorithmic trust, and impulsive behavior.

By analyzing the nexus between algorithmic performance expectations, trust, and impulsive buying, this research seeks to refine our theoretical understanding of how AI reshapes human consumption (Bilal et al., 2024). Practically, the insights gleaned here will offer a roadmap for retailers and platform developers to design more transparent and effective recommendation engines (Arias et al., 2024), ultimately bridging the gap between advanced marketing technology and consumer-centric practice.

THEORETICAL FRAMEWORK

The Persuasion Knowledge Model

The Persuasion Knowledge Model (PKM), as conceptualized by Friestad and Wright (1994), offers a robust theoretical foundation for dissecting how consumers interpret algorithm-driven recommendations in the e-commerce landscape. This framework posits that individuals are not passive recipients; rather, they actively cultivate a sophisticated understanding of marketing tactics, which subsequently dictates their evaluative responses to promotional communications (Boerman et al., 2017). In the realm of algorithmic intervention, the PKM's relevance is amplified. Consumers do not merely assess the technical precision of a suggestion defined here as algorithmic performance expectations but also scrutinize the underlying motives of the system, questioning whether it serves as a helpful assistant or a manipulative tool designed to steer their purchasing autonomy (Wien & Peluso, 2021). Thus, the PKM elucidates the psychological pathway where trust in recommendation systems emerges as a pivotal mediator, bridging the gap between perceived algorithmic efficiency and the drive for impulsive consumption.

Furthermore, the PKM underscores the vital role of transparency in algorithmic design as a prerequisite for fostering and sustaining consumer trust (Wang et al., 2023). The theory predicts a favorable cognitive response when users perceive this algorithm as objective and utilitarian instruments rather than covert manipulative agents (Castelo et al., 2019). By applying this model, the present study facilitates a nuanced analysis of how consumer perceptions regarding algorithmic goals and performance shape impulsive buying tendencies through the prism of trust formation. Empirical precedents have cautioned that hyper-personalized recommendations may occasionally trigger consumer "reactance" if they are perceived to infringe upon privacy or personal boundaries (Ameen et al., 2021) a phenomenon that aligns seamlessly with the PKM's core propositions. Consequently, by integrating the Persuasion Knowledge Model, this research transcends simple

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causal analysis, offering practical directives for the development of ethical and high-performing recommendation systems.

Algorithmic Performance Expectations and Trust in Algorithm-Generated Recommendations

Prior literature consistently demonstrates that consumer trust in algorithmic recommendations is fundamentally anchored in their expectations regarding the system's performance and utility (Ghasemaghaei et al., 2019; Komiak & Benbasat, 2006). A study by Kim et al. (2021) reveals that when consumers perceive a recommendation system as being highly capable of deciphering their unique preferences a core facet of performance expectations their institutional trust in the system escalates significantly. This is corroborated by Castelo et al. (2019), who suggest that algorithms perceived as competent and value-adding are more likely to be embraced by users. Essentially, the nexus between performance expectations and trust reflects a cognitive evaluative process where consumers weigh the underlying motives and objectives of the recommendation engine.

The Persuasion Knowledge Model (PKM) provides further clarity on this dynamic, suggesting that trust flourishes when consumers interpret high algorithmic performance as an altruistic attempt to facilitate, rather than manipulate, their purchasing decisions (Boerman et al., 2017). Conversely, even a technically superior algorithm may fail to garner trust if consumers detect "hidden persuasion" or aggressive marketing tactics (Accenture, 2023). Castelo et al. (2019) reinforce this perspective by emphasizing that transparency regarding algorithmic mechanics can fortify the positive correlation between performance expectations and trust. Consequently, it is anticipated that as consumers' perceptions of an algorithm’s competence increase, their confidence in the resulting recommendations will follow suit.

H_1: Algorithmic performance expectations exert a positive influence on trust in algorithm-generated recommendations.

Trust in Algorithm-Generated Recommendations and Impulsive Buying Behavior

Within the e-commerce landscape, consumer trust in algorithmic suggestions serves as a potent predictor of impulsive buying behavior. Empirical evidence from Kimiagari and Asadi Malafe (2021) suggests that individuals possessing a high degree of trust in such recommendations are 2.3 times more likely to engage in impulsive transactions compared to their skeptical counterparts. This finding is further supported by Ampadu et al. (2022), who identify trust as a critical mediator bridging the gap between system quality and spontaneous purchasing decisions. Collectively, these studies underscore the vital role of trust in facilitating impulsivity, although the magnitude of this effect may fluctuate depending on consumer demographics and product characteristics. When consumers vest their trust in an algorithm, perceiving it as a competent entity aligned with their personal needs, they are inclined to de-escalate their typical persuasion-defense mechanisms (Wien & Peluso, 2021).

Drawing from the Persuasion Knowledge Model (PKM), trust can be conceptualized as a "cognitive license" that allows algorithmic recommendations to influence behavior without triggering an exhaustive or critical evaluative process (Friestad & Wright, 1994). Research by Castelo et al. (2019) reinforces this notion, demonstrating that under conditions of high trust, consumers allocate significantly less cognitive effort toward scrutinizing recommendations, thereby increasing their susceptibility to purchasing impulses. Consequently, it is hypothesized that an elevated level of trust in algorithm-generated suggestions will result in a heightened propensity for impulsive buying behavior.

H_2: Trust in algorithm-generated recommendations exerts a positive influence on impulsive buying behavior.

The theoretical framework and the resulting hypothesized paths are synthesized in the conceptual model illustrated in **Figure 1**.

Figure 1. Research Model

METHODOLOGY

Research Design

This study employs a quantitative approach, utilizing a structured survey distributed to e-commerce users within the Yogyakarta region. To ensure that every participant had an equal and independent probability of being selected, a simple random sampling technique was implemented. To ensure that every participant had an equal and independent probability of being selected, a simple random sampling technique was implemented. The minimum required sample size was determined using the Slovin formula with a 5% margin of error ($e = 0.05$) and an estimated population of an infinite number of e-commerce users in Yogyakarta, yielding a minimum of 100 respondents. To anticipate non-response or incomplete questionnaires, the sample was inflated by 16%, resulting in a final sample of 116 respondents. Data analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM), a robust statistical tool specifically chosen for its efficacy in interpreting the complex correlations between observed indicators and latent variables within the hypothesized model (Hair et al., 2006). The entire research process, from data collection to analysis, was executed over a dedicated six-month period.

Operational Definitions and Variable Measurement

The research focuses on three primary constructs: Algorithmic Performance Expectations, Trust in Algorithm-Generated Recommendations, and Impulsive Buying Behavior. Algorithmic Performance Expectations are defined as the consumer's perception regarding the algorithm's superiority over human judgment in providing accurate, consistent, and beneficial product suggestions. Trust in Algorithm-Generated Recommendations captures the extent of consumer confidence in the system's reliability, integrity, and benevolence. Impulsive Buying Behavior refers to spontaneous purchases driven by a sudden urge during an online shopping session, without prior planning. Each construct was operationalized using a 5-point Likert scale, ranging from 1 ("Strongly Disagree") to 5 ("Strongly Agree").

Questionnaire Development

The research instrument was adapted from previously validated scales (Hair et al., 2006; Gallin & Portes, 2024), following a rigorous multi-stage process. First, the original instruments underwent a forward-backward translation and cultural adaptation to ensure contextual relevance within the Indonesian e-commerce environment. Second, the translated items were subjected to a two-tier validation process. Face validity was initially assessed by a panel of experts in

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Management Accounting and Information Systems. Subsequently, a pilot study was conducted with a small, randomly selected group of respondents to verify the instrument's preliminary validity and reliability. The summarized framework of the research instrument and its corresponding items are presented in Table 1.

Table 1. Research Instrument

Variable	Questionnaire	Reference
Algorithm performance expectancy	1. I believe that recommendations delivered by an algorithm are more accurate than recommendations delivered by humans. 2. I believe that recommendations delivered by an algorithm contain less errors than recommendations delivered by humans. 3. I believe that recommendations delivered by an algorithm could provide more consistent advice than recommendations delivered by humans. 4. I believe that recommendations delivered by an algorithm could deliver faster advice than recommendations delivered by humans. 5. I trust recommendations delivered by algorithms. 6. Recommendations delivered by algorithms are very trustworthy.	Gallin & Portes (2024)
Trust in product recommendations	1. I have confidence in recommendations delivered by algorithms. 2. Recommendations delivered by algorithms are reliable.	
Impulse buying	1. In this situation, I experience a number of sudden urges to buy products I have not planned to purchase. 2. In this situation, I see a number of things I want to buy even though they are not on my shopping list. 3. In this situation, I feel a sudden urge to buy something.	

RESULTS

Respondent Profile

The final dataset for this study comprised 116 online shoppers. In terms of gender distribution, the sample was predominantly female, accounting for 88 respondents (75.86%), while males represented 24.14% of the total (28 respondents). The age demographics revealed a relatively young respondent base: 66 individuals (56.9%) were aged between 17 and 25 years, 42 individuals (36.2%) fell within the 26–40 age bracket, and the remaining 8 individuals were aged 40–60 years.

Regarding educational background, the majority of participants held an undergraduate degree (S1/D4), totaling 74 respondents. This was followed by high school graduates (22 respondents), Master's degree holders (19 respondents), and one respondent with a junior high school education. Professionally, the sample was diverse: students constituted the largest group (56 respondents), followed by professionals in the education sector (27 respondents), the banking industry (11 respondents), and government institutions (2 respondents). An additional 20

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respondents identified as working in various other sectors. A comprehensive summary of the respondents' demographic profiles is presented in Table 2.

Table 2. Demographic Profile of Respondents

No	Characteristics	Respondents	Total	
1	Gender	Male	28	1
		Female	88	
		Total	116	
2	Age	17-25	66	2
		26-40	42	
		40-60	8	
		Total	116	
3	Education	SMP	1	3
		SMA/K	22	
		S1/D4	74	
		S2	19	
		Total	116	
4	Job	Education	27	4
		Banking	11	
		Governance	2	
		Student	56	
		Other	20	
		Total	116	

Measurement Model Assessment

The empirical analysis in this study follows a rigorous two-step procedure: first, the measurement model was evaluated to assess the validity and reliability of the instruments; second, the structural model was used to examine the hypothesized relationships among variables (Hair et al., 2006). The robustness of the constructs was scrutinized using three primary metrics: loading factors, Average Variance Extracted (AVE), and composite reliability (CR).

According to the measurement model results, all indicators successfully met the established thresholds for convergent validity, with loading factors exceeding 0.7 and AVE values surpassing the 0.5 benchmark. Specifically, the measurement framework consists of two indicators for the Algorithmic Performance Expectations construct, four indicators for Trust, and three indicators for Impulsive Buying Behavior. Furthermore, the internal consistency of the model was confirmed, as the composite reliability for each latent variable remained consistently above the 0.70 threshold. this finding, summarized in Tables 3, 4, and 5, verify that the measurement instruments are both reliable and valid for further structural analysis.

Table 3. Indicator Loading Factors

No	Variable	Indicator	Value
1	Algorithm Performance Expectancy	KA1	0.876
		KA3	0.898
2	Trust in Product Recommendations	KR1	0.89
		KR2	0.867
		KR3	0.91
		KR4	0.87
3	Impulse Buying	IB1	0.881
		IB2	0.782
		IB3	0.931

Table 4. AVE

No	Variable	Average variance extracted (AVE)
1.	Algorithm Performance Expectancy	0.787
2.	Trust in Product Recommendations	0.782
3.	Impulse Buying	0.751

Table 5. Composite Reliability

No	Variable	Value
1	Algorithm Performance Expectancy	0.73
2	Trust in Product Recommendations	0.907
3	Impulse Buying	0.831

Following the validation of the measurement model, the structural model was evaluated to test the research hypotheses. To determine the statistical significance of the hypothesized paths, a bootstrapping procedure was executed using SmartPLS 3, involving 116 sub-samples. The detailed outcomes of this structural analysis, including the path coefficients and their respective significance levels, are presented in Table 6 and visualized in the conceptual diagram in Figure 3.

Table 6. Summary of Hypotheses Testing Results

	Original sample (O)	T-statistics	P-Values	Result
Algorithm Performance Expectancy -> Trust in Product Recommendations	0.627	10.089	0.000	Significant
Trust in Product Recommendations -> Impulse Buying	0.423	3.923	0.000	Significant

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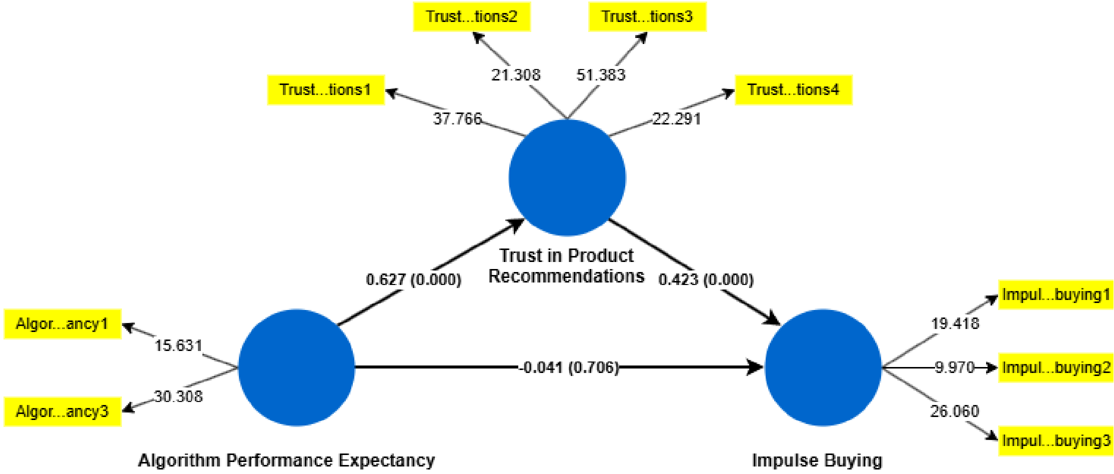

Figure 2. Structural Model
Source : SmartPLS

DISCUSSION

This research investigated the intricate nexus between algorithmic performance expectations, trust in automated recommendations, and impulsive buying behavior among e-commerce consumers in Yogyakarta. Initial assessments of the measurement model established the robust validity and reliability of the constructs, with all indicators exceeding the requisite thresholds for factor loadings (>0.7), AVE (>0.5), and composite reliability (>0.7).

The structural evaluation yielded significant empirical support for H1, confirming that algorithmic performance expectations exert a potent positive influence on consumer trust (β = 0,627, t = 10,089, p < 0,05) This result resonates with the foundational work of Komiak and Benbasat (2006) and Ghasemaghaei et al. (2019), both of whom argued that the perceived competence of an algorithm is a primary precursor to trust. Furthermore, this finding aligns with the insights of Castelo et al. (2019), suggesting that when users perceive a system as accurate and transparent, their skepticism diminishes, replaced by a reliance on the algorithm's consistency. Essentially, this result imply that the technical "utility" of an algorithm is not merely a functional attribute but a psychological bridge to consumer confidence.

Similarly, H2 was robustly supported, demonstrating that trust in algorithm-generated recommendations is a significant driver of impulsive buying (β = 0,423, t = 3,923, p < 0,05). This finding underscores the transformative role of trust in facilitating spontaneous consumption. Our results are consistent with Kimiagari and Asadi Malafe (2021), who posited that trusted recommendations could more than double the likelihood of impulsive transactions. From the perspective of the Persuasion Knowledge Model (PKM) (Friestad & Wright, 1994), this relationship suggests that trust functions as a "heuristic shortcut." When consumers vest their confidence in an algorithm, they effectively lower their cognitive defenses and critical scrutiny, thereby becoming more susceptible to the sudden psychological urges that characterize impulsive purchasing. In synthesis, this study reaffirms the tenets of the PKM within the digital economy. It highlights that the efficacy of AI-driven marketing is contingent upon a dual-layered process: the algorithm must first prove its technical performance to secure consumer trust, which subsequently acts as the catalyst for unmapped shopping behaviors.

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Beyond the direct effects, the mediating role of Trust in Algorithm-Generated Recommendations warrants specific attention. Although not formally hypothesized as a mediation test, the combined significant paths from algorithmic performance expectations to Trust in Algorithm-Generated Recommendations (β = 0.627) and Trust in Algorithm-Generated Recommendations to impulsive buying (β = 0.423) provide empirical grounds for indirect effects. A formal mediation analysis (bootstrapping procedure) revealed that Trust in Algorithm-Generated Recommendations partially mediates the relationship between algorithmic performance expectations and impulsive buying. This finding suggests that algorithmic performance expectations influence impulsive behavior through two routes, a direct pathway and an indirect pathway via Trust in Algorithm-Generated Recommendations. The indirect pathway indicates that consumers do not spontaneously purchase based on algorithmic performance alone; rather, they first evaluate the algorithm's trustworthiness before surrendering to impulsive urges. This mediating mechanism aligns with the core proposition of the PKM, wherein consumers activate their persuasion knowledge to appraise the persuasive agent (the algorithm). If the algorithm is deemed trustworthy (high Trust in Algorithm-Generated Recommendations), persuasion knowledge is suppressed, and impulsive buying ensues. Conversely, if trust is absent, consumers may engage in resistance or coping behaviors. Thus, Trust in Algorithm-Generated Recommendations serves as the psychological "gatekeeper" that translates objective algorithmic performance into subjective impulsive responses.

In synthesis, this study reaffirms the tenets of the PKM within the digital economy. It highlights that the efficacy of AI-driven marketing is contingent upon a dual-layered process: the algorithm must first prove its technical performance to secure consumer trust (the mediator), which subsequently acts as the catalyst for unplanned shopping behaviors. By explicitly demonstrating the mediating role of Trust in Algorithm-Generated Recommendations, this research contributes a more nuanced understanding of how and why algorithmic performance translates into consumer spontaneity.

CONCLUSION

This study concludes that algorithmic performance expectations influence impulsive buying behavior through two distinct pathways: a direct pathway and an indirect pathway mediated by Trust in Algorithm-Generated Recommendations. The indirect effect confirms that Trust in Algorithm-Generated Recommendations partially mediates this relationship, indicating that consumers do not act impulsively based on algorithmic performance alone; rather, they first evaluate the algorithm's trustworthiness before surrendering to impulsive urges. From the perspective of the Persuasion Knowledge Model (PKM), trust in Algorithm-Generated Recommendations functions as a psychological gatekeeper. When consumers perceive an algorithm as accurate, benevolent, and integral (high Trust in Algorithm-Generated Recommendations), their persuasion knowledge is suppressed, lowering cognitive defenses and critical scrutiny. This suppression makes them more susceptible to spontaneous purchasing. Conversely, when trust is absent, consumers may engage in resistance or coping behaviors. Thus, this study advances PKM by demonstrating that trust does not merely coexist with persuasion knowledge but actively mediates the translation of algorithmic performance into impulsive responses. Practically, this findings underscore that e-commerce platforms must prioritize not only technical accuracy but also the perceived benevolence and integrity of their AI recommendation systems. Within the competitive landscape of Indonesian mobile-first e-commerce (e.g., Shopee, Tokopedia, Lazada), building Trust in Algorithm-Generated Recommendations is a strategic imperative for converting algorithmic efficiency into unplanned sales.

Furthermore, this research contributes to the broader global agenda by aligning with SDG 8 (Decent Work and Economic Growth); it demonstrates how AI-driven innovations can stimulate sales and bolster the digital economy, particularly in emerging markets like Indonesia (Global Goals, 2023). Additionally, by focusing on the optimization of digital infrastructure for inclusive economic development, this study supports SDG 9 (Industry, Innovation, and Infrastructure) (United Nations, 2023). To build upon this finding, future research should address current limitations by exploring more diverse populations and cross-cultural contexts, thereby validating the universal applicability of this model.

LIMITATIONS AND IMPLICATIONS

Theoretically, this research advances the Persuasion Knowledge Model (PKM) by extending its application to algorithm-generated suggestions (Friestad & Wright, 1994; Gallin & Portes, 2024). It offers a nuanced understanding of how modern consumers decipher and respond to AI-driven marketing tactics (Wien & Peluso, 2021). By identifying trust as the definitive mediator between perceived algorithmic competence and spontaneous purchasing, this study enriches the literature on impulsive behavior. It illuminates the dual role of algorithms: serving simultaneously as persuasive marketing instruments and functional decision-making aids. For practitioners, this results emphasize that long-term sales growth in the AI era is contingent upon a foundation of transparency that mitigates consumer scepticism.

Despite its contributions, this study is not without limitations. The demographic homogeneity of the sample primarily consisting of students and the specific geographical focus on Yogyakarta may constrain the generalizability of the findings to broader or more diverse populations. Consequently, future scholarly inquiries should aim to replicate this model across varied age groups and cultural settings to further refine the nexus between algorithmic performance and consumer psychology.

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