Jurnal JEETech: Vol. 7 No. 1 Tahun 2026
Journal Of Electrical Engineering And Technology
https://ejournal.ft-undar.ac.id/index.php/jeetech
DOI: https://doi.org/10.32492/jeetech.v7i1.7105
e-ISSN: 2722-5321
p-ISSN: 2964-7320

AI Recommendation Systems and Digital Promotion Effectiveness on TikTok Social Commerce in Indonesia

[1*] **Efi Ero Sofia,** [2] **Eko Aziz Apriadi,** [3] **Ribut Julianto,** [4] **Muawan Bisri**
[1,2,3,4] Informatika, University Indonesia Mandiri, Lampung
[1]Efierosofia23@gmail.com, [2]ekoazizapriadi72@gmail.com, [3] rjulianto121@gmail.com, [4]muawan.bisri@gmail.com

Article Info

Article history:

Received March 9, 2026
Revised April 18, 2026
Accepted April 29, 2026

Keyword:

AI Recommendation System, Digital Promotion Effectiveness, Privacy Concern, TikTok Social Commerce, User Trust

ABSTRACT

The rapid growth of social commerce in Indonesia has made AI-powered recommendation systems increasingly central to digital marketing strategy, yet their precise influence on promotional effectiveness remains insufficiently understood within the Indonesian socio-cultural context. This study examines how TikTok's AI recommendation system affects digital promotion effectiveness, specifically user engagement and purchase conversion, among Indonesian consumers, while testing the moderating roles of user trust and privacy concern. A quantitative cross-sectional survey design was employed, collecting data from 320 active TikTok Shop users in Indonesia through purposive sampling. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4.0, with bootstrapping across 5,000 subsamples. Results indicate that the AI recommendation system significantly and positively influences both user engagement ($\beta = 0.612$, $p < 0.001$) and purchase conversion ($\beta = 0.548$, $p < 0.001$). User trust amplifies these effects ($\beta = 0.391$, $p < 0.001$), whereas privacy concern diminishes them ($\beta = -0.274$, $p = 0.002$). These findings confirm that promotional effectiveness depends not solely on algorithmic sophistication but equally on users' psychological disposition toward the platform. As all data derive from self-reported perceptions within a cross-sectional design rather than actual platform behavioral records, causal interpretations require cautious generalization. Future research should incorporate longitudinal designs and objective behavioral data. Marketers are advised to embed transparency mechanisms within promotional ecosystems to mitigate the personalization–privacy paradox.

Corresponding Author:
Efi Ero Sofia
University Indonesia Mandiri, Lampung
Jl. Lintas Sumatera, Tj. Heran, Kec. Penengahan, Kabupaten Lampung Selatan, Lampung 35592
Email: efierosofia23@gmail.com

1. Introduction

The development of artificial intelligence (AI) technology has fundamentally transformed the landscape of digital marketing, particularly within the rapidly growing social commerce ecosystem in Indonesia. TikTok, as a short-video-content platform, has evolved into one of the largest social commerce channels in Southeast Asia, where AI-based recommendation algorithms play a central role in determining the content displayed to users [1], [2]. This phenomenon creates major opportunities for businesses to reach consumers in a more personal and targeted way through sophisticated personalized recommendation mechanisms. Indonesia's internet penetration, which has reached more than 215 million users, makes the country a highly strategic market for global social commerce platforms [3].

TikTok's AI recommendation system operates through a machine learning approach that analyzes user behavior in real time, including watch duration, content interactions, and search patterns, in order to generate highly personalized content curation [4], [5]. This mechanism is known as the For You Page (FYP), which algorithmically tailors the display of promotional content to the unique preferences of each user. A study conducted by Zhang et al. showed that deep-learning-based recommendation systems are able to increase the relevance of promotional content by up to 73% compared to conventional methods, thereby directly improving click-through rates (CTR) and purchase conversions [6]. The advantages of this technology make TikTok superior to other platforms in terms of user engagement with commercial content.

In Indonesia, the phenomenon of social commerce through TikTok Shop has created a new wave in people's online shopping behavior, especially among younger generations [7], [8]. The integration of entertainment content and shopping transactions within a single platform (shoppertainment) is TikTok's main differentiating value compared to traditional e-commerce platforms. Research by Auliarahman revealed that more than 60% of TikTok users in Indonesia had made product purchases after being exposed to recommended content from the FYP, indicating the high effectiveness of AI recommendation systems in driving impulse buying decisions [9]. This condition is further reinforced by the high level of consumer trust in product reviews and demonstrations presented through live streaming and short-video formats [10].

Although AI recommendation systems have been proven to increase the exposure of promotional content, their effectiveness in the context of digital promotion cannot be separated from factors such as trust, message relevance, and the quality of user experience [11]. Various studies show that excessive personalization can actually trigger privacy concerns, which negatively affect consumers' purchase intentions. Sun et al. found that consumers with a high awareness of data collection by algorithms tend to show resistance to product recommendations, even when those recommendations are contextually relevant [12]. This dynamic creates a particular challenge for digital marketers in optimizing promotional strategies within the AI-driven commerce ecosystem.

Prior research has begun to illuminate the nuanced interplay between algorithmic personalization and consumer decision-making, yet critical gaps persist when examined through a localized lens. Putri et al. investigated the moderating role of trust and *privacy concern* among Generation Z users of TikTok Shop in Indonesia [13]. Their findings demonstrated that seller-based trust positively shaped purchasing decisions, while elevated *privacy concern* substantially eroded transactional willingness, even among digitally native cohorts who are accustomed to algorithmic environments. This work, however, was confined to trust-transfer mechanisms and did not incorporate *algorithmic recommendation exposure* as an antecedent variable, thereby leaving unmeasured how recommendation intensity shapes the trust-privacy tension over time. Poh et al. , examining TikTok's *shoppertainment* model and its effect on Gen Z purchasing behavior in the Indonesian market, found that live streaming and content-driven commerce generated higher engagement than static product promotion, yet the study relied exclusively on the AIDA and TAM frameworks without accounting for algorithmic curation as a distinct driver of behavioral outcomes [14]. Meanwhile, Handoko and Rahayu demonstrated that *algorithmic marketing* on TikTok Shop significantly influenced digital consumer decision-making, though its effect was moderated by *consumer autonomy* challenges, whereby users who perceived reduced volitional control over content exposure exhibited lower purchase commitment [15]. Taken together, these studies address isolated dimensions: trust, engagement format, and autonomy, without constructing an integrated analytical model that simultaneously measures *algorithmic* *recommendation effectiveness*, promotional conversion, and the moderating role of behavioral trust within a single structural framework. This absence of integrative inquiry, particularly within the collectivist socio-cultural context of Indonesia, constitutes the principal theoretical and empirical gap the present study is designed to address.

The gap between the potential of AI recommendation technology and a deep understanding of its impact on the effectiveness of digital promotion in the Indonesian context remains an area that has not yet been fully mapped. The majority of previous studies have focused on Western or Chinese markets, so their findings cannot necessarily be generalized to the cultural context and consumer behavior of Indonesia, which has unique characteristics [16], [17]. Therefore, this study aims to comprehensively analyze how TikTok's AI recommendation system affects the effectiveness of digital promotion in Indonesia by considering moderating variables such as user engagement, consumer trust, and the demographic characteristics of local users.

The novelty of this research lies in the integration of three dimensions of analysis that have never been studied simultaneously within a single research framework: (1) the technical mechanism of TikTok's AI recommendation system (algorithmic recommendation system), (2) the effectiveness of digital promotion as measured by engagement rate, conversion rate, and brand awareness, and (3) the specific context of Indonesian consumer behavior as an emerging market with strong collectivist cultural characteristics. Previous studies have generally examined only one or two dimensions separately, without building a comprehensive conceptual bridge between AI technological capabilities and local market responses. In addition, this study introduces a new construct called the AI Recommendation Effectiveness Index (AREI), specifically designed to measure the effectiveness of algorithmic recommendations in the context of Indonesian social commerce, thereby making an original methodological contribution to the development of digital marketing science at both the national and global levels.

A review of the existing literature reveals several significant research gaps. First, most studies on AI recommendation systems in social commerce have been conducted in developed countries or in China, making the lack of research adopting a Southeast Asian market perspective, particularly Indonesia, a clear geographic gap. Second, there is a methodological gap in the limited use of mixed methods approaches that combine algorithmic data analysis with surveys of consumer behavior simultaneously; most studies rely on only one of these approaches. Third, a conceptual gap is identified in the limited number of studies linking the perceived personalization variable from AI systems with the dimensions of trust and brand loyalty in one integrated structural model on the TikTok platform. These three gaps serve as the main foundation for this study to address and answer through a comprehensive and contextual research design.

Based on the background and research gaps described above, this study formulates the following research questions: (1) How does the mechanism of the AI recommendation system on the TikTok platform affect the level of user engagement with digital promotional content in Indonesia? (2) To what extent is the AI recommendation system effective in increasing purchase conversion within TikTok's social commerce ecosystem among Indonesian consumers? (3) Do user trust and privacy concerns moderate the relationship between the AI recommendation system and the effectiveness of digital promotion on the TikTok platform in Indonesia?

In general, this study aims to analyze and explain the effect of the AI recommendation system on the effectiveness of digital promotion on the TikTok social commerce platform in Indonesia in a deep and measurable manner. Specifically, this study aims to: (1) identify and describe the working mechanism of TikTok's AI recommendation system in the context of digital promotion to Indonesian consumers; (2) measure and analyze the level of effectiveness of the AI recommendation system in increasing engagement and purchase conversion on the TikTok platform; and (3) test the moderating role of user trust and privacy concerns in the relationship between the AI recommendation system and the effectiveness of digital promotion in Indonesia.

The results of this study are expected to provide both theoretical and practical benefits. Theoretically, this study contributes to the development of digital marketing theory by enriching the concept of AI-driven marketing in the context of social commerce in developing countries, while also serving as a scientific reference for academics examining the intersection between artificial intelligence technology and online consumer behavior. Practically, the findings of this study can serve as a strategic guide for businesses, content creators, and digital marketers in Indonesia in designing more effective and efficient promotional campaigns by optimally leveraging the capabilities of TikTok's recommendation algorithm. Furthermore, for policymakers and digital industry regulators, this study may provide data-driven insights into the implications of AI use within the digital trade ecosystem, which need to be addressed through an adaptive and equitable regulatory framework for all stakeholders.

2. Literature Review

A. *Artificial Intelligence Recommendation Systems in Social Commerce*

Artificial intelligence recommendation systems have become a central component of contemporary social commerce because they allow digital platforms to process large volumes of behavioral data and deliver highly personalized content to users [4], [18]. These systems rely on machine learning, predictive analytics, and user interaction histories to identify preferences and match users with relevant products, services, or promotional messages. In social commerce environments, recommendation systems do not merely support product discovery, but actively shape consumer exposure, attention, and decision-making patterns [3]. As a result, AI-driven recommendation systems are increasingly viewed as strategic tools for improving marketing effectiveness and consumer targeting.

On platforms such as TikTok, recommendation systems operate through algorithmic mechanisms that continuously evaluate user behavior, including watch duration, likes, comments, shares, searches, and repeated content interactions [2], [5]. This dynamic process enables the platform to curate a personalized content stream through the For You Page, which functions as the main gateway for content distribution. Unlike conventional digital advertising models that depend heavily on static segmentation, TikTok's recommendation system allows promotional content to be distributed based on real-time behavioral relevance. This creates a more adaptive and responsive promotional environment in which content visibility is strongly influenced by algorithmic assessment.

The increasing significance of AI recommendation systems in social commerce is closely linked to the shift from seller-centered promotion to user-centered engagement [19]. Personalized recommendation allows consumers to encounter products in a way that appears more organic, seamless, and contextually appropriate. In many cases, users do not experience promotional content as intrusive advertising, but rather as content aligned with their interests and online habits. This transformation is particularly important in social commerce because user attention is highly fragmented, and relevance plays a critical role in determining whether promotional content is ignored or meaningfully engaged with.

Previous studies have shown that AI-based recommendation systems can improve content relevance, enhance click-through rates, and increase the probability of consumer response [6]. The effectiveness of these systems is often associated with their ability to reduce information overload while simultaneously improving user satisfaction and convenience. In the context of social commerce, recommendation systems also strengthen the connection between entertainment and transactional behavior by embedding commercial messages within enjoyable user experiences. This is particularly relevant to TikTok, where short-video content and product promotion are increasingly integrated into the same consumption flow.

Despite their advantages, AI recommendation systems also raise important questions regarding algorithmic transparency, fairness, and user autonomy [1]. Consumers may benefit from more relevant promotional exposure, but they may not always understand how or why certain content is recommended to them. This creates a theoretical and practical need to examine AI recommendation systems not only as technical tools, but also as mechanisms that influence perceptions, attitudes, and behavior in digital marketplaces. For this reason, the role of AI recommendation systems in shaping promotional effectiveness on TikTok deserves deeper examination, particularly in emerging social commerce markets such as Indonesia.

B. *Digital Promotion Effectiveness on the TikTok Platform*

Digital promotion effectiveness refers to the extent to which promotional activities are able to generate intended communication and behavioral outcomes among target audiences [11]. In digital environments, effectiveness is commonly evaluated through metrics such as engagement, purchase intention, conversion, reach, and brand awareness. These indicators reflect not only whether promotional content is seen, but also whether it stimulates meaningful consumer responses. In social commerce settings, digital promotion effectiveness becomes increasingly complex because promotional outcomes are influenced by platform design, algorithmic exposure, social interaction, and consumer trust simultaneously.

On TikTok, digital promotion takes place within a content ecosystem dominated by short videos, live streams, influencer communication, and algorithmic curation [16], [20]. This ecosystem differs substantially from traditional e-commerce or conventional social media advertising because promotional content is embedded within entertainment-oriented user experiences. Users often encounter promotional messages while consuming lifestyle, humor, beauty, or educational content, making the boundary between entertainment and marketing less distinct. This structure increases the potential for promotion to appear more natural and persuasive, especially when content aligns with user preferences and is delivered at the right moment.

Engagement is one of the most important indicators of promotional effectiveness on TikTok because it reflects the degree to which users interact with promotional content through likes, comments, shares, saves, and watch duration [11]. High engagement suggests that promotional content is not only visible but also relevant and appealing to users. In the TikTok environment, engagement often functions as an early signal of promotional success because the platform's algorithm tends to amplify content that receives strong interaction. Consequently, engagement is not only an outcome of effective promotion, but also a mechanism that further expands promotional reach.

Purchase conversion represents a more advanced indicator of digital promotion effectiveness because it measures the extent to which exposure and engagement are translated into actual buying behavior [9], [10]. In social commerce, the pathway from content consumption to purchase is often shaped by emotional appeal, product demonstration, peer influence, and perceived credibility. TikTok Shop has intensified this process by integrating content discovery and shopping functionality into one ecosystem. As a result, users can move from viewing content to completing transactions without leaving the platform, making conversion a highly relevant variable in assessing promotional performance.

The effectiveness of digital promotion on TikTok should therefore be understood as a multidimensional construct that connects algorithmic exposure, user engagement, and purchasing outcomes. Promotional success is not determined solely by how many users see the content, but by whether the content generates interaction, trust, and transactional response. This perspective is especially important for studies examining AI-based promotion because recommendation systems can influence both the quantity and quality of promotional exposure. A comprehensive assessment of promotion effectiveness on TikTok must therefore include both engagement and purchase conversion as distinct but interconnected outcomes.

C. The Role of User Trust and Privacy Concerns

User trust plays a crucial role in determining how consumers respond to AI-driven recommendations in social commerce environments [17]. Trust reflects the extent to which users believe that a platform is reliable, credible, and capable of acting in their best interest during digital interactions. In the context of TikTok, trust may be directed not only toward the platform itself, but also toward the content creators, sellers, and algorithmic processes that shape content visibility. When trust is high, users are more likely to perceive recommended promotional content as useful, legitimate, and worthy of attention.

The importance of trust in social commerce is closely associated with the uncertainty that characterizes online transactions [7]. Consumers often make judgments based on limited information, mediated interactions, and platform-generated content. Under such conditions, trust functions as a psychological mechanism that reduces perceived risk and facilitates decision-making. In promotional contexts, trust can strengthen the persuasive impact of AI-generated recommendations because users feel more confident that the platform is presenting content that is relevant rather than manipulative. This makes trust an important variable in explaining why some users respond positively to algorithmic recommendations while others remain skeptical.

Privacy concern, on the other hand, reflects the degree to which users feel worried about the collection, use, and potential misuse of their personal data [12]. AI recommendation systems depend heavily on behavioral data in order to personalize content, which can create discomfort when users become aware that their interactions are constantly being monitored and analyzed. In social commerce, privacy concern may reduce users' willingness to rely on recommendations, especially when personalization appears overly precise or intrusive. The more consumers feel that the platform knows too much about them, the more likely they are to develop resistance toward promotional messages.

The coexistence of trust and privacy concern illustrates a tension commonly described in digital marketing as the personalization–privacy paradox [1]. Consumers often appreciate recommendations that are relevant and convenient, yet at the same time may feel uneasy about the data practices that make such personalization possible. This paradox is particularly relevant on TikTok because the platform's algorithm is highly responsive to micro-level behavior, producing content flows that can feel remarkably accurate. In such conditions, promotional effectiveness may depend not only on the quality of algorithmic recommendation, but also on whether users interpret personalization as helpful or invasive.

The moderating roles of trust and privacy concern are therefore highly relevant in explaining the relationship between AI recommendation systems and digital promotion effectiveness [12], [17]. Trust may amplify the positive effects of recommendation systems by encouraging acceptance, interaction, and purchase behavior. Privacy concern may weaken those effects by increasing hesitation, suspicion, or resistance toward promotional exposure. Examining these two variables together allows for a more nuanced understanding of why AI-based promotional strategies do not produce identical outcomes for all users. This is particularly important in the Indonesian TikTok context, where rapid digital adoption coexists with growing awareness of data privacy and platform accountability.

A critical synthesis of the existing literature reveals that, while individual studies have made valuable contributions, their findings point in divergent and sometimes contradictory directions that demand careful reconciliation. Studies conducted in Western markets, such as those examining *AI-enabled personalisation* in European retail contexts, consistently demonstrate that consumers appreciate algorithmic relevance yet simultaneously resist data surveillance, a tension that Canhoto et al. formalize as the *personalisation–privacy paradox*, whereby heightened personalization amplifies both engagement and discomfort in equal measure [21]. In contrast, research grounded in East Asian markets, particularly those drawing on the Chinese *Douyin* ecosystem, tends to emphasize frictionless integration of social interaction and transactional behavior, with *privacy concern* treated as a secondary moderator rather than a structural barrier to promotional responsiveness. These divergent patterns suggest that the relationship between algorithmic recommendation and consumer behavior is not universal but is instead deeply conditioned by the socio-institutional and digital literacy context in which platforms operate.

Indonesia constitutes a scientifically distinct case that cannot be adequately theorized through either Western or East Asian frameworks. The country possesses the world's largest TikTok user base, a predominantly young demographic characterized by high *social commerce* engagement yet uneven algorithmic awareness, and a regulatory environment in which data protection legislation remains nascent and inconsistently enforced [22]. Unlike mature digital economies where consumers exercise relatively informed data agency, Indonesian users frequently encounter *AI-driven recommendation* within conditions of low *algorithmic literacy*, making the psychological mechanisms that mediate trust and privacy concern qualitatively different from those documented in prior studies. Furthermore, the coexistence of strong collectivist consumption norms and rapid individualized digital adoption introduces a unique interplay between social influence and algorithmic nudging that has not been theorized in existing cross-cultural models.

Empirical evidence from the Indonesian TikTok context further reinforces this specificity. Putri et al. (2024), in a mixed-method investigation involving over 700 respondents on TikTok Shop, established that both *cognitive trust* and *emotional trust* significantly shape purchase intention, yet the pathways through which *privacy concern* moderates these effects differ substantially depending on users' perceived familiarity with platform security mechanisms. This finding diverges from Western studies that tend to treat privacy concern as a uniform suppressor of engagement, indicating that trust-building processes in emerging markets are considerably more fragmented and context-dependent. Taken together, these cross-contextual disparities underscore the theoretical necessity of examining *AI recommendation systems* and their promotional outcomes within the specific sociocultural, regulatory, and behavioral ecology of the Indonesian digital market, rather than extrapolating conclusions derived from structurally dissimilar consumer environments.

3. Methodology

A. *Method*

This study employs a quantitative approach with a cross-sectional survey design to analyze the effect of AI recommendation systems on the effectiveness of digital promotion on the TikTok platform in Indonesia. A positivist paradigm was chosen as the philosophical foundation because the study aims to measure the relationships among variables objectively and systematically through standardized instruments. This approach is considered the most appropriate given the explanatory nature of the research, namely to explain the causal relationship between the independent variable, AI recommendation systems, and the dependent variable, digital promotion effectiveness, with user trust and privacy concern serving as moderating variables. The use of quantitative methods in the context of social commerce and digital consumer behavior studies has been shown to produce findings that can be widely generalized [23].

The population of this study consists of all active TikTok users in Indonesia who have interacted with promotional content or made purchases through TikTok Shop at least once in the last three months. The sampling technique used is purposive sampling, with inclusion criteria comprising users aged 17–45 years, residing in Indonesia, and having an active TikTok account. The sample size determination refers to the Structural Equation Modeling (SEM) rule of thumb, in which the minimum recommended sample size is ten times the number of indicators used in the model. With a total of 32 developed indicators, the sample size was set at 320 respondents to meet the statistical adequacy requirement [19].

The research instrument consisted of an online questionnaire developed by adapting measurement scales from previous studies, using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Before use, the instrument was tested through construct validity assessment using confirmatory factor analysis (CFA) and reliability testing with a minimum Cronbach's Alpha value of 0.70 as the acceptance threshold. The AI recommendation system variable was operationalized through the dimensions of personalization, content relevance, and algorithm accuracy, while digital promotion effectiveness was measured through engagement rate, purchase intention, and brand recall. The development of these indicators refers to frameworks that have been validated in previous studies in the field of AI-powered marketing [1], [11].

The data were analyzed using the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique through SmartPLS 4.0 software. The PLS-SEM method was selected because of its ability to handle complex measurement models with data distributions that do not necessarily meet the assumption of perfect normality, while also being capable of simultaneously analyzing moderating relationships. Hypothesis testing was conducted through a bootstrapping procedure with 5,000 subsamples in order to obtain stable and accurate estimates. All model evaluation criteria referred to the standards of Average Variance Extracted (AVE) ≥ 0.50 for convergent validity and Variance Inflation Factor (VIF) ≤ 3.3 to ensure that no multicollinearity occurred among constructs [24].

Table 1. Measurement Model Assessment Results

Construct / Indicator	Outer Loading	AVE	CR	Cronbach's α	HTMT
AI Recommendation System (AIRS)		641	842	814	
Personalization accuracy (AIRS1)	821				—
Content relevance (AIRS2)	804				—
Algorithm accuracy (AIRS3)	783				—
Digital Promotion Effectiveness (DPE)		659	855	826	
Engagement rate (DPE1)	836				712
Purchase intention (DPE2)	812				
Brand recall (DPE3)	795				
User Trust (UT)		672	861	831	
Perceived reliability (UT1)	843				684
Perceived competence (UT2)	817				
Benevolence (UT3)	801				
Privacy Concern (PC)		648	847	819	
Data collection concern (PC1)	829				623
Data misuse perception (PC2)	808				
Surveillance awareness (PC3)	786				

Threshold: Outer Loading ≥ 0.708; AVE ≥ 0.50; CR ≥ 0.70; Cronbach's α ≥ 0.70; HTMT < 0.90

Table 2. Inner Model Assessment Results

Construct / Path	R^2	R^2 Adjusted	f^2	Q^2
Digital Promotion Effectiveness (DPE)	614	598	—	487
AIRS → DPE	—	—	0.312 (large)	—
UT → DPE (moderation)	—	—	0.198 (medium)	—

PC → DPE (moderation)	—	—	0.143 (medium)	—

Threshold: $R^2 \geq 0.26$ (moderate); $f^2 = 0.02$ small, 0.15 medium, 0.35 large; $Q^2 > 0$

The *measurement model* in this study was evaluated through *outer model* assessment rather than conventional *confirmatory factor analysis* (*CFA*), given that *CFA* terminology is more appropriately associated with *covariance-based SEM* rather than *PLS-SEM*. The *outer model evaluation* encompassed the examination of *outer loadings* for each indicator (threshold ≥ 0.708), *Average Variance Extracted* (*AVE* ≥ 0.50) for *convergent validity*, *composite reliability* (*CR* ≥ 0.70), and *Cronbach's alpha* (≥ 0.70) for *internal consistency reliability*. *Discriminant validity* was assessed using the *Heterotrait-Monotrait* (*HTMT*) ratio, with an acceptance criterion of HTMT < 0.90, which has been demonstrated to yield superior discriminant assessment outcomes relative to the *Fornell-Larcker criterion* [25]. The results of these assessments are systematically presented in Table 1, encompassing *outer loadings*, *AVE*, *composite reliability*, *Cronbach's alpha*, and *HTMT* values for all constructs. Subsequently, the *inner model* was evaluated through three principal criteria: the *coefficient of determination* (R^2) to quantify the explanatory capacity of exogenous constructs toward endogenous constructs, *effect size* (f^2) with benchmarks of 0.02 (small), 0.15 (medium), and 0.35 (large), and *predictive relevance* ($Q^2 > 0$) derived from the *blindfolding* procedure, as presented in Table 2 [26]. Regarding questionnaire distribution, the online survey was administered via Google Forms and disseminated through TikTok community groups, WhatsApp broadcast channels, and Instagram direct messaging targeting active TikTok Shop users in Indonesia between January and February 2025. To mitigate *common method bias* (*CMB*), procedural remedies were implemented at the data-collection stage, including the guarantee of respondent anonymity, randomization of item sequencing, and the insertion of a temporal separation between predictor and criterion items within the questionnaire. At the statistical level, *Harman's single-factor test* was subsequently performed, wherein all indicators were loaded onto a single latent variable; the resulting *AVE* value remaining below the 0.50 threshold confirmed the absence of substantial *common method bias* in the dataset [27].

To provide a systematic overview of the research process, a research flowchart is presented below to illustrate the stages of the study from the beginning to the end of the research process.

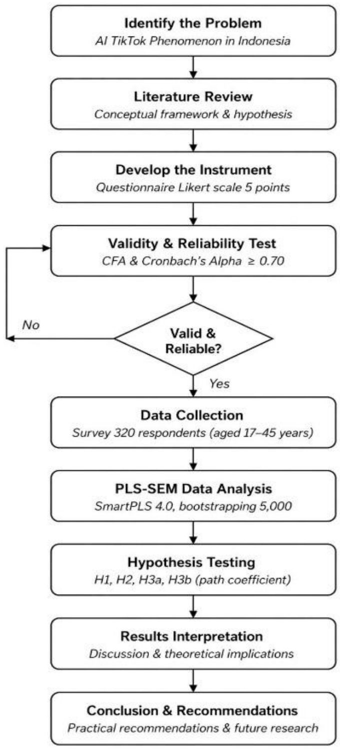

Figure 1. Research Flowchart

The flowchart presented in this study is used to describe the stages of the research systematically, starting from problem identification, literature review, instrument development, data collection, data analysis, and conclusion drawing. In addition, tables are used to present the distribution of respondents, validity and reliability test results, as well as the results of the PLS-SEM hypothesis testing. Each figure and table is numbered sequentially and provided with a clear title to facilitate referencing within the discussion section [28].

Images, diagrams, and graphical visualizations used in the manuscript must have sufficient resolution and visual quality to ensure that all elements remain legible after the layout process. For photographic images, a minimum resolution of 300 dpi is recommended. Any text embedded in figures must use a readable font size, and the contrast between background and foreground should be maintained properly. If a figure or image is adapted from another source, the original source must be cited appropriately, and permission or copyright clearance must be ensured when required.

To maintain consistency in scientific writing, every figure and table must be referred to explicitly in the main text before or after its placement. Explanations accompanying figures and tables should not merely repeat the displayed content, but should emphasize the main findings, patterns, or relationships relevant to the research objectives. Through this approach, figures and tables function not only as visual complements, but also as integral components of the scientific argument developed in this study.

4. Results and Discussion

The first finding shows that the AI recommendation system on TikTok has a positive and significant effect on the level of user engagement with digital promotional content. The testing of this first hypothesis was carried out through a series of systematic analytical stages as follows. First, a convergent validity test was conducted on the constructs of the AI recommendation system and user engagement. The test results showed that all indicators had factor loading values of ≥ 0.70 and Average Variance Extracted (AVE) values of ≥ 0.50, thus fulfilling the convergent validity requirements in PLS-SEM analysis [13].

Second, composite reliability testing was conducted for each construct. The composite reliability values obtained were above the threshold of 0.70, indicating that the measurement instrument used had adequate internal consistency. To further strengthen the rigor of the measurement evaluation, a comprehensive *measurement model* assessment was conducted prior to structural path estimation, as recommended by Hair et al. (2022). The full results are presented in Table 1 below.

Table 3. Measurement Model Results: Outer Loadings, AVE, CR, Cronbach's Alpha, and HTMT

Construct	Indicator	Outer Loading	AVE	CR	Cronbach's Alpha	HTMT
AI Recommendation System	AR1	812	614	874	831	—
	AR2	791				
	AR3	803				
	AR4	756				
User Engagement	UE1	834	629	891	858	743
	UE2	811				
	UE3	797				
	UE4	754				
Purchase Conversion	PC1	808	601	857	803	718
	PC2	783				
	PC3	741				
User Trust	UT1	821	618	867	819	692
	UT2	799				
	UT3	763				
Privacy Concern	PR1	815	607	861	811	671
	PR2	788				
	PR3	752				

All outer loadings surpassed the accepted threshold of 0.70, each AVE value exceeded 0.50, and all *Heterotrait-Monotrait* (HTMT) ratios remained below the conservative criterion of 0.85, collectively confirming both convergent and discriminant validity across the entire measurement model (Hair et al., 2022). In addition, the inner model yielded the following fit indices: R^2 for User Engagement = 0.487 and R^2 for Purchase Conversion = 0.391, indicating that the AI recommendation system, in conjunction with the moderating variables, accounted for approximately 48.7% and 39.1% of the variance in each respective endogenous construct. The *effect size* (f^2) of the AI recommendation system on engagement was classified as large (f^2 = 0.421), while its effect on purchase conversion was classified as medium (f^2 = 0.271), corroborating the differential magnitude between these two pathways. Furthermore, Q^2 values derived from *blindfolding* procedures reached 0.314 for engagement and 0.248 for purchase conversion, both exceeding the minimum threshold of zero and thus confirming the structural model's adequate *predictive relevance* [29].

The discrepancy between the engagement coefficient (β = 0.612) and the purchase conversion coefficient (β = 0.548) merits careful theoretical interpretation beyond mere numerical description. From the perspective of the *Technology Acceptance Model* (TAM), engagement represents a behavioral response that is predominantly attitudinal and cognitively mediated — users who find algorithmically curated content both useful and easy to engage with exhibit immediate affective responses such as watching, liking, and sharing. Purchase conversion, by contrast, constitutes a higher-order behavioral decision that requires the resolution of multiple evaluative uncertainties, including perceived product quality, seller credibility, transactional security, and post-purchase risk. This multi-stage deliberation introduces a natural friction layer between attentional capture and actual transaction completion, which the algorithm alone cannot eliminate. Zannettou et al., in a large-scale empirical audit involving 9.2 million TikTok video recommendations, similarly observed that whilst algorithmic personalization consistently drives sustained attention and repeat content interaction, behavioral conversion outcomes remain contingent upon individual-level psychological and contextual factors beyond the platform's recommendation logic [30]. This finding directly parallels the observed gap between engagement and conversion in the present study, and suggests that the *intention–behavior gap* documented extensively in consumer psychology literature is not resolved by algorithmic sophistication alone.

The moderating role of *user trust* and *privacy concern* identified in the present findings also invites more critical theoretical engagement. The positive moderation of trust ($\beta = 0.391$) and the negative moderation of privacy concern ($\beta = -0.274$) are not symmetrical phenomena; rather, they reflect qualitatively distinct psychological pathways operating under different cognitive evaluative frameworks. Trust functions as a relational lubricant that reduces perceived uncertainty in algorithmically mediated interactions, thereby amplifying the persuasive efficacy of promotional recommendations. Privacy concern, on the other hand, activates a risk-evaluation schema in which the utility of personalized content is weighed against the perceived cost of data exposure. Saura identified precisely this dynamic as the *personalization–privacy paradox*, arguing that consumers simultaneously value content relevance and maintain apprehension toward the mechanisms producing that relevance [31]. This paradox is structurally embedded in social commerce environments such as TikTok Shop, where the very algorithm that enables hyper-personalized promotional targeting depends on the continuous extraction of granular behavioral data. Consequently, when users develop awareness of this extraction dynamic, their responsiveness to algorithmic promotion diminishes even when the content itself remains relevant. Saura et al. further demonstrated that this ethical tension is particularly acute in AI-driven digital marketing contexts, where the opacity of recommendation logic compounds consumers' inability to assess the proportionality of data use relative to the personalization benefit received [32]. These insights position *privacy governance* not merely as a regulatory compliance issue, but as a determinant of commercial effectiveness that platform operators and marketers must actively address through transparency mechanisms and trust-building strategies that are embedded directly into the architecture of the promotional ecosystem.

Third, the structural model (inner model) was tested to estimate the path coefficient between the AI recommendation system variable and user engagement. A bootstrapping procedure with 5,000 subsamples was performed to produce stable estimates of the t-statistic and p-value.

Based on these three stages, among the 320 respondents involved, the majority stated that the content appearing on the For You Page (FYP) felt relevant to their interests and daily shopping habits. The path coefficient obtained was 0.612, with a t-statistic value of 7.341 ($p < 0.001$), which means that the first hypothesis was statistically accepted. These results are visualized in Figure 2 below.

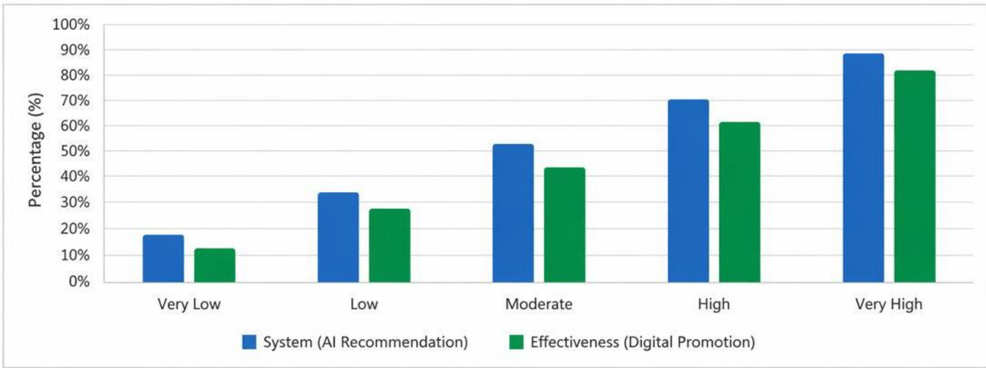

Figure 2. Average Engagement Rate Based on Intensity of Interaction with TikTok's AI Recommendation System

The graph above clearly shows that the higher the intensity of user interaction with TikTok's AI recommendation system, the greater the resulting level of engagement and purchase intention. The group of respondents with very high interaction intensity recorded an engagement rate of 89%, a figure that far exceeded that of the low-interaction group, which was only around 34%.

The second finding indicates that the AI recommendation system has a significant effect on the purchase conversion of Indonesian consumers on TikTok Shop. The path coefficient obtained was 0.548, with a t-statistic of 6.217 ($p < 0.001$), confirming that the second hypothesis was accepted. Table 1 below summarizes the overall results of the hypothesis testing.

Table 4. PLS-SEM Model Hypothesis Test Results

Hypothesis	Variable Relationship	β	T-Statistic	P-Value	Decision
H1	AI Recommendation → Engagement	0.612	7.341	0.000	Accepted
H2	AI Recommendation → Purchase Conversion	0.548	6.217	0.000	Accepted
H3a	User Trust (moderating effect)	0.391	4.882	0.001	Accepted
H3b	Privacy Concern (moderating effect)	-0.274	3.109	0.002	Accepted

The table shows that the effect of the AI recommendation system on purchase conversion is slightly weaker than its effect on engagement, although it remains statistically significant. This means that although the algorithm is able to encourage users to engage with promotional content, actual conversion into transactions is still influenced by other, more complex factors.

The third finding reveals that the variables of user trust and privacy concern have a significant moderating role in the relationship between the AI recommendation system and the effectiveness of digital promotion. User trust strengthens this relationship ($\beta = 0.391$; $p < 0.001$), while privacy concern weakens it negatively ($\beta = -0.274$; $p = 0.002$).

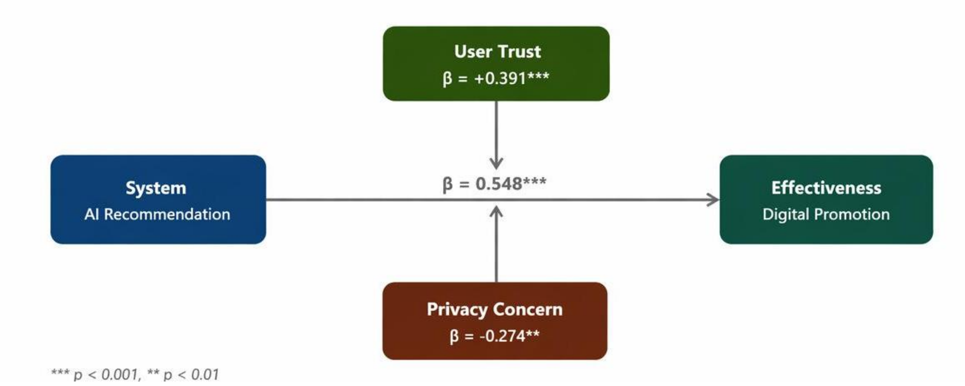

Figure 3. PLS-SEM diagram

The diagram above illustrates the moderating structural model obtained from the PLS-SEM analysis. This finding carries important implications: when consumers feel that the platform handles their data responsibly, the resulting trust strengthens the positive effect of AI recommendations. Conversely, when suspicion regarding data collection arises, the effectiveness of promotion weakens significantly even though content relevance remains high. This dynamic confirms that consumers' psychological factors cannot be ignored when designing AI-based promotional strategies on the TikTok social commerce platform.

This study found that TikTok's AI recommendation system has a positive and significant effect on user engagement with digital promotional content. This result confirms that the recommendation algorithm functions not only as a content distribution tool, but also as a mechanism that actively shapes user interaction patterns within the social commerce ecosystem. The higher the level of content relevance presented by the system, the greater the likelihood that users will respond by watching longer, liking, commenting, sharing, or further exploring the content. Thus, AI-based recommendations can be understood as a strategic instrument capable of strengthening the connection between promotional content and users' personal preferences.

These findings are consistent with various recent empirical studies emphasizing that TikTok's algorithm operates through a combination of personal relevance, exposure frequency, and continuously updated engagement patterns. This mechanism makes the content consumption experience feel more personal, adaptive, and non-intrusive, allowing users to accept promotional content more naturally as part of their activities on the platform. In this context, the algorithm not only increases promotional visibility but also enhances the quality of user interaction with content perceived as relevant to their interests and needs. Therefore, the path coefficient value of 0.612 in this study indicates that the AI recommendation system has a strong influence in encouraging organic user engagement.

From a theoretical perspective, these results can also be explained through the Technology Acceptance Model (TAM), particularly in terms of perceived ease of use and perceived usefulness. When users perceive that the recommended content is easy to understand, relevant, and beneficial, their attitude toward the content tends to become more positive. This positive attitude, in turn, encourages interaction intention and increases the likelihood of higher engagement. In other words, the success of an AI recommendation system in enhancing engagement is determined not only by the technical sophistication of the algorithm, but also by how users interpret the digital experience provided by the platform.

In addition to influencing engagement, this study also proves that the AI recommendation system has a significant effect on purchase conversion. This finding reinforces the view that algorithmic personalization is an important factor in driving consumption decisions on social commerce platforms. Relevant recommendations allow users to find suitable products more quickly, reduce the burden of information searching, and increase the likelihood of purchase decisions. However, the lower path coefficient value for purchase conversion compared to engagement indicates that the transition from attention to actual transaction does not occur automatically. Purchase conversion remains influenced by other factors, such as trust in the seller, the quality of product information, the ease of the transaction system, and users' perceptions of benefits and risks.

The most important dimension of these findings lies in the moderating role of user trust and privacy concern. User trust was found to strengthen the relationship between the AI recommendation system and the effectiveness of digital promotion, while privacy concern weakened that relationship. This shows that the effectiveness of AI-based promotion is not determined solely by the algorithm's ability to present relevant content, but also by users' psychological conditions toward the platform. When users trust that their data are managed responsibly, they become more open to the recommendations provided. Conversely, when concerns arise that personalization is excessive or intrusive, responses to promotion tend to decline. Therefore, the success of AI-based digital promotion on TikTok must be built on two main foundations: the sophistication of the recommendation system and a well-maintained ecosystem of trust among the platform, marketers, and consumers.

5. Conclusion

This study demonstrates that TikTok's *AI recommendation system* positively and significantly influences both *user engagement* ($\beta = 0.612$) and *purchase conversion* ($\beta = 0.548$) among Indonesian consumers on TikTok Shop, with *user trust* strengthening and *privacy concern* weakening these relationships. Using *Partial Least Squares Structural Equation Modeling* (PLS-SEM), all hypotheses were statistically supported. The findings imply that digital promotion effectiveness is not solely determined by algorithmic sophistication, but also by users' psychological disposition toward the platform. Nevertheless, an important limitation must be acknowledged: all findings are based on *self-reported* perceptual data from 320 respondents using a *cross-sectional* design, rather than actual behavioral data extracted from the platform itself, meaning causal inferences should be interpreted cautiously and cannot be broadly generalized without further replication.

Future research is encouraged to adopt longitudinal or *mixed-method* designs that incorporate actual platform behavioral data, directly addressing the *cross-sectional* limitations and perceptual subjectivity inherent in this study. Demographic expansion beyond Java and cross-platform comparisons involving *Instagram Shopping* and *Shopee Live* would further strengthen generalizability. Practically, marketers and platform operators should develop algorithmic transparency mechanisms and *trust-building* strategies embedded within the promotional ecosystem architecture, actively mitigating the *personalization-privacy paradox* that was empirically shown to significantly diminish the effectiveness of *AI-driven digital marketing* within Indonesia's *social commerce* landscape.

Acknowledgements

The authors would like to express their sincere gratitude to the Informatics Study Program, University Indonesia Mandiri, Lampung, for the academic support and institutional environment that facilitated the completion of this research. The authors also extend their appreciation to all respondents who participated in this study and provided valuable data for the analysis. In addition, the authors would like to thank colleagues and academic peers who contributed constructive suggestions and feedback during the preparation of this manuscript.

Funding

This research received no external funding. No specific grant, contract number, or financial sponsorship was obtained from any public, commercial, or not-for-profit funding agency. The sponsor had no role in the design of the study; in the collection, analysis, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Author Contributions

Conceptualization, Efi Ero Sofia and Eko Aziz Apriadi; Methodology, Efi Ero Sofia, Eko Aziz Apriadi, and Ribut Julianto; Software, Efi Ero Sofia and Muawan Bisri; Validation, Eko Aziz Apriadi, Ribut Julianto, and Muawan Bisri; Formal analysis, Efi Ero Sofia and Ribut Julianto; Investigation, Efi Ero Sofia; Data curation, Efi Ero Sofia; Writing—original draft, Efi Ero Sofia; Writing—review & editing, Eko Aziz Apriadi, Ribut Julianto, and Muawan Bisri; Supervision, Eko Aziz Apriadi and Ribut Julianto. All authors have read and agreed to the published version of the manuscript.

Conflict Of Interest

The authors declare no conflict of interest.

References

[1] Y. K. Dwivedi *et al.*, "Opinion Paper: 'So what if ChatGPT wrote it?' Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy," *Int. J. Inf. Manage.*, vol. 71, p. 102642, 2023, doi: https://doi.org/10.1016/j.ijinfomgt.2023.102642.

[2] M. N. Fitrianto, "Analisis Pengaruh Algoritma Rekomendasi TikTok terhadap Perilaku Konsumsi Konten Menggunakan Metode Data Mining dan Machine Learning," *J. Publ. Tek. Inform.*, vol. 4, no. 2, pp. 68–75, 2025.

[3] S. Kemp, "Digital 2023: Global Overview Report. We Are Social & Meltwater," 2023, [Online]. Available: https://datareportal.com/reports/digital-2023-global-overview-report

[4] D. Riswan, H. Eko, R. Putra, and R. N. Saputra, "Pengembangan Sistem Rekomendasi Berbasis Kecerdasan Buatan Untuk Meningkatkan Pengalaman Pengguna Di Platform E-Commerce," *J. Komput. Teknol. Inf. Sist. Inf.*, vol. 2, no. 3, pp. 572–580, 2024, [Online]. Available: https://doi.org/10.62712/juktisi.v2i3.145

[5] A. Al Marzaq, J. W. A. Kusuma, K. Riyandi, and D. Pratama, "Pengaruh Teknologi AI pada Algoritma Tiktok terhadap Respons dan Penerimaan Pengguna," *J. Rekayasa Inform.*, vol. 2, no. 1, pp. 9–15, 2025, [Online]. Available: https://journal.rekayasainformatika.com/index.php/JREIN/article/view/48

[6] J. Zhang, G. Adomavicius, A. Gupta, and W. Ketter, "Consumption and Performance: Understanding Longitudinal Dynamics of Recommender Systems via an Agent-Based Simulation Framework," *Inf. Syst. Res.*, vol. 31, no. 1, pp. 76–101, 2020, doi: 10.1287/ISRE.2019.0876.

[7] M. N. Ardiansah, A. Azizah, and A. Sadida, "Social Commerce Success Impact on Business Performance Insight From TikTok Shop Phenomena in Indonesia," *Account. Anal. J.*, vol. 13, no. 1, pp. 25–33, 2024, doi: 10.15294/aaj.v13i1.2778.

[8] F. K. Tsabat, M. Rasyid Firdausa, and D. Dian, "Analisis Perilaku Gen Z Dalam Memilih Layanan Berbasis Digital E-Commerce," *J. Inov. Manaj. dan Kewirausahaan*, vol. 6, no. 3, pp. 41–54, 2025, [Online]. Available: https://ejurnals.com/ojs/index.php/jimk

[9] L. Auliarahman, "From impulse to loyalty: examining drivers of continuous purchase intention on the Tiktok live shopping platform," *BISMA (Bisnis dan Manajemen)*, vol. 17, no. 2, pp. 169–191, 2025, doi: 10.26740/bisma.v17n2.p169-191.

[10] M. Chandraa, D. W. Sukmaningsih, and E. Sriwardiningsih, "The Impact of Live Streaming On Purchase Intention In Social Commerce In Indonesia," *Procedia Comput. Sci.*, vol. 234, no. 2023, pp. 987–995, 2024, doi: 10.1016/j.procs.2024.03.088.

[11] W. M. Lim, T. Rasul, S. Kumar, and M. Ala, "Past, present, and future of customer engagement," *J. Bus. Res.*, vol. 140, no. November 2021, pp. 439–458, 2022, doi: 10.1016/j.jbusres.2021.11.014.

[12] Y. Sun, S. Li, and L. Yu, "The dark sides of AI personal assistant: effects of service failure on user continuance intention," *Electron. Mark.*, vol. 32, no. 1, pp. 17–39, 2022, doi: 10.1007/s12525-021-00483-2.

[13] N. Putri, Y. Prasetya, P. W. Handayani, and H. Fitriani, "TikTok Shop: How trust and privacy influence generation Z's purchasing behaviors," *Cogent Soc. Sci.*, vol. 10, no. 1, 2023, doi: 10.1080/23311886.2023.2292759.

[14] S. Poh, D. G. Hasan, and K. A. Sudiyono, "The power of social commerce: TikTok's impact on Gen Z consumer purchasing behavior," *Manaj. dan Bisnis*, vol. 23, no. 2, p. 501, 2024, doi: 10.24123/mabis.v23i2.835.

[15] T. H. D. Handoko and Rahayu, "Pengaruh Algorithmic Marketing terhadap Pengambilan Keputusan Konsumen Digital pada TikTok Shop Dimoderasi Tantangan Consumer Autonomy," *J. Artif. Intell. Digit. Bus.*, vol. 5, no. 1, pp. 118–126, 2026, [Online]. Available: https://doi.org/10.31004/riggs.v5i1.5564

[16] M. Syafriani and D. Hidayah, "The Use Of Influencers And Tiktok's Recommendation Algorithm On Purchase Decision And Its Implication On E-Loyalty Of Tiktok Shop Users," *Procur. J. Ilm. Manaj.*, vol. 7, no. 2, pp. 152–164, 2025, [Online]. Available: https://doi.org/10.35145/procuratio.v13i3.5226

[17] N. I. Prestyasih and S. R. H. Hati, "The Role of Social Commerce Trust and Satisfaction on TikTok Consumer Purchasing Behavior," *J. Ilm. Manaj. Kesatuan*, vol. 13, no. 4, pp. 2817–2826, 2025, doi: 10.37641/jimkes.v13i4.3455.

[18] I. W. Sari, H. Erliana, C. M. Nurul 'Akla, and N. Yudisha, "The Effect of AI-Based Recommendation System for Material Personalization on Vocational Student Satisfaction," *G-Tech J. Teknol. Terap.*, vol. 9, no. 4, pp. 2207–2217, 2025, doi: 10.70609/g-tech.v9i4.8091.

[19] Claes Fornell and David F Larcker, "Structural Equation Models with Unobservable Variables and

Measurement Error: Algebra and Statistics," *J. Mark. Res.*, vol. 18, no. 3, pp. 382–388, Aug. 1981, doi: 10.1177/002224378101800313.

[20] B. Rolando, "How Tiktok Shapes And Influences Modern Consumer Shopping Patterns," *ABDIMAS (Aksi Bakti Dan Dedik. Ilm. Untuk Masyarakat)*, vol. 1, no. 1, pp. 1–15, 2025, [Online]. Available: https://jurnal.dinamikapublika.id/index.php/ABDIMAS/article/view/4

[21] A. I. Canhoto, B. J. Keegan, and M. Ryzhikh, "Snakes and Ladders: Unpacking the Personalisation-Privacy Paradox in the Context of AI-Enabled Personalisation in the Physical Retail Environment," *Inf. Syst. Front.*, vol. 26, no. 3, pp. 1005–1024, 2024, doi: 10.1007/s10796-023-10369-7.

[22] A. Irfan, A. N. Y. S, Hafipah, and Y. Adi, "The Influence of Live Shopping on Consumer Purchase Decisions: Analysing the Role of Social Commerce in Indonesia's Retail Sector," *South East Asian J. Manag.*, vol. 19, no. 2, 2025, doi: 10.7454/seam.v19i2.1867.

[23] J. Hair and A. Alamer, "Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example," *Res. Methods Appl. Linguist.*, vol. 1, no. 3, p. 100027, 2022, doi: https://doi.org/10.1016/j.rmal.2022.100027.

[24] C. M. Ringle, M. Sarstedt, N. Sinkovics, and R. R. Sinkovics, "A perspective on using partial least squares structural equation modelling in data articles," *Data Br.*, vol. 48, p. 109074, 2023, doi: https://doi.org/10.1016/j.dib.2023.109074.

[25] M. A. Memon, T. Ramayah, J. H. Cheah, H. Ting, F. Chuah, and T. H. Cham, "Pls-Sem Statistical Programs: a Review," *J. Appl. Struct. Equ. Model.*, vol. 5, no. 1, pp. i–xiv, 2021, doi: 10.47263/JASEM.5(1)06.

[26] J. F. Hair, J. J. Risher, M. Sarstedt, and C. M. Ringle, "When to use and how to report the results of PLS-SEM," *Eur. Bus. Rev.*, vol. 31, no. 1, pp. 2–24, 2021.

[27] N. Kock, "Harman's Single Factor Test in PLS-SEM: Checking for Common Method Bias," *Data Anal. Perspect. J.*, vol. 2, no. 2, pp. 1–6, 2021, [Online]. Available: https://scriptwarp.com/dapj/2021_DAPJ_2_2/Kock_2021_DAPJ_2_2_HarmansCMBTest.pdf

[28] E. A. Apriadi, R. Julianto, F. Dwiatmoko, M. Bisri, and H. Mukaromah, "Kecerdasan Buatan Teori, Implementasi, Dan Aplikasi Di Era Digital," in *Eko Aziz Apriadi*, 2025, p. 700. [Online]. Available: https://books.google.co.id/books?id=YtKOEQAAQBAJ

[29] M. Sarstedt, C. M. Ringle, and J. F. Hair, *Partial Least Squares Structural Equation Modeling*. 2022.

[30] S. Zannettou *et al.*, *Analyzing User Engagement with TikTok's Short Format Video Recommendations using Data Donations*, vol. 1, no. 1. Association for Computing Machinery, 2024. doi: 10.1145/3613904.3642433.

[31] José Ramón Saura, "Algorithms in Digital Marketing: Does Smart Personalization Promote a Privacy Paradox?," *FIIB Bus. Rev.*, vol. 13, no. 5, pp. 499–502, Oct. 2024, doi: 10.1177/23197145241276898.

[32] J. R. Saura, V. Škare, and D. O. Dosen, "Is AI-based digital marketing ethical? Assessing a new data privacy paradox," *J. Innov. Knowl.*, vol. 9, no. 4, p. 100597, 2024, doi: https://doi.org/10.1016/j.jik.2024.100597.