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AI-Recommendation and UTAUT2 Factors in Shaping Consumer Attitudes and Purchase Intentions in E-Commerce

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A B S T R A C T

The rapid growth of smartphone usage has increased consumer access to digital marketplaces such as Shopee, where AI recommendation systems are widely used to enhance user experience. However, the extent to which AI recommendation and UTAUT2 constructs influence consumer attitude and purchase intention in e-commerce remains insufficiently explored. This study aims to examine the role of AI recommendation (AIR), performance expectancy (PE), effort expectancy (EE), and hedonic motivation (HM) in shaping consumer attitude (ATE) and purchase intention (ITP). This study employs a quantitative approach using survey data collected from 463 Shopee users in Indonesia. The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM).The results show that AI recommendation, effort expectancy, and hedonic motivation positively influence consumer attitude, while performance expectancy has a significant negative effect. In addition, consumer attitude, AI recommendation, performance expectancy, and effort expectancy positively influence purchase intention, whereas hedonic motivation negatively affects purchase intention. These findings suggest that purchase intention is influenced not only by affective responses but also by functional evaluations of technology. This study contributes to the literature on AI recommendation and UTAUT2 in the e-commerce context and provides practical insights for optimizing AI-driven personalization strategies to improve consumer engagement and conversion.

KATA KUNCI

Rekomendasi AI, Ekspektasi Kinerja, Ekspektasi Usaha, Motivasi Hedonis, Niat Pembelian

A B S T R A K

Pertumbuhan penggunaan *smartphone* yang pesat telah meningkatkan akses konsumen terhadap *marketplace* digital seperti Shopee yang memanfaatkan sistem rekomendasi berbasis kecerdasan buatan untuk meningkatkan pengalaman pengguna. Namun, pengaruh rekomendasi AI dan konstruk UTAUT2 terhadap sikap dan niat pembelian konsumen dalam konteks e-*commerce* masih memerlukan kajian lebih lanjut. Penelitian ini bertujuan untuk menganalisis pengaruh rekomendasi AI, ekspektasi kinerja, ekspektasi usaha, dan motivasi hedonis terhadap sikap konsumen serta niat pembelian. Penelitian ini menggunakan pendekatan kuantitatif dengan data yang diperoleh melalui survei terhadap 463 pengguna aktif Shopee di Indonesia dan dianalisis menggunakan *Partial Least Squares Structural Equation Modeling* (PLS-SEM). Hasil penelitian menunjukkan bahwa rekomendasi AI, ekspektasi usaha, dan motivasi hedonis berpengaruh positif terhadap sikap konsumen, sedangkan ekspektasi kinerja berpengaruh negatif signifikan terhadap sikap konsumen. Selain itu, sikap konsumen, rekomendasi AI, ekspektasi kinerja, dan ekspektasi usaha berpengaruh positif terhadap niat pembelian, sementara motivasi hedonis berpengaruh negatif terhadap niat pembelian. Temuan ini menunjukkan bahwa niat pembelian dipengaruhi oleh faktor afektif maupun evaluasi fungsional terhadap teknologi yang digunakan. Penelitian ini memberikan kontribusi terhadap pengembangan literatur mengenai rekomendasi AI dan UTAUT2 dalam konteks *e-commerce* serta implikasi praktis bagi optimalisasi strategi personalisasi berbasis AI untuk meningkatkan keterlibatan dan niat pembelian konsumen.

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1. Introduction

1.1. Research Background

The increasing level of internet penetration worldwide, including 80.66% of the total population or approximately 229 million users in Indonesia, indicates that technology has deeply integrated into everyday life which provides many conveniences [1]. Along with the expansion of internet usage, the adoption of mobile phones is estimated to reach 89% of the population, particularly among young adult groups [2]. That large number of active mobile phone users has increased user's reliance on platforms on these devices, particularly mobile applications which have become more integrated into society, enabling individuals to perform many activities online and creating new forms of digital trade, commonly known as e-commerce.

The expansion of e-commerce has also accelerated the popularity of online shopping, allowing consumers to easily browse, compare and purchase products [3]. To enhance user experience, many e-commerce companies integrate recommendation systems that assist consumers in finding products that align with their interest and needs [4]. Several studies suggest that artificial intelligence based recommendation systems in e-commerce platforms, including Shopee can influence consumer's ITP. These not only simplify the product search process, but also create a more enjoyable hedonic shopping experience for users [5].

However, consumer responses to AIR systems are not only influenced by hedonic aspects, but also by their perceptions regarding usefulness and ease of use using e-commerce [6]. These perceptions can shape consumers' attitudes, which are essential in influencing behavioral response in online shopping environments. A positive attitude toward using e-commerce may subsequently encourage consumers to develop stronger purchase intentions [7].

Despite the growing implementation of AIR systems in e-commerce, prior studies still show inconsistent findings regarding how AIR systems influence consumer attitudes and purchase intentions. Some studies found that personalized AIR significantly improve consumers' ATE and behavioral intentions [8], while other studies reported that consumers may perceive AIR systems as intrusive, manipulative, or lacking transparency, which can reduce trust and weaken ITP [9]. Furthermore, previous studies have predominantly focused on the direct relationship between AIR systems and ITP, while limited attention has been given to the mediating role of consumers' ATE, particularly in the context of Shopee as one of the leading e-commerce platforms in Indonesia [10].

To better understand how these technological factors influence, this study adopts the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). UTAUT2 proposes that seven key factors influencing an individual's use of technology and acceptance are EE, PE, social influence, HM, facilitating conditions, price value, and behavioral. However, this study specifically focuses on PE, EE, and HM because these constructs are considered the most relevant in explaining consumers' cognitive and emotional evaluations toward AI-based recommendation systems in e-commerce usage. In contrast, other UTAUT2 constructs such as social influence, facilitating conditions, price value, and habit were excluded because this study emphasizes consumers' internal perceptions and attitudes toward AIR features rather than external support factors or post-adoption habitual behavior [11]. Therefore, this study contributes to the literature by integrating AIR systems with selected UTAUT2 constructs to explain consumer attitudes and purchase intentions simultaneously, thereby providing a more focused understanding of how AI-driven personalization and technology acceptance factors interact within the Indonesian e-commerce context, particularly Shopee.

1.2. Literature Research

1.2.1. Grand Theory

Researcher proposed Theory of Acceptance and Use of Technology 2 (UTAUT2) model, which is known as a reliable framework for studying technology and adoption and user behavior. There are several constructs of UTAUT2, which include PE, EE, social influence, HM, facilitating conditions, price value, and behavioral intention which are moderated by gender, age, and experience [12]. The UTAUT2 model has been extensively applied in information systems research, and it has been given a lot of attention by scholars, as it is able to explain about 75% of behavioral intentions for technology adoption [13], [14]. The model is commonly employed to analyze users' acceptance of technology innovations, such as e-commerce [15], [16].

1.2.2. AI-Based Recommendation

AI-based Recommendation (AIR) systems are an important part of online shopping experiences with customized product recommendations. These systems are using advanced algorithms to analyze user behavior and demographic data to make recommendations that greatly impacting consumers' psychology that influenced their decision-making processes [17]. AIR is measured by indicators reflecting the extent to which Shopee provides accurate product recommendations, based on users' needs, preferences, interests, and activity [18]. Recently, research has been highlighting the significance of understanding how AIR are impacting consumers' decision-making [19], [20]. Therefore, these two hypotheses are proposed:

H1: AIR contributes positively on ATE

H6: AIR contributes positively on ITP

1.2.3. Performance Expectancy

Performance Expectancy (PE) is the belief that technology can improve an individual's performance for their activities [21]. It has been found as an influential predictor of future technology acceptance in various studies [22]. PE is operationalized through indicators reflecting the extent to which Shopee enhances users' shopping effectiveness, efficiency, and productivity [21]. Earlier findings also suggest that PE has influence on ITP [23]. These concepts provide the basis for proposing two hypotheses:

H2: PE exerts a positive impact on ATE

H7: PE exerts a positive impact on ITP

1.2.4. Effort Expectancy

Effort Expectancy (EE) describes how easy consumers consider a technology is easy to use. When it requires minimal effort, users tend to feel more comfortable [24]. EE is operationalized through indicators reflecting the ease of using Shopee, including ease of learning and clarity of user interaction, previous study also states that the EE has an effect on behavioral intention. [21]. In compliance with these concepts, this research proposes these hypotheses:

H3: EE contributes positively to ATE

H8: EE contributes positively to ITP

1.2.5. Hedonic Motivation

Hedonic Motivation (HM) refers to the emotional and experiential aspects derived from shopping activities, where consumers seek enjoyment, excitement, and sensory stimulation rather than purely functional benefits [25]. In this context, shopping is not merely a goal-oriented activity, but also a source of pleasure, characterized by feelings such as joy, arousal, escapism, and fantasy [26]. Previous states the important role of HM in technology adoption [27], [28]. The accuracy of the recommendations serve a crucial factor as a motivator for the users' enjoyment that could influence their intentions [29]. Based on these concepts, this research explores two hypotheses:

H4: HM reflects a positive relationship on ATE

H9: HM reflects a positive relationship on ITP

1.2.6. Attitude Towards Using E-Commerce

Attitude Towards Using E-Commerce (ATE) technology reflects individuals' overall evaluation and responses to engaging with some platforms, including their effort to use, ease of use and perceived benefits or enjoyment derived from the technology. ATE is operationalized through indicators reflecting users' perceptions that using e-commerce is good, favorable, valuable, considered a trend, and positively influences them [30]. A positive ATE would imply consumers' willingness to continue enjoying and using technology for their daily shopping process [31].

1.2.7. Intention to Purchase

Intention to Purchase (ITP) is commonly defined as the consideration, interest, and buying tendency of a consumer toward a product or service, whereby they are able to evaluate a number of options before deciding on a product or service [32]. ITP is measured by indicators capturing users' interest and trust in Shopee products, as well as their willingness to recommend them to others [33]. In addition, the recommendations by the e-commerce applications may result in the HM of the consumers to undertake spontaneous purchases on a particular platform [34]. There are studies that also proven that EE are able to affect the ITP of consumers [7], [6], [18], [35]. Thus, the following relationship is hypothesized:

H5: ATE is positively related to ITP

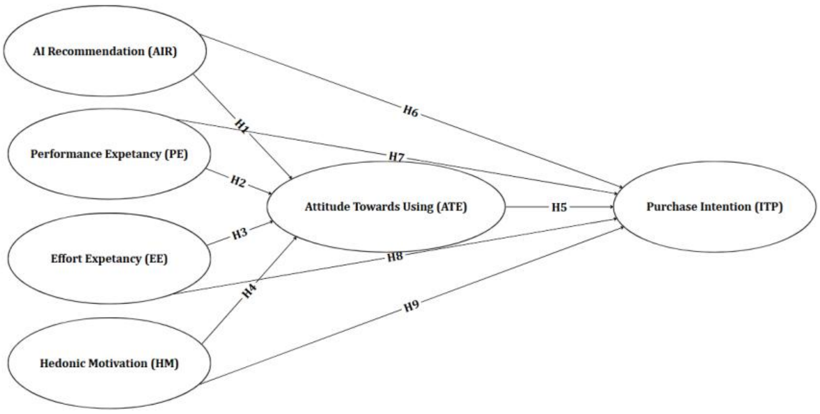

Figure 1. Research Model

2. Research Methods

This research adopted a quantitative methodology to explore the effect of AIR, PE, EE, and HM on consumers' ATE and their ITP. The population of this research is students from Surabaya as a metropolitan city, with a high level of internet penetration and digital adoption, which reflects the characteristics of urban e-commerce users [2]. Therefore, the sample is considered appropriate to represent active e-commerce users in a metropolitan environment. Following the rule of thumb for determining sample size, the non-probability sampling method was employed by selecting 463 students living in Surabaya as the sample [36]. The criteria for respondents in this study include: (1) students aged 21–36 years residing in Surabaya, representing young adults; (2) individuals with prior experience using Shopee; and (3) individuals who have made at least one online purchase. These criteria ensure that respondents possess sufficient experience to evaluate AIR systems.

This research used primarily data that was collected through online questionnaires via Google Form. A seven-point Likert scale was employed to assess responses, with 1 indicating strongly disagree and 7 indicating strongly agree [37]. The research data were analyzed using descriptive statistics, that consist of respondents' profile characteristics, such as gender, level of education and experience in using e-commerce platforms [12], [38]. Experience was determined based on the time and frequency of consumers using e-commerce for shopping and monthly expenses were recorded in order to analyze the pattern of consumers' expenditure using e-commerce platforms. Furthermore, Partial Least Squares (PLS) was employed to analyze the data, which is a multivariate data analysis technique used for calculating optimum weights of different variables to determine the influence of independent and dependent variables [39].

Data analysis starts with the outer model assessment, whose purpose is to verify that the measurement model meets acceptable standards [40]. For an indicator to be valid, it has to meet the conditions: outer loading must be above than 0.7; Average Variance Extracted (AVE) has to be higher than 0.5, and commonality exceeds 0.5. In addition, discriminant validity is assessed to confirm that all constructs are empirically distinct from one another, using cross-loadings, the Fornell-Larcker criterion (√AVE) must be higher than correlations with other constructs; and HTMT ratios have to be more than 0.85. Following the validity assessment, construct reliability is examined to determine the consistency of the measurements and the potential for error. A construct is considered reliable if Cronbach's alpha (α) is above 0.6 and composite reliability (CR) is higher than 0.7, but values of alpha approaching 0.6 are still deemed acceptable.

Afterwards, inner model assessment is applied to evaluate the structural links between variables. R-Square (R^2) measures the proportion of variance in the dependent variables that can be explained by the independent variables. In the final stage, hypothesis testing is conducted to evaluate the significance of variable relationships. This is done by comparing the T-statistics with the critical value T-Table. Using a 5% significance, the hypothesis is considered significant if T-statistics is greater than 1.96, otherwise it is not significant [39].

3. Result and Discussion

3.1 Result

This survey research was carried out by giving out surveys to 463 participants who fall into the category of students residing in Surabaya and have previous experience of buying items on e-commerce sites. The participants were 38.4% male and 61.6% female. As far as their previous experience with Shopee goes, most of the participants have used the app for 3-4 years (45.6%), followed by people who have used it for more than 4 years (30.7%). In addition, (21.6%) of the participants have experience of using Shopee from 1-3 years, and only (2.2%) of them have been using it for less than one year, which is the smallest group.

As regards the purchasing frequency, it has been observed that (46.2%) participants usually make between 3-5 transactions per month, while (26.6%) people have been seen making 1-2 transactions per month. Further, (22.5%) participants make purchases above five times per month, whereas the least number of people make purchases below once per month (22%). As for the average monthly expenses incurred from Shopee purchases, the largest group of respondents (37.1%) spent between Rp 1,000,000 - Rp 2,000,000. This was followed by (28.5%) who spent between Rp 500,000 - Rp 1,000,000. Meanwhile, (20.1%) spent less than Rp 500,000, and (14.3%) spent more than Rp 2,000,000 per month.

Table 1. Outer Model Assessment

Latent Construction	Observed Variables	Factor Loadings
AIR (X1)	Shopee matches product needs	0.953
	Shopee identifies user interests	0.765
	Shopee matches preferences	0.648
	Shopee gives activity recommendations	0.887
PE (X2)	Shopee is useful for shopping	0.954
	Shopee enables faster shopping	0.789
	Shopee improves shopping productivity	0.806
EE (X3)	Shopee is easy to use	0.965
	Shopee is easy to learn	0.840
	Shopee interaction is understandable	0.889
HM (X4)	Shopee is fun	0.937
	Shopee is enjoyable	0.864
	Shopee is entertaining	0.937
ATE (Y1)	Using Shopee is good	0.961
	Using Shopee is favorable	0.855
	Shopee has positive influence	0.959
	Using Shopee is valuable	0.954
	Using Shopee is trendy	0.979
ITP (Y2)	Interest in Shopee purchase	0.967
	Trust in Shopee products	0.860
	I will purchase Shopee products	0.965
	I will recommend Shopee product	0.956

Furthermore, Table 2 demonstrates that the structural model is also satisfied with the required standards. The R^2 value of ATE (Y1) is 0.971, implying that the independent variables AIR (X1), PE (X2), and EE (X3) jointly account for 97.1%, while 2.9% is accounted for by factors other than those contained in this research. Also, the R^2 value of ITP (Y2) is 0.981, implying that the same independent variables account for 98.1%, while the other 1.9% is due to factors other than those in this research.

Table 2. Models of Validity and Reliability

Latent Construction	Cronbach's Alpha	AVE	CR	R^2
AIR (X1)	0.832	0.675	0.891	
PE (X2)	0.809	0.728	0.888	
EE (X3)	0.880	0.927	0.927	
HM (X4)	0.899	0.834	0.938	
ATE (Y1)	0.968	0.889	0.976	0.971
ITP (Y2)	0.954	0.880	0.967	0.981

Survey results from 463 respondents are analyzed to obtain path coefficients (β) and T-statistics (t-values), as presented in Table 3 and Figure 2. They are interpreted as follows: H1 shows that AIR exerts a positive influence on ATE (β = 0.322; t = 7.982); H2 shows that PE exerts a negative influence on ATE (β = -0.294; t = 3.516); H3 shows that EE has a positive relationship with ATE (β = 0.322; t = 7.622); H4 indicates that HM is positively related to ATE (β = 0.648; t = 6.068); H5 suggests that ATE contributes positively to ITP (β = 0.574; t = 4.819); H6 shows that AIR is positively associated with ITP (β = 0.185; t = 9.398); H7 reveals that PE substantially impacts ITP (β = 0.241; t = 2.009); H8 indicates that EE positively affects ITP (β = 0.237; t = 10.890); and H9 shows that HM negatively affects ITP (β = -0.235; t = 2.984).

Table 3. Hypothesis Test

Hypothesis	Description	Path Coefficient (β)	T-Statistics (t)	Information
H1	AIR → ATE	0.322	7.982	Supported
H2	PE → ATE	-0.294	3.516	Supported
H3	EE → ATE	0.322	7.622	Supported
H4	HM → ATE	0.648	6.068	Supported
H5	ATE → ITP	0.574	4.819	Supported
H6	AIR → ITP	0.185	9.398	Supported
H7	PE → ITP	0.241	2.009	Supported
H8	EE → ITP	0.237	10.890	Supported
H9	HM → ITP	-0.235	2.984	Supported

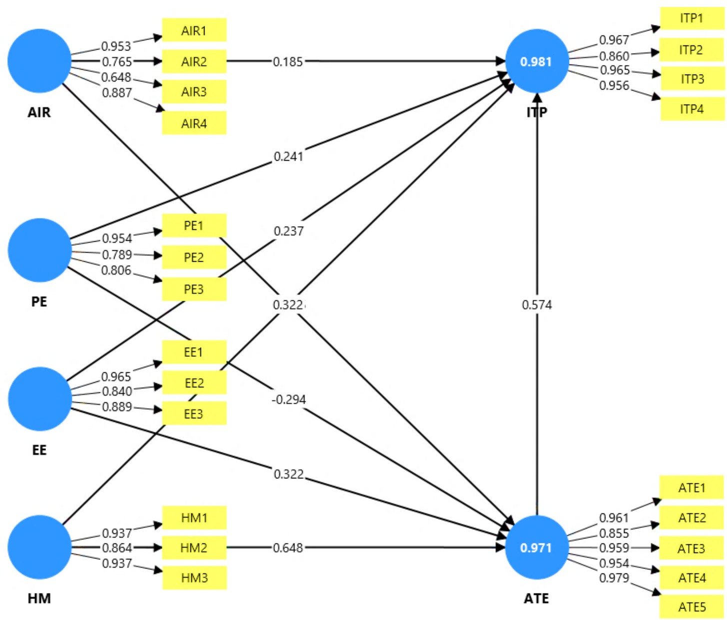

Figure 2. Partial Least Square Results

3.2 Discussion

The results indicate that all hypothesized relationships are statistically supported; however, two relationships (H2 and H9) exhibit negative directions, indicating effects opposite to the initial expectations. The first hypothesis test confirms that AIR exerts a positive influence with ATE by increasing perceived relevance and reducing cognitive effort in product search. When users perceive that Shopee accurately matches their needs and preferences, they develop more positive evaluations of the platform, in line with previous [8], [41].

The results of the second hypothesis test indicate that PE has a negative effect on ATE. Although the relationship is statistically significant, this finding suggests that perceived usefulness does not necessarily enhance users' positive evaluation of the platform. One possible explanation is that Shopee's functional benefits, such as price comparison, promotions, and automated recommendations, may shift user focus toward utilitarian task completion rather than experiential evaluation, thereby weakening affective responses. For example, users may primarily engage with the platform to compare prices, search for discounts, or complete transactions efficiently rather than to enjoy the shopping experience itself. As a result, user evaluation tends to become more goal-oriented and efficiency-driven, which may reduce the formation of a more positive overall attitude toward the platform. This finding is consistent with prior research [13], [42] which suggest that functional value does not always translate into a more favorable attitude in digital platform usage.

Findings from the third hypothesis test show a positive relationship between the EE on ATE. When users perceive that Shopee is easy to use, easy to learn, and provides clear interaction, they feel more comfortable and confident, which contributes to a more positive attitude, in line with previous study [43].

The analysis of the fourth hypothesis test demonstrates that HM is positively related to ATE. When users experience enjoyment, fun, and entertainment while using Shopee, they are more likely to develop not only positive evaluations but also a deeper emotional attachment to the platform. Another research also shows that HM mainly leads to emotional satisfaction and imaginative experiences, where the value comes from how users feel during the activity rather than from the product itself [44], [45].

The fifth hypothesis test confirms that ATE contributes positively to ITP through a positive attitude reflected in enjoyment, interest, and engagement. This attitude is formed through overall evaluations of perceived benefits, usefulness, and pleasant experiences within the e-commerce platform, aligned with previous research [46], [47].

The results of the sixth hypothesis test state that AIR is positively associated with ITP. This suggests that Shopee's personalized recommendations, such as "Recommended for You" and "You May Also Like," increase ITP by matching user preferences and reducing search effort. Previous studies also show that easy to use AIR enhance purchase, consistent with TAM, highlighting perceived ease of use as an integral factor of user behavior and acceptance [48], [49].

The seventh hypothesis test shows that PE substantially impacts ITP, similar to previous studies [50], [51]. In Shopee, this is reflected through promotions that enhance value and efficiency. This finding aligns with the UTAUT2 framework, which identifies PE to be highly correlated with behavioral intention, as users tend to adopt technology that positively influences task performance [21].

The eighth hypothesis test shows a strong positive correlation for EE on ITP, indicated by a high t-value. In Shopee, this is reflected through its user-friendly interface, intuitive search, one-click checkout, categorized listings, and AI-based filtering, which simplify the shopping process from search to purchase. Prior studies also confirm that ease of use increases users' willingness to adopt and continue using e-commerce [52].

The final hypothesis test shows that HM negatively affects ITP. In the context of Shopee, users often engage in browsing activities driven by entertainment value, such as exploring product recommendations, flash sales, and promotional content which tend to encourage entertainment-oriented rather than purchase-oriented behavior. Previous research suggests that hedonic-oriented platform usage may lead to browsing behavior without purchase commitment, as users tend to focus on enjoyment rather than decision-making urgency [13], [53].

4. Conclusion

These findings show that e-commerce user behavior follows a dual mechanism: affective factors (enjoyment and personalization) strengthen attitude, while cognitive and utilitarian factors (performance and EE) directly influence ITP. This suggests that in Shopee, purchase behavior is not always mediated by attitude, but can also arise from direct functional evaluations. Based on these findings, e-commerce companies should improve AIR systems by enhancing relevance, contextual accuracy, and better personalization. Recommendations should not only be based on general product similarity, but also consider users' price range, preferred product categories, and style preferences to better match their needs. In Shopee, this includes not only simplifying the checkout process but also making it easier for users to select and apply the most relevant vouchers and promotions, which are not always fully automatic depending on the type of offer. The scope of this study is limited to the Shopee platform, meaning the findings may not fully represent user behavior across different e-commerce platforms. Future studies may extend the model by including trust and personalization quality to better explain ITP in AI-driven e-commerce environments. Trust refers to users' confidence in products, sellers, and transaction security, while personalization quality reflects how well AIR match users' preferences, including price range, product relevance and consumers' style. These factors may influence how cognitive evaluations affect ITP.

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