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Purchase Intention Analysis in Augmented Reality Marketing: SOR Implementation Framework

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ABSTRACT: The rapid competition in the developing industry makes it increasingly important for business actors and marketers to pay attention to several important factors that can determine consumer purchasing decisions, namely based on the SOR framework. The researcher intend to expand literature by extending the S-O-R framework to the context of AR-based marketing in the telecommunications sector, by introducing a novel conceptual model connecting augmentation, product informativeness, and personalized recommendations to purchase intention via choice beliefs and perceived usefulness. The research approach used is quantitative research, by distributing questionnaires to 308 telecommunications service users in Batam City. The findings reveal that augmentation and product informativeness have a significant effect on choice trust. Product informativeness also have a significant direct effect on purchase intentions, although personalized recommendations cannot prove a significant relationship with purchase intentions. Regarding its mediation effect, researchers proved that choice trust is able to mediate the relationship between augmentation and product informativeness with purchase intentions. Perceived usefulness is able to mediate the relationship between product informativeness and purchase intentions, personalized recommendations do not significantly influence purchase intentions. It is important for telecommunication service companies to boost purchase intentions by building trust in choice, benefits felt by customers by maximizing the usefulness of augmentation-related features, product informativeness, and ability to provide effective recommendations for customers. Future researchers can make efforts to implement further research related to augmented reality marketing factors in their influence on purchase intentions, with different variable or research object.

Keywords: Augmentation, Product Informativeness, Perceived Usefulness, Personalized Recommendations, Purchase Intention.

INTRODUCTION

Technological advances significantly transform people's lives. Various societal activities are increasingly being replaced by existing automated technologies, one of which is the presence of Augmented Reality (AR), which provide simulations of real-world environments through computer-generated content (Kumar, 2022). In the marketing sphere, AR is seen as a new strategic field that has great potential to declare changes in the virtual world (Kang et al., 2020). The latest report from Insights in 2020 in Söderström et al. (2024) estimates that the global AR market size will reach $4.16 billion in 2020, with estimates indicating a 20-fold growth over the next 8 years.

Efforts to maintain and build customer loyalty, by initiating repeat purchases, are considered a crucial aspect for the success of business actors in the long term (Smink et al., 2019). This is followed by the importance of understanding how AR features can encourage continuous purchases and use. This is because AR applications are designed for repeated use, where it is important to understand how the technology can affect users through various stages (Chen & Lin, 2022).

As AR gains traction in e-commerce, researchers are increasingly interested in exploring its application in marketing programs (Söderström et al., 2024). In this context, AR tends to offer unique aspects of its local presence, which can be expressed as a form of user perception of AR content that is physically presented (Kowalczuk et al., 2021). Previous research indicates that the use of AR for online customer experiences and online shopping activities can maximize user satisfaction and engagement (Qadri et al., 2023). It is also undeniable that consumers often find AR enjoyable considering that it can significantly change their shopping experience (Ebrahimabad et al., 2024). However, there are some consumers who feel disadvantaged by the presence of AR considering that they cannot physically interact with the marketed product (Hwang et al., 2020). Despite these limitations, there is strong evidence to support the usefulness of AR for users, in forming the right purchasing decisions, while providing a more interactive and enjoyable shopping experience (Kang et al., 2020).

Purchase decision, or purchase intention is defined as a consumer's desire, interest, or intention to make a purchase of a product or service (Park & Kim, 2023). This can reflect the level of consumer commitment and interest in a particular product, which can be influenced by various factors (Barta et al., 2023). In this context, understanding purchase intention is considered essential for companies, considering that it can help in forming effective marketing strategies to attract and retain customers (Guo & Zhang, 2024). Wijaya et al. (2024) and Rovina & Saputra (2024) also stated that the purchase intention of a product/service is assessed as the result of an internal evaluation process of various determining factors, including perceptions of the brand, product quality, price, or external factors such as recommendations or promotions carried out through digital content.

Therefore, it is important for business actors and marketers to pay attention to several important factors that can determine consumer purchasing decisions, namely based on the SOR framework. This framework is a form of model that considers 3 main elements, namely stimuli that function as external factors that influence individuals, such as product design, advertising, or AR experiences. In the context of marketing, these stimuli can contain several elements that can attract consumers' attention (Trisna Jaya & Jaw, 2024). Meanwhile, organisms refer to the internal processes experienced by individuals, including cognition, perception, and emotions, including in efforts to interpret the stimuli they receive, while responses contain actions taken by individuals as a result of stimuli from internal processes, which can include purchasing decisions (Kang et al., 2020).

Stimulus is related to aspects of entertainment content and information content. Entertainment content is related to augmentation. Augmentation, or known as the addition or enhancement of information in the user experience through AR features, which can provide interactivity (Söderström et al., 2024), tends to allow consumers to gain a more immersive experience related to their products (Voicu et al., 2023; Hwang et al., 2020). In this case, augmentation can influence choice beliefs (Söderström et al., 2024). This refers to the form of consumer confidence in making purchasing decisions by providing more complete and relevant information (Hwang et al., 2020; Qadri et al., 2023).

Another aspect, namely information content, includes product informativeness, namely the extent to which marketers present detailed, complete, and clear information about the product (Voicu et al., 2023; Qadri et al., 2023), which can meet consumer desires and needs through effective efforts (Vo et al., 2022). Product information can also influence choice beliefs, where when a product is considered informative, consumers tend to feel more confident in choosing it because they believe that the product will provide better benefits than more conventional alternatives (Wu et al., 2024; Voicu et al., 2023). In this context, clear and attractive product information can create confidence that they are making the right decision (Dogra et al., 2023). Furthermore, product informativeness can also maximize perceived benefits, which underlines the extent to which consumers feel that the product will meet their needs or enhance their experience (Trisna Jaya et al., 2024; Hwang et al., 2020). Products that have clear information are generally equipped with various explanations of benefits, which makes them more useful in the eyes of users (Peukert et al., 2019; Voicu et al., 2023).

Another factor is personalized recommendations, which refers to a series of systems that provide product or content suggestions tailored to individual user preferences and behaviors (Söderström et al., 2024; Tu & Jia, 2024). When users receive appropriate and relevant recommendations, they feel that the system satisfies their preferences and is able to meet their needs better (Zimmerman et al., 2023). This can create a perception related to the benefits or usefulness of a product/service that they can feel (Nawres et al., 2024). Therefore, personalized recommendations not only make the shopping experience more efficient and enjoyable, but also increase users' perceptions of the usefulness of the products offered, because they find it easier to find what they need (Peukert et al., 2019).

Other factors such as choice beliefs and perceived benefits can be determinants of purchase intention. In this case, choice beliefs provide a sense of confidence that the decision taken is the right one, thereby reducing doubt and increasing the desire to buy (Söderström et al., 2024). Likewise, the higher the perception of benefits (perceived usefulness) that will be felt by customers, the more likely they are to switch from consideration to purchase decision (Sengupta & Cao, 2022).

Previous studies e.g., (Söderström et al., 2024) have focused on retail or furniture-based AR applications (such as IKEA Place), while this study applies the S-O-R framework in the telecommunications industry, which remains underexplored in AR research. Hence, this study would benefit from a deeper engagement with how this extension challenges or modifies the SOR framework. It introduces a novel conceptual model that connects augmentation, product informativeness, and personalized recommendations to purchase intention via choice beliefs and perceived usefulness. The practical implications are clearly articulated for industry professionals, offering guidance for designing effective AR marketing strategies, while incorporating a broader societal perspective, such as issues of digital equity and access, could further enhance the study's overall impact and relevance.

Augmentation, as a form of adding or enhancing information in the user experience through AR features, which can provide interactivity, is marked to influence choice confidence (Söderström et al., 2024). This refers to the form of consumer confidence in making purchasing decisions by providing more complete and relevant information (Hwang et al., 2020; Qadri et al., 2023). When consumers have access to additional information and clear visualizations about the product, they feel more confident in choosing the right product (Peukert et al., 2019; Vo et al., 2022).

H1: Augmentation has a significant effect on choice confidence

Product informativeness, refers to the extent to which marketers present detailed, complete, and clear information about the product (Voicu et al., 2023; Qadri et al., 2023), which can meet consumers' wants and needs through effective efforts (Vo et al., 2022). Product information can also influence choice confidence, where when a product is considered informative, consumers tend to feel more confident in choosing it because they believe that the product will provide better benefits than more conventional alternatives (Wu et al., 2024; Voicu et al., 2023). In this context, clear and attractive product information can create confidence that they are making the right decision (Dogra et al., 2023).

H2: Product informativeness has a significant effect on choice confidence

Product informativeness can also maximize perceived usefulness, which underlines the extent to which consumers feel that the product will meet their needs or enhance their experience (Trisna Jaya et al., 2024; Hwang et al., 2020). Products that have clear information are generally equipped with various explanations of benefits, which make them more useful in the eyes of users (Peukert et al., 2019; Voicu et al., 2023). In this case, the better, clearer, and more complete the information presented regarding the product presented, the better the perception of customers regarding the product (Dogra et al., 2023). In other words, consumers who can read and understand the detailed information content in a product can increasingly enable consumers to ensure that the product can meet their needs and preferences (Vo et al., 2022).

H3: Product informativeness has a significant effect on perceived usefulness

Personalized recommendations, which refers to a chain system that provides product or content suggestions tailored to individual user preferences and behaviors (Söderström et al., 2024; Tu & Jia, 2024). When users receive appropriate and relevant recommendations, they feel that the system satisfies their preferences and is able to better meet their needs (Zimmerman et al., 2023). This increases users' confidence that the recommended products or services will be useful and meet their expectations (Nawres et al., 2024). Therefore, personalized recommendations not only make the shopping experience more efficient and enjoyable, but also increase users' perceptions of the usefulness of the products offered, as they find it easier to find what they need (Peukert et al., 2019).

H4: Personalized recommendations have a significant effect on perceived usefulness

Choice confidence provides a sense of confidence that the decision taken is the right one, thereby reducing doubt and increasing the desire to buy (Söderström et al., 2024). When consumers feel confident in their choices, they tend to make purchasing decisions more quickly without getting caught up in over-analysis (Han et al., 2021; Gil-Lopez et al., 2023). In addition, a good guarantee or return policy can also strengthen choice confidence, because consumers feel they have protection if the decision taken does not meet their expectations (Ebrahimabad et al., 2024; Dogra et al., 2023).

H5: Choice confidence has a significant effect on purchase intention

Perceived usefulness refers to the extent to which consumers feel that a product or service can meet their needs or improve their quality of life (Kumar, 2022; Voicu et al., 2023). This factor is very important in influencing purchase intention, because if consumers believe that the product offered can provide real benefits, they will be more likely to make a purchase (Nawres et al., 2024). In addition, clear information about the features and benefits of the product can also increase this perception, thereby encouraging an increase in the intention to purchase the product (Söderström et al., 2024; Smink et al., 2019).

H6: Perceived usefulness has a significant effect on purchase intention

Augmentation, which represents an increase in information related to user experience through AR features, is characterized as being able to influence purchasing decisions by forming beliefs in themselves to choose certain products/services (Söderström et al., 2024). They can have a belief that the decision taken is correct and meets their needs, hopes, and expectations (Hwang et al., 2020; Qadri et al., 2023). In addition, when consumers get access to additional information, they can trust their decisions more in choosing a product, so they are more likely to buy or use products from that service (Peukert et al., 2019; Vo et al., 2022).

H7: Augmentation has a significant effect on purchasing intentions through the mediation of choice trust

Product informativeness represents how complete, clear, and detailed the information presented regarding a marked product/service can influence purchase intention (Voicu et al., 2023; Qadri et al., 2023), through the formation of beliefs in customers (Vo et al., 2022). In this case, when a product is considered informative, consumers tend to feel more confident in choosing it, so that their intention to purchase becomes more optimal (Wu et al., 2024). Other research by Dogra et al. (2023) also states that clear and attractive product information can create confidence that they are making more appropriate purchasing decisions.

H8: Product informativeness has a significant effect on purchase intention through the mediation of choice trust

Product informativeness can also influence purchase intention, through efforts to maximize perceived benefits, which underlines the extent to which consumers feel that the product will meet their needs or enhance their experience (Tu & Jia, 2024; Trisna Jaya et al., 2024; Hwang et al., 2020). Products that present clear information are generally equipped with various explanations of benefits, which make them more useful for their customers, so that they can be more motivated to make a purchase decision (Purwianti et al., 2024; Voicu et al., 2023).

H9: Product informativeness has a significant effect on purchase intention through the

mediation of perceived usefulness

Personalized recommendations can also affect customers' intention to make a purchase, by forming trust and views on the usefulness of the product or service (Park & Kim, 2023; Söderström et al., 2024). When users receive appropriate and relevant recommendations, they feel that the system understands their preferences and needs (Kowalczuk et al., 2021). If the system is seen as very supportive and helpful to customers, they are more likely to adopt the system and purchase its products/services (Peukert et al., 2019; Nawres et al., 2024).

H10: Personalized recommendations have a significant effect on purchase intention through the mediation of perceived usefulness

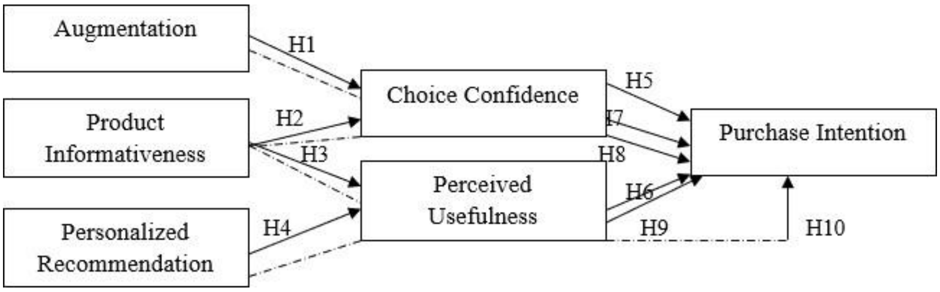

Figure 1. Research Model

METHOD

This study uses a quantitative method with a focus on the type of associative research. The quantitative approach is characterized as a research method that uses data to analyze the relationship between variables, which is expressed in the form of numbers (Hair Jr et al., 2021). This type of research is a hypothesis testing research (hypothesis testing). In this study, the aim to test whether the theory holds true or can be verified. Specifically, the study is purposed to test the influence of factors in the SOR framework on purchasing intentions of telecommunications service users in Batam City. Sampling is based on the purposive sampling technique, namely sampling according to the researcher's considerations, by utilizing the theory of Hair Jr et al. (2019) that 1 questionnaire item is represented by 10 respondents, so because in this study there are 15 items, the minimum number of samples in this study is 150. However, to increase the validity, reliability, and generalizability of the results, the researcher added the number of respondents to 308 people. The construct contained 3 items of augmentation, 3 items of product informativeness, 2 items of personalized recommendations, 2 items of choice confidence, 3 items of perceived usefulness, and 2 items of purchase intention. The data collection method used in this study was through the distribution of questionnaires, through online platform over a two months period in April-June 2025. The collected data is analyzed to represent the answers to the research problems, which utilizes inferential and descriptive analysis, to be able to carry out SEM-PLS testing, specifically the inner-outer model testing to prove the hypothesis (Purwanto & Sudargini, 2021). Inner modelling is applied to test the path coefficients, indirect effects, r-square test, and goodness of fit index, whereas the outer modelling is applied to employ validity and reliability test (Saputra et al., 2024).

RESULT AND DISCUSSION

Demographic Analysis of Respondents

Researchers took a sample of 308 people over a period of 2-3 months, from April – June 2025. The description of the respondent data includes gender, age, last education, whether the respondent has used the augmented reality feature, the telecommunications services currently used, and the telecommunications service provider company they use.

Table 1. Respondent Descriptive Statistics

Criteria	Category	Frequency	Percentage
Gender	Male	161	52,3%
	Female	147	47,7%
Total		308	100.0%
Age	<18 years old	8	2.6%
	18 – 25 years old	126	40.9%
	26 – 30 years old	144	46.8%
	>30 years old	30	9.7%
Total		308	100.0%
Education status	SMA/SMK	73	23,7%
	Diploma	80	26,0%
	Sarjana (S1)	142	46,1%
	Magister (S2)	13	4,2%
Total		308	100.0%
Whether or not the respondent ever use Augmented Marketing	Have ever	305	99,0%
	Have not	3	1,0%
Total		308	100.0%
Types of Telecommunication Service Used	Cellular service	67	21,8%
	Internet service	117	38,0%
	Television and video service	55	17,8%
	VoIP (Voice over InternetProtocol) service	27	8,8%
Internet of Things (IoT) channel service		32	10,4%
	Telemedicine service	10	3,2%
Total		308	100.0%
Telecommunication Companies which service is used	Telkomsel	74	24,0%
	Indosat	56	18,2%
	XL Axiata	62	20,1%
	Smartfren	31	10,1%

Criteria	Category	Frequency	Percentage
	First Media	33	10,7%
	Indihome	52	16,9%
Total		308	100.0%

Source: Primary Data Processed by the Researcher (2025)

Regarding whether the respondents have used the augmented reality feature, most respondents (305 people) or 99.0% have used it, and only a small portion (1.0%) of respondents have never used it. However, of course all of them have used telecommunications services, with the most widely used types of telecommunications services being internet services 38.0%, followed by cellular services 21.8%, television & video services 17.8%, IoT network services 10.4%, VoIP services 8.8%, and telemedicine services 3.2%. During this period, the largest group of respondents used services from Telkomsel (24.0%), followed by XL Axiata 20.1%, Indosat 18.2%, Indihome 16.9%, First Media 10.7%, and Smartfren 10.1%.

Outer Model Calculation

Outer Loading

In this study, outer model testing was conducted using the outer loading technique. In this context, outer loading refers to the factor load value of each indicator. A question is declared valid if the outer load value is > 0.5 (Saputra et al., 2024). In line with the findings described in table 2, it can be inferred that all variable research items show a result value above 0.6, so they are declared valid and do not require the deletion of any variable items.

Table 2. Outer Loading

Variable Items	Outer Loading	Conclusion
AUG_1	0.834	Valid
AUG_2	0.842	Valid
AUG_3	0.903	Valid
PI_1	0.864	Valid
PI_2	0.825	Valid
PI_3	0.878	Valid
PR_1	0.832	Valid
PR_2	0.828	Valid
CC_1	0.801	Valid
CC_2	0.784	Valid
PU_1	0.824	Valid
PU_2	0.775	Valid
PU_3	0.816	Valid
PI_1	0.801	Valid
PI_2	0.846	Valid

Source: Primary Data Processed by the Researcher (2025)

Average Variance Extracted (AVE)

To ensure that the correlation of the research variables is good, a convergent validity test is carried out through average variance extraction (Christiarini et al., 2024). In these provisions, if the AVE value obtained is > 0.5, it indicates that the variable is valid (Saputra et al., 2024). Referring to these provisions, all variables have met the convergent validity requirements considering that the AVE value of each variable is above 0.5, as presented in table 3 below.

Table 3. AVE (Average Variance Extracted)

Variable	AVE	Conclusion
Augmentation	0.684	Valid
Product Informativeness	0.682	Valid
Personalized Recommendation	0.596	Valid
Choice Confidence	0.604	Valid
Perceived Usefulness	0.614	Valid
Purchase Intention	0.596	Valid

Source: Primary Data Processed by the Researcher (2025)

Discriminant Validity

Based on the validity criteria submitted, in order to conclude the validity of a variable, the construct value must have a greater weight than its indicators. Researchers implement discriminant validity through 3 main approaches.

Cross Loadings

This test is intended to identify the relationship between the indicators. In this case, based on the provisions above, the indicators collected in each variable must have a value of at least 0.7. The results in table 4 show that it has met the validity criteria with a value of > 0.7 (Christiarini, 2025).

Table 4. Cross Loadings

Variable	Augmentation	Product Informativeness	Personalized Recommendation	Choice Confidence	Perceived Usefulness	Purchase Intention
AUG_1	0.877	0.738	0.810	0.781	0.821	0.739
AUG_2	0.892	0.790	0.867	0.826	0.814	0.801
AUG_3	0.824	0.694	0.791	0.710	0.742	0.723
PInf_1	0.850	0.701	0.785	0.703	0.903	0.799
PInf_2	0.829	0.713	0.852	0.737	0.817	0.882
PInf_3	0.785	0.742	0.859	0.744	0.832	0.902
PR_1	0.782	0.766	0.854	0.763	0.901	0.906
PR_2	0.741	0.879	0.752	0.770	0.847	0.753
CC_1	0.791	0.910	0.776	0.805	0.746	0.761

Variable	Augmentation	Product Informativeness	Personalized Recommendation	Choice Confidence	Perceived Usefulness	Purchase Intention
CC_2	0.763	0.910	0.732	0.835	0.731	0.714
PU_1	0.845	0.739	0.878	0.738	0.798	0.869
PU_2	0.764	0.699	0.855	0.741	0.814	0.836
PU_3	0.778	0.719	0.867	0.743	0.884	0.850
PI_1	0.847	0.729	0.841	0.794	0.848	0.764
PI_2	0.871	0.757	0.890	0.819	0.847	0.814

Source: Primary Data Processed by the Researcher (2025)

Fornell-Lacker Criterion

Another method used to assess discriminant validity is by using the Fornell-Lacker Criterion. If the square root value of the AVE for a construct is greater than the correlation between the construct and other constructs in the model, then it can be considered an indication of good validity (Saputra et al., 2024). Based on the results presented in table 5, it can be concluded that all variables have met these criteria, because each variable has a correlation between the appropriate indicators.

Table 5. Fornell Larcker Criterion

Variable	Augmentation	Product Informativeness	Personalized Recommendation	Choice Confidence	Perceived Usefulness	Purchase Intention
Augmentation	0.786					
Product Informativeness	0.659	0.778				
Personalized Recommendation	0.666	0.595	0.782			
Choice Confidence	0.744	0.752	0.647	0.710		
Perceived Usefulness	0.704	0.724	0.719	0.711	0.731	
Purchase Intention	0.715	0.675	0.656	0.771	0.636	0.772

Source: Primary Data Processed by the Researcher (2025)

Heterotrait-Monotrait Ratio (HTMT Ratio)

The HTMT test is also an approach to testing discriminant validity. If the HTMT value is <0.9, then the meaning of the number is good, and its discriminant validity has been realized well (Hair Jr et al., 2021).

Table 6. Heterotrait-Monotrait Ratio

Variable	Augmentation	Product Informativeness	Personalized Recommendation	Choice Confidence	Perceived Usefulness	Purchase Intention
Augmentation						
Product Informativeness	0.866					
Personalized Recommendation	1.034	0.988				
Choice Confidence	0.818	1.157	1.045			
Perceived Usefulness	0.881	1.081	1.130	1.037		
Purchase Intention	0.959	0.962	0.983	1.070	0.850	

Source: Primary Data Processed by the Researcher (2025)

In line with the findings above, it can be concluded that there are 11 correlation relationships between variables that show values above 0.9. Meanwhile, there are only 4 correlations that meet the HTMT standard or below 0.9. So, it can be said that the HTMT requirements have not passed the test. However, testing using other methods such as cross loadings and Fornell Lacker Criterion has met the criteria and is given a valid rating, indicating the validity of constructs.

Reliability Test

Basically, reliability shows the extent to which a measurement can produce reliable data. The reliability test is used to determine the consistency of the measuring instrument, whether the measuring instrument used is reliable and remains consistent. In the SPSS program, the method that is often used is to use the Cronbach Alpha method. This study uses the theory of (Hair Jr et al., 2021), which states that an instrument can be said to be reliable if the Cronbach Alpha value ≥ 0.6. Table 7 presented that all of the overall figure for the Composite reliability is above 0.7 and the Cronbach Alpha value is above 0.6. This means that all question items are declared reliable and can be used for in-depth research.

Table 7. Reliability Test

Variable	Cronbach's Alpha	Composite Reliability
Augmentation	0.728	0.837
Product Informativeness	0.758	0.828
Personalized Recommendation	0.769	0.746
Choice Confidence	0.737	0.758
Perceived Usefulness	0.796	0.772
Purchase Intention	0.731	0.745

Source: Primary Data Processed by the Researcher (2025)

Inner Model Calculation Path Coefficients

In order to test the structural model without mediation, path coefficient testing is used, which is shown to test the magnitude of the influence given by the independent variable to the dependent variable directly, or between the latent variable and other latent variables. The significance value obtained from a relationship between variables can be stated in the path coefficient table as stated in the T-statistic column (Hair Jr et al., 2019). In this case, it should be noted that a relationship can be limited to significance with a significance level of 0.05. If it has a T test value> 1.96, or a p value <0.05.

Table 8. Path Coefficients

Path	T Statistics	P Values	Hypothesis	Conclusion
AUG -> CC	2.138	0.033	H1	Accepted
PInf -> CC	4.101	0.000	H2	Accepted
PInf -> PU	5.163	0.000	H3	Accepted
PR -> PU	1.822	0.068	H4	Rejected
CC -> PI	5.065	0.000	H5	Accepted
PU -> PI	3.981	0.000	H6	Accepted

Source: Primary Data Processed by the Researcher (2025)

a. H1 Testing

The analysis shows that H1 is supported, indicating that *augmentation* has a significant positive effect on *choice confidence*. This result is evidenced by the T-statistic value of 2**.138** and a P-value of 0.033, which is well below the 0.05 threshold. Thus, the findings suggest that when augmentation is applied, consumers feel more confident in making their choices.

b. H2 Testing

The results confirm that H2 is supported, meaning *product informativeness* significantly influences *choice confidence*. The T-statistic value of 4.101 and the P-value of 0.000 demonstrate a strong and statistically significant effect. This implies that providing detailed and clear product information enhances consumers' confidence when making purchasing decisions.

c. H3 Testing

The testing results indicate that H3 is supported, showing that *product informativeness* also has a significant positive effect on *perceived usefulness*. With a T-statistic of 5.163 and a P-value of 0.000, the evidence is highly significant. This highlights the critical role of informative product content in shaping consumers' perceptions that the product (or system) is beneficial and practical.

d. H4 Testing

The analysis reveals that H4 is not supported, as *personalized recommendations* do not have a statistically significant effect on *perceived usefulness*. The T-statistic is 1.822 and the P-value is 0.068, which is above the standard significance level of 0.05. This suggests that while personalized recommendations may add value in some contexts, in this study they did not significantly enhance consumers' perceptions of usefulness.

e. H5 Testing

The results confirm that H5 is supported, indicating that *choice confidence* has a significant and positive effect on *purchase intention*. The T-statistic value of 5.065 and a P-value of 0.000 provide strong evidence for this relationship. In practical terms, when consumers feel confident about their choices, they are more likely to follow through with an actual purchase.

f. H6 Testing

Finally, the findings show that H6 is supported, meaning *perceived usefulness* significantly influences *purchase intention*. The T-statistic value of 3.981 and a P-value of 0.000 indicate strong statistical support. This suggests that when consumers perceive a product or system as useful, they are more inclined to develop purchase intentions.

Indirect Effects

In an effort to test the structural model with its mediation, an indirect effect test was carried out, which is intended to show the magnitude of the influence shown by the latent variable on other latent variables but indirectly (Hair Jr et al., 2021). In this context, the acquisition of significance values between relationships can be identified in the indirect effect table for the T test column (Hair Jr et al., 2019). A relationship can be categorized as significant with a significance level of 0.05. If it has a T test value> 1.96, or a p value <0.05.

Table 9. Indirect Effects

Path	T Statistics	P Values	Hypothesis	Conclusion
AUG -> CC -> PI	3.018	0.006	H7	Accepted
PInf -> CC -> PI	4.163	0.000	H8	Accepted
PInf -> PU -> PI	5.671	0.000	H9	Accepted
PR -> PU -> PI	1.786	0.074	H10	Rejected

Source: Primary Data Processed by the Researcher (2025)

a. H7 Testing

The results demonstrate that H7 is supported**,** indicating that *choice confidence* plays a significant mediating role in the relationship between *augmentation* and *purchase intention*. The T-statistic value of 3.018 and P-value of 0.006 confirm that the mediation effect is statistically significant. This finding implies that augmentation alone may not directly drive purchase intention, but it strengthens consumers' confidence in their choices, which in turn increases their likelihood of making a purchase.

b. H8 Testing

The testing confirms that H8 is supported**,** showing that *choice confidence* significantly mediates the effect of *product informativeness* on *purchase intention*. With a T-statistic of 4.163 and a P-value of 0.000, the mediation pathway is strongly significant. This suggests that when consumers are provided with informative product content, it enhances their confidence in decision-making, which subsequently translates into stronger purchase intentions.

c. H9 Testing

The results indicate that H9 is supported, meaning that *perceived usefulness* significantly mediates the relationship between *product informativeness* and *purchase intention*. The T-statistic value of 5.671 and a P-value of 0.000 provide strong evidence for this effect. This highlights that informativeness improves consumers' perceptions of usefulness, which then positively influences their intention to purchase.

d. H10 Testing

The analysis reveals that H10 is not supported**,** as *perceived usefulness* does not significantly mediate the relationship between *personalized recommendations* and *purchase intention*. The T-statistic of 1.786 and P-value of 0.074 exceed the 0.05 threshold, indicating the absence of a significant mediation effect. This suggests that in this context, personalized recommendations do not meaningfully enhance perceptions of usefulness, and thus fail to stimulate purchase intentions through this pathway.

R-Square Test

This test is intended to measure the extent to which the model is able to explain the variation of the dependent variable (Hair Jr et al., 2021). Adjusted R Square means that R Square has been adjusted to the degree of each number of squares included in the Adjusted R Square calculation (Rovina & Saputra, 2024). The coefficient of determination value is 0 (zero) or 1 (one). The results of the R-Square test are displayed in Table 10.

Table 10. R-Square

Variable	R-Square	Adjusted R-Square
Choice Confidence	0.482	0.479
Perceived Usefulness	0.513	0.510
Purchase Intention	0.607	0.603

Source: Primary Data Processed by the Researcher (2025)

The coefficient of determination (R-Square) is used to assess how much variance in the dependent variable can be explained by the independent variables in the model. The Adjusted R-Square provides a more conservative estimate by correcting for the number of predictors, ensuring that the value is not inflated by model complexity.

Choice Cm onfidence (R^2 = 0.482; Adj. R^2 = 0.479)

This means that approximately **48.2% of the variance in choice confidence** can be explained by its predictors (e.g., augmentation and product informativeness). The adjusted R^2 value of 47.9% indicates that the explanatory power remains strong even after accounting for the number of predictors, suggesting that the model is robust.

Perceived Usefulness ($R^2 = 0.513$; Adj. $R^2 = 0.510$)

Here, the independent variables (e.g., product informativeness and personalized recommendations) explain about **51.3% of the variance in perceived usefulness**. The adjusted value (51.0%) shows very little reduction, which confirms that the predictors substantially contribute to explaining perceived usefulness.

Purchase Intention ($R^2 = 0.607$; Adj. $R^2 = 0.603$)

The model explains approximately **60.7% of the variance in purchase intention**, which is relatively high for behavioral research. The adjusted R^2 (60.3%) again shows only a slight decrease, indicating that the predictors (choice confidence and perceived usefulness) are strong determinants of consumers' purchase intentions.

The model demonstrates **moderate to strong explanatory power**, with purchase intention being the most strongly explained construct. This suggests that the variables chosen (augmentation, informativeness, choice confidence, and perceived usefulness) are appropriate and meaningful in predicting consumer behavior.

Quality Index Test

In this study, the quality index used is goodness of fit (GoF). Goodness of fit is a form of comparison given between the specified model and the covariance matrix between indicators or observed values. In this context, a goodness of fit value can be stated as low if the value is greater than 0.10. Medium if the value is > 0.25, and high if > 0.36. In this case, the calculation of the GoF value of 0.578 was obtained, meaning that the quality is high (Chen et al., 2022; Dogra et al., 2023; Liu et al., 2022; Nasution et al., 2020; Sihombing et al., 2023)

$GoF\ Index = \sqrt{\text{Average AVE x Average R-Square}}$

$GoF\ Index = \sqrt{0.629\ x\ 0.531}$

$GoF\ Index = 0.578$

The results of this study provide important insights into how AR-based marketing features influence consumer psychology and purchase behavior within the telecommunications industry. Overall, the findings reinforce the validity of the S–O–R framework in explaining how technological stimuli, which includes augmentation, informativeness, and personalization, affect internal consumer responses (choice confidence and perceived usefulness), which in turn shape purchase intention.

First, the significant effect of augmentation on choice confidence demonstrates that AR features that enrich consumers' perceptions of products, by providing realistic, interactive visualizations, enhance their decision assurance (Söderström et al., 2024). This finding aligns with prior research by who emphasized that AR-driven augmentation reduces uncertainty and facilitates cognitive clarity during product evaluation (Vo et al., 2022). In the context of telecommunications, where intangible services are often difficult to visualize, augmentation appears to play a compensatory role by transforming abstract offerings into concrete, perceivable experiences. This supports the theoretical premise that technological enhancement can increase consumer self-efficacy and confidence, thereby strengthening behavioral intentions (Peukert et al., 2019).

Similarly, product informativeness was found to exert a positive influence on both choice confidence and perceived usefulness, underscoring the centrality of information quality in digital decision-making. The results echo earlier findings Voicu et al. (2023), suggesting that when consumers perceive marketing content as complete, clear, and relevant, they are more likely to trust their judgments and view the product as valuable (Qadri et al., 2023). From an S–O–R perspective, informativeness serves as a cognitive stimulus that shapes the "organism" stage by fostering a sense of control and competence, ultimately motivating the "response" of purchase intention. These findings also corroborate the TAM perspective, which posits that perceived usefulness is a critical antecedent of adoption and purchasing behavior (Vo et al., 2022).

In contrast, personalized recommendations did not significantly affect perceived usefulness, suggesting that personalization alone may not always be perceived as beneficial. This result resonates with the findings of Nawres et al., (2024), who observed that personalization effects can be muted when consumers question the transparency, quality, or privacy implications of AI-based recommendations. This divergence from earlier studies (Zimmermann et al., 2024). implies that the effectiveness of personalization is contingent upon contextual and psychological moderators such as algorithmic trust, perceived relevance, and consumer control. Thus, personalization may enhance user experience only when it is perceived as authentic and privacy-conscious, rather than overly intrusive or commercially motivated (Tu & Jia, 2024).

The strong influence of choice confidence and perceived usefulness on purchase intention underscores the importance of psychological assurance in the digital purchase process. When consumers feel confident about their choices, they experience reduced cognitive dissonance and greater decisiveness, leading to stronger purchase motivation (Gil-Lopez et al., 2023). Likewise, products perceived as useful or beneficial directly stimulate the intention to buy, consistent with the Technology Acceptance Model (Han et al., 2021). These results collectively suggest that both cognitive (usefulness) and affective (confidence) evaluations serve as essential psychological mechanisms driving consumer behavior in AR-enhanced contexts (Dogra et al., 2023).

The mediation analyses further enrich this understanding. Choice confidence was found to mediate the relationships between both augmentation and informativeness with purchase intention, revealing that technological stimuli influence behavioral outcomes primarily through enhancing consumers' internal certainty. This finding confirms the mediating role of confidence highlighted by Voicu et al. (2023) and Smink et al. (2019), emphasizing that the effectiveness of AR lies not only in its sensory appeal but also in its ability to reinforce user conviction in decision-making. Similarly, perceived usefulness mediated the effect of product informativeness on purchase intention, suggesting that well-presented information improves perceptions of utility, which subsequently drive purchasing behavior (Nawres et al., 2024).

Conversely, the mediating role of perceived usefulness in the relationship between personalized recommendations and purchase intention was not supported. This non-significance indicates that personalization, while technologically advanced, may not automatically translate into perceived utility. This may reflect issues of algorithmic opacity, over-recommendation, or privacy concerns, as factors that have been increasingly discussed in contemporary digital marketing literature (Kowalczuk et al., 2021; Peukert et al., 2019). Therefore, personalization strategies in AR contexts must be carefully balanced to ensure that they add genuine value to the consumer experience rather than triggering skepticism or fatigue (Park & Kim, 2023).

This study is not without limitations. First, the research employed a cross-sectional survey design, which restricts the ability to draw strong causal inferences between constructs. Second, the sample was drawn from a specific consumer context, which may limit the generalizability of the findings across different cultural, demographic, or industry settings. Third, the study focused on augmentation, product informativeness, and personalized recommendations as the primary antecedents of consumer behavior, while other relevant variables such as trust, perceived risk, or technological readiness were not included in the model. Fourth, the measurement relied on self-reported data, which may be subject to common method bias and social desirability effects. Finally, the finding that personalized recommendations did not significantly influence perceived usefulness suggests that additional contextual factors, such as recommendation quality, algorithm transparency, or consumer privacy concerns, may need to be considered to better explain this relationship.

Building on the limitations of this study, several avenues for future research are suggested. First, scholars may adopt longitudinal or experimental designs to establish stronger causal relationships between augmentation, product informativeness, personalization, and consumer decision-making outcomes. Second, future studies could test the model across different industries and cultural contexts to assess the generalizability of the findings. Third, additional constructs such as trust, perceived risk, customer experience, or technological readiness should be incorporated to provide a more comprehensive understanding of purchase intention in AI-enhanced commerce. Fourth, given that personalized recommendations did not significantly affect perceived usefulness in this study, further research is needed to examine moderating factors such as algorithm transparency, recommendation quality, or consumer privacy concerns. Finally, employing mixed-method approaches, combining surveys with behavioral tracking or experimental interventions, would strengthen validity and offer richer insights into how AI-driven features shape consumer behavior.

CONCLUSION

The findings reveal that augmentation and product informativeness play a crucial role in shaping consumers' perceptions of usefulness and ease of use, ultimately enhancing their purchase intentions, whereas personalized recommendations did not significantly affect perceived usefulness. Theoretically, this research extends the Technology Acceptance Model (TAM) framework by integrating AI-related constructs, offering new insights into how intelligent technologies shape consumer behavior in digital commerce. Practically, the results highlight the importance for marketers and system designers to focus on developing AI features that enhance product informativeness and user augmentation rather than relying solely on personalization strategies.

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