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Augmented reality improving consumer choice confidence during COVID-19

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Abstract

During COVID-19, augmented reality gives a breakthrough on marketing products. This research aims to analyze the impact of augmented reality on consumer choice confidence through perceived media usefulness, where consumer knowledge will be a moderating variable between augmented reality on perceived media usefulness. The sample of this research is the consumer of Ray-Ban sunglasses who has experience trying the augmented reality application. Based on the statistical analysis, this research found that augmented reality significantly impacts consumer knowledge and choice confidence. This finding means that augmented reality technology is scientifically proven to bring the on-site shopping experience into virtual reality. This research will also contribute to more simple measuring PLS-SEM's model fit using SQRT formula.

Keywords: Augmented reality, choice confidence, costumer knowledge.

Introduction

The Covid-19 pandemic has forced the Indonesian Government to implement the LSSR (Large-Scale Social Restrictions in Bahasa Indonesia it called *Pembatasan Sosial Berskala Besar* is abbreviated as PSBB). LSSR is imposed in almost all regions, especially in the big cities (Purnama & Susanna, 2020). At the beginning of the pandemic, the Government temporarily closed shopping centers such as malls and large retail stores that might be crowds potential which was considered a source of the spread of the virus (Djalante et al., 2020; Olivia et al., 2020). This situation makes businesses in Indonesia enter a "new normal" period where people, including businesses, become used to LSSR and work from home (Hidayatullah et al., 2020; Kusumawati et al., 2021). During the pandemic, many sales were made through online media using e-commerce.

E-commerce applications are expected to increase speed, intensify, and reduce the cost of relationships between companies with other external entities such as suppliers, distributors, partners, and consumers compared to conventional methods. E-commerce is not just a mechanism for selling goods or services through the internet but also for the occurrence of a business transformation that use information technology (IT) that changes the way companies look at doing business activities, especially during the Covid and post Covid time (Vyas et al., 2021, 2022). The use of e-commerce systems should benefit many parties, especially consumers and producers, by cutting intermediaries and reducing costs.

The development of ecommerce has significantly shifted people's activities, including changing how consumers' shopping. This situation has changed how producers sell their products, selling at competitive prices, and reaching more comprehensive consumer segmentation through communication and online transactions (Brusch & Rappel, 2020; Ulas, 2019). These advantages have created a significant emerging development of e-commerce websites and offered various online products (Kovács et al., 2021; Kovács & Nábrádi, 2020). However, these developments and advantages have not entirely covered the on-site shopping experiences (Akram et al., 2020), especially for basic foods and fashion (Szilvia & László, 2015). On-site shopping gives consumers an edge to interact with the product directly. They can see, touch and try the product firsthand (Mantra et al., 2019). Even consumers can also interact with the seller or the shop assistant to inquire information about the product. These experiences are not fully acquired by consumers through online shop. As a result, consumers are often disappointed when they have the product in their hands (Barari et al., 2020).

To bridge this consumer dissatisfaction, augmented reality is a breakthrough that offers solutions to the above problems through technology that can bring the virtual world into the real world (Ling, 2017). Augmented Reality (AR) is a technology that combines the unreal (virtual) or digital content with the real world in real-time. Integration that occurs using AR technology can be seen in two or three dimensions using special devices such as smartphones, personal computers, or other wearable devices (Lv et al., 2015; Yovcheva et al., 2012). This technology is able to improve user perception and interaction with the real world. This technology can also be applied to marketing to improve consumer perception and experience. AR engages consumers by providing better visual recognition and emotional engagement than traditional advertising, thereby increasing consumer knowledge of product information.

One popular example of AR in mobile applications is Pokemon GO. This augmented reality game managed to become a global phenomenon earning $207 million in its first month—overtaking any other mobile game. In the first three months since its launch, Pokemon GO was very popular and contributed 45% of the time spent by users playing top-20 Android games (Guo et al., 2022). However, augmented reality is not only useful for games. Social media apps, such as Instagram and Snapchat, are showing that AR can be used to improve user experience and engagement. For example, Snapchat introduced “City Painter” in 2020, so users can virtually spray paint in stores to create murals. This virtual spray is also the origin of the Local Lenses feature introduced to Snapchat users (Hawker & Carah, 2021; Nur Amalia Atikah et al., 2021).

Another feature of AR in a virtual try-on setting is its ability to enhance information, which helps reassure consumers of their choice. One example of retailers in e-commerce that have already implemented AR technologies is Ray-Ban (Iqbal & Campbell, 2022). Ray-Ban, a famous sunglasses company, also started using Augmented Reality to promote their product to provide consumers with a better impression of how its sunglasses will look on them. Currently, Ray-Ban has created a mirror application to be downloaded for usage. The application name was FIT3D, and it allowed consumers to try on the Ray-Ban sunglasses without any hassle of going to the actual shop. Consumers can try it online via a webcam that will attach the sunglasses to their faces through AR (Milanova & Aldaeif, 2021).

Recently, the rapid development of AR in Indonesia is in the context of its burgeoning digital economy. Indonesia is home to the highest number of so-called unicorns – start-ups valued in excess of $1bn – among all 10 ASEAN members. A 2019 report by Google, Temasek, and Bain projected that Indonesia's digital economy, which at the time was already the largest and fastest-growing in the region, would expand from a value of $40bn in 2019 to $130bn by 2025. According to Oxford Business Group (OBG), Indonesian President Joko Widodo is prioritizing digitalization integrated with AR as a part of Industry 4.0 technology to stimulate the economic recovery from Covid-19 (Tumiwa et al., 2022), as detailed in OBG's annual 2020 report on Indonesia (Oxford Business Group, 2020). Indonesia's position as a critical reference point in the global AR and VR (virtual reality) sight was confirmed by choosing Jakarta as a venue for the third International Conference on Virtual Reality Technology, held in December 2020 (ICVRT, 2020). In short, it seems inevitable that the sector will continue to grow in the coming months and years, offering a range of opportunities to investors.

Since the application of augmented reality in e-commerce is still relatively new, studies that analyze augmented reality concerning the factors that encourage consumers to use the technology and its impact on consumer choice confidence are still limited. Previous research has been done about how VR affect on consumer choice but they did not find any evidence on their research (Meißner et al., 2020) and limited to VR system. However, back to research by Lu & Smith (2007) found that AR can provide a better experience and gives more information to consumer. It is believed that AR contribute to reducing purchase uncertainty, yet choice confidence has not yet been considered in AR research (Sun et al., 2022). Another qualitative research by Romano et al. (2021) and Kowalczuk et al. (2021) found that AR can influence choice confidence, and can also amplify cognitive response at the post-purchase stage. Thus, this finding should be tested into a small group research object with quantitative approach.

Therefore, to fill the research gap, this research will explore the relationship between AR technology in improving consumer choice confidence and consumer knowledge. This research is expected to contribute to the existing literature in AR technologies in ecommerce. It is expected to aid managers in understanding the importance of AR technology in an increasingly connected world to better assist consumers in developing their choice confidence.

Theoretical Background and Hypotheses

Augmented Reality (AR)

Augmented Reality is a combination of the virtual world and the real world. Virtual objects can be text, animations, 3D models, or videos that feel the virtual object is in its environment. AR can enhance or enrich consumers' experience. AR creates a superimposed overlay of the consumer environment in the electronically generated setting (Javornik, 2016). It allows consumers to view themselves wearing various virtual products without physically visiting directly in a store (Baytar et al., 2020; tom Dieck & Jung, 2018). Consumers generally seek information from online content to reduce product uncertainty before purchase (Kim & Krishnan, 2015; Sun et al., 2022). Therefore, with AR's ability to provide digital objects in a real-time environment, consumers may feel safe or secure when purchasing in e-commerce with AR technology's assistance.

Prior study by Kowalczuk et al. (2021) has identified the three most relevant AR characteristics through the experiential hierarchy model (EHM) perspectives. The core of the EHM constitutes a comprehensive consumer response system, which consists of affective, cognitive, and behavioral responses. EHM also related to about interactivity and product informativeness (Söderström, 2021). Interactivity defined as the extent to which consumers can directly interact with virtual products, constitutes a core characteristic of immersive experiences (Yim et al., 2017). In an AR context, interactivity reflects the degree to which consumers can position virtual products in their actual physical environment and use 360-degree rotation to inspect them thoroughly. Product informativeness is defined as the degree to which mobile online touchpoints provide helpful product information for purchase decisions (Kang et al., 2020; Kowalczuk et al., 2021; Sun et al., 2022). AR has the potential to compensate for this information deficit by simulating shopping experiences and allowing consumers to experience virtual products directly (Baytar et al., 2020). Thus, AR provides additional information by consolidating reality and virtuality, establishing highly informative product presentations. Subsequently, reality congruence comprises virtual and real products. In online selling product presentations, 3D authenticity captures this fit between the real and displayed objects (Kang et al., 2020; Milanova & Aldaeif, 2021). If the product presentations are of poor quality or the wrong size, pixelated, inaccurate, or unrealistic, they do not create value for the consumer. For these reasons, reality congruence elicits positive consumer responses to both product presentation types.

Consumer Knowledge

The syntax keyword search and definition of consumer knowledge is closely related to customer knowledge and product knowledge. However, the customer knowledge and product knowledge is often linked to actions designed and how firms might generate, share, and renew this know how (Ballantyne & Varey, 2006). This research classifies consumer knowledge in psychological terms, more managerially and sociologically oriented studies. (Llewellyn, 2021). The definition of consumer knowledge is stems from Oxenfeldt (1950) that define the consumer knowledge is a consumer's understanding of a product, and consumers could use this information in the decision-making process. Subsequently, Sujan (1985) purpose the strategy to use the information about it. According to Park et al. (1994), consumer knowledge can also be divided into subjective knowledge, objective knowledge (actual knowledge), and experience-based knowledge.

Consumer Choice Confidence

Peterson and Pitz (1988) argue about the consumer choice linkage with use of information and recent research by Andrew (2016) and Heitmann et al. (2007) support it with the satisfaction. In this research, the definition of consumer choice confidence is the certainty of consumers' attitudes towards the choices made and they believes that the choice is correct (Andrews, 2016; Andrews & Allen, 2016; Peterson & Pitz, 1988; Tsai & Mcgill, 2011). Confidence in product choice is determined by the information obtained (Kowalczuk et al., 2021). The emergence of a product choice is seen when consumers have beliefs about the product's benefits and then evaluate the product attributes with the level of satisfaction and they will give different weights to each product (Heitmann et al., 2007). Choice confidence is generated via metacognitions about the information supporting decision (Tsai & Mcgill, 2011). Thus, this research defines consumer choice as a primary preference based on the information quality to increase testing satisfaction with a product.

Research Framework and Hypothesis

In the context of e-commerce (online shopping), it is widely known that increased interactivity and vividness allow consumers to more effectively gather information about products by enabling visual examination of realistically displayed virtual products (Kowalczuk et al., 2021; Yim et al., 2017). These characteristic is in AR technology that can improve the quality of consumer search experiences, thereby enhancing cognitive response (Kowalczuk et al., 2021; Salam et al., 2021). According to Kowalczuk et al. (2021), one of the factor of cognitive response is choice confidance. With AR, consumers can more freely interactively inspect vividly and realistically generated virtual product images (Yim et al., 2017). Therefore, the characteristics of AR technology are expected to have a positive effect on consumer choice confidence;

H_1: AR has significant influence on consumer choice confidence

The connection between AR and consumer choice is stems from the emerging phenomenon of consumer choice affected by technology (Xia, 1999). Fernández del Amo et al (2018) addressed that knowledge discovery is crucial as it will create awareness of identifying opportunities and the barriers and challenges faced during the adoption process. Subsequently, consumer knowledge should be added to the model to control systematic differences in their actual knowledge concerning augmented reality in general (Chylinski et al., 2020; Fernández del Amo et al., 2018). AR apps contribute to reducing purchase uncertainty, the role of online media could improve the shopping process by enabling consumers to sort and group information, by increasing the number of options available, and by allowing the consumers to access peer opinions and ratings (Meuter et al., 2000). Potentially, there is more information available online (Baytar et al., 2020; Lu & Smith, 2007; Sepasgozar, n.d.; tom Dieck & Jung, 2018; Yovcheva et al., 2012). The consumers will likely devote more cognitive effort to their decision process because they can see the potential additional benefits through the extra effort.

H_2: AR has significant influence on consumer knowledge

Since AR apps contribute to reducing purchase uncertainty, the role of augmented reality could improve the shopping process by enabling consumers to sort and group information, increase the number of options available, and allowing the consumers to access peer opinions and ratings (Baytar et al., 2020; Meuter et al., 2000; tom Dieck & Jung, 2018). The consumers will likely devote more cognitive effort to their decision process because they can see the potential additional benefits through the extra effort (Kowalczuk et al., 2021; Romano et al., 2021). Consumers repeatedly exposed to a stimulus with better knowledge about the information become familiar with it (Söderström, 2021), which leads to higher confidence in their judgment and ultimately determines their preference/choice.

H_3: Consumer knowledge has significant influence on consumer choice confident

The relationship between augmented reality, consumer knowledge, and consumer choice confidence is shown in figure 1.

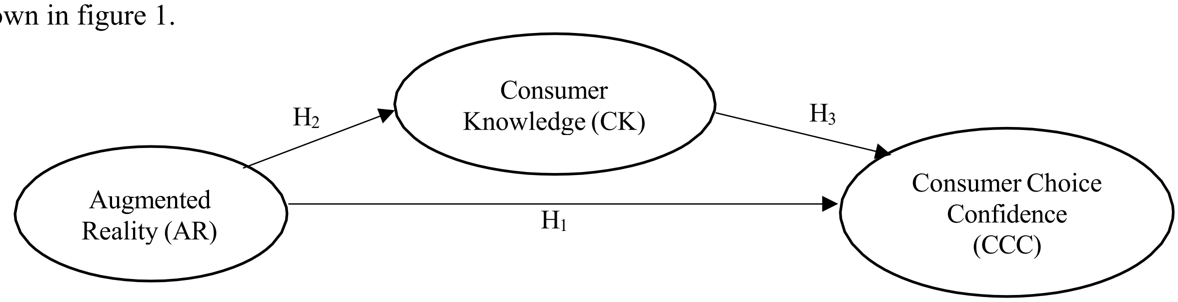

Figure 1. Research Framework and Hypotheses

Methodology

Research Procedure

This research used a quantitative method with data collected from 272 respondents of e-commerce buyers in Indonesia using structured questionnaires that consist of respondent characteristics and variable measurement. Since this research aims to explore the theory, this research uses the purposive sampling technique for respondents with online shopping experiences and own compatible devices to access the AR website. Subsequently, respondents have to access Ray-ban Virtual Try-on website on their smart device. Then respondents were asked to identify a particular model of sunglasses they would like to purchase after using AR technology for at least 5 – 15 minutes as a minimum time required to examine the online product design (Baytar et al., 2020; Yim et al., 2017). After using the application, they were asked to complete the questionnaires to evaluate their experience.

Data Analysis and Variable Measurement

This research uses descriptive analysis for the respondent characteristic and Partial Least Square path modeling (PLS-PM) to test the research hypotheses. The stages of analysis using this method consist of outer model analysis, inner model analysis, and hypothesis testing. The measurement of latent variables and manifest variables are shown in the table 1 below:

Table 1. Latent Variables and Manifest Variables

Latent Variable	Items	Manifest Variable	
Augmented Reality (AR)	AR1	Interactivity	Profound picture
	AR2		Interaction features
	AR3	System Quality	Sophisticated menu
	AR4		Promptly responsive to consumer requests and provides good results
	AR5		Performs its functions quickly and efficiently
	AR6	Product Informativeness	Provides detailed information about the products
	AR7		Provides information to compare products
	AR8	Reality Congruence	Presents virtual products impressively and attractively.
	AR9		High product design and realistic.
Consumer Knowledge (CK)	CK1	Subjective Knowledge	Understanding about product prestige
	CK2		Personal taste
	CK3	Objective knowledge (actual knowledge)	Knowledge information about product warranty
	CK4		Understanding of product quality
	CK5	Experience-based knowledge	Knowledge of product efficacy
	CK6		Information related to product satisfaction to consumer
	CK7		Familiarity with the product
Consumer Choice Confidence (CCC)	CCC1	Understand/Infer Meaning	
	CCC2	Information Form	
	CCC3	Information Sufficiency	
	CCC4	Preference Clarity	
	CCC5	Distinguish Differences	

Results

Respondent Characteristic

Table 2. Respondent Characteristic

	Frequency	(%)
Gender		
Male	123	45.2
Female	149	54.8
Age		
20 - 25	25	9.2
26 - 30	21	7.7
31 - 35	178	65.4
36 - 40	48	17.6
Education		
High School	38	14.0
Bachelor	206	75.7
Master	28	10.3
	Frequency	**(%)**
Occupation		
Student	50	18.4
Employee	95	34.9
Professional	45	16.5
Entrepreneur	45	16.5
Other	37	13.6
Online Purchase Frequency		
Never	0	0
Low	126	46.3
High	146	53.7

Evaluation of Measurement Models (Outer Mode I)

This research has three latent variable. Exogenous variable is AR and endogenous variable are CK and CCC. The following is a picture of a structural model design:

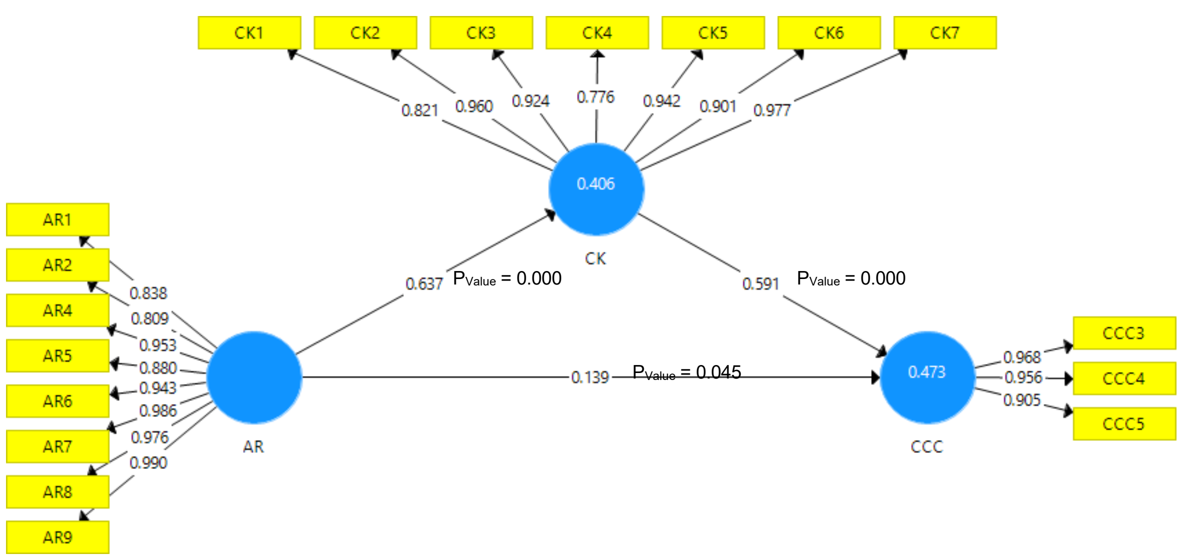

Figure 1. Structural Model Design

Figure 1 shows the PLS-SEM structural model with the weight of outer loading for the outer model and path coefficient and p-value for the inner model. Based on the results of the PLS Algorithm Run 1, it was found that the manifest variables AR3, CCC1, and CCC2 had an outer loading value below 0.5. These values are not meet the threshold of outer loading (Chin, 1998). Thus, the manifest variables had to be dropped from the equation model.

Convergent Validity Test

Testing the validity of reflective indicators can be done by using the correlation between indicator scores and construct scores. Measurement with reflective indicators shows a change in an indicator in a construct if other indicators in the same construct change. The calculations using the computer program SmartPLS 3.0 are illustrated in table 3. The good correlation can meet convergent validity if a loading value is greater than 0.5 (Chin, 1998; Joe F. Hair et al., 2020; Joseph F. Hair et al., 2019). The output shows in Tables 3 and 4 that the loading factor gives a value greater then recommended value 0.5. Thus, showing that the indicators/manifest variables used in this research have met the convergent validity.

Discriminant Validity Test

Reflective indicators need to be tested for discriminant validity by comparing the values in the cross-loading table. An indicator is declared valid if it has the highest loading factor value to the intended construct compared to the value of the loading factor to other constructs (Chin, 1998; Joe F. Hair et al., 2020; Joseph F. Hair et al., 2019). The result of output Fornell-Larcker Criterion and Cross-Loading is shown in table 3 and 4 below:

Table 3. Fornell-Larcker Criterion

	AR	**CCC**	**CK**
AR	0.924		
CCC	0.515	0.943	
CK	0.637	0.68	0.903

Table 4. Output Cross Loading

	AR	CCC	CK
AR1	**0.838**	0.372	0.485
AR2	**0.809**	0.386	0.584
AR4	**0.953**	0.46	0.58
AR5	**0.88**	0.443	0.542
AR6	**0.943**	0.559	0.639
AR7	**0.986**	0.528	0.638
AR8	**0.976**	0.533	0.613
AR9	**0.99**	0.493	0.609
CCC3	0.49	**0.968**	0.613

	AR	CCC	CK
CCC4	0.475	**0.956**	0.633
CCC5	0.492	**0.905**	0.673
CK1	0.595	0.574	**0.821**
CK2	0.59	0.667	**0.96**
CK3	0.593	0.638	**0.924**
CK4	0.446	0.538	**0.776**
CK5	0.552	0.591	**0.942**
CK6	0.639	0.615	**0.901**
CK7	0.592	0.659	**0.977**

Reliability Test

A latent variable can have good reliability if the composite reliability value is 0.7 or close to 0.7 (Chin, 1998; Joe F. Hair et al., 2020; Joseph F. Hair et al., 2019). All latent variables measured in this study have

Cronbach's Alpha and Composite Reliability values meet the criteria. Thus, all latent variables are reliable, as shown in table 5 below:

Table 5. Construct Reliability and Validity

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
AR	0.975	0.98	0.979	0.854
CCC	0.938	0.938	0.96	0.89
CK	0.961	0.965	0.968	0.815

Evaluation of the Structural Model (Inner Model)

Evaluation of structural models in SEM with PLS is carried out by conducting several tests analyses as follows:

Testing the Coefficient of Determination (R^2)

The value of R^2 depends on the research. However, there is a threshold value as an acceptable minimum level of 0.10 (Chin, 1998; Joseph F. Hair et al., 2021; Sarstedt et al., 2017). Furthermore, this research uses the category description of the R^2 as follows:

- R^2 value> 0.7 is categorized as strong
- R^2 value of 0.67 is categorized as substantial
- R^2 value of 0.33 is categorized as moderate
- R^2 value of 0.19 is categorized as weak

The output for the R^2 value shows in table 6 below:

Table 6. Output Calculation R^2

	R^2	R^2 Adjusted
CCC	0.473	0.47
CK	0.406	0.404

Test of Effect Size (f^2)

The effect size f^2 shows the change in the R^2 value when a specified exogenous construct is omitted from the model (Cohen, 2013). This indicator helps evaluate whether the omitted construct significantly impacts the endogenous constructs. f^2 result shows in table 7 as follow:

Table 7. Effect Size (f^2)

	AR	CCC	CK
AR		0.022	**0.684**
CCC			
CK		**0.395**	

The effect size f^2 in table 7 confirms that AR has significant to CK. This table also shows that the good model to predict CCC is AR and CK.

Predictive Relevance Q^2

The predictive relevance Q^2 will measure the predictive capability of the research model. If Q^2 is greater than 0, the PLS-SEM model is predictive of the given endogenous variable under investigation. The predictive relevance Q^2 is shown in table 8 below:

Table 8. Construct Crossvalidated Redundancy (Q^2)

	SSO	SSE	Q² (=1-SSE/SSO)
AR	2176	2176	
CCC	816	480.858	0.411
CK	1904	1285.596	0.325

This study shows that the value of Q^2 is greater than 0, meaning that this model is accepted.

Goodness of Fit of the Model

Next is the calculation of the Goodness of Fit of the model, abbreviated as GoF. There is no exact goodness of fit model measurement in PLS-SEM since PLS-SEM is different from covariance based structural equation modeling (CB-SEM) (Sarstedt et al., 2016). According to the Smart PLS website, some researchers offer a set of fit measures (Ringle et al., 2015). However, some fit measures imply restrictive assumptions on the residual covariances, which PLS-SEM does not imply when estimating the model. They added that the outer residuals of composite models are not required to be uncorrelated. Hence, the model fit estimating calculation/GoF are inappropriate for PLS-SEM. However, SmartPLS software provides fit measurement to mimic CB-SEM models with the consistent PLS approach. The Fit measurement as shown in the table 9:

Table 9. Model Fit

	Saturated Model	Estimated Model
SRMR	0.068	0.068
d_ULS	0.782	0.782
d_G	4.646	4.646
Chi-Square	3682.568	3682.568
NFI	0.666	0.666
rms Theta	0.318	

Table 9 above shows the calculation of model fit by SmartPLS. However, according to the SmartPLS website, the GoF cannot reliably distinguish valid from invalid models, and since its applicability is limited to specific model setups, researchers should avoid its use as a goodness of fit measure because the model fit is only useful for a PLS multigroup analysis (PLS-MGA) (Ringle et al., 2015).
Therefore, this research suggests a more straightforward calculation of GoF by using the R^2 root formula (SQRT). The robust of this research formula is the combination of the outer model calculation of AVE and inner model R^2. The calculation of the GoF using SQRT is shown on table 10:

Table 10. The GoF Model

	R^2	AVE
CCC	0.473	0.89
CK	0.406	0.815
Average	0.4395	0.8525
√(AVE x R2)	0.612106	

Table 10 shows that the GoF value exceeds the cut-off value of 0.36 (Chin, 1998; Henseler & Sarstedt, 2013). Means that the research model is fit.

Test of Significance

The significance test in SEM models with PLS aims to determine the effects of exogenous variables on endogenous variables. Figure 1 shows the significance of the constructed variable as regards other variables. The calculation of Hypothesis is shown on table 11 below:

Table 11. Path Coefficients and Hypothesis testing

Hypothesis	Relationship	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Decision
H_1	AR -> CCC	0.139	0.135	0.069	2.005	0.045	Accepted
H_2	AR -> CK	0.637	0.641	0.048	13.366	0.000	Accepted
H_3	CK -> CCC	0.591	0.595	0.062	9.515	0.000	Accepted

Based on the Table 11 result, this research accept all the hypothesis.

Conclusion, Managerial Implication, Limitation, and Further Research Direction

The sample in this study is respondents aged 20-40 years who were believed to have a better acceptance of technology than other age ranges. From the data analysis, augmented reality significantly influences consumer knowledge and consumer choice confidence. This research supports the previous research about the influence of augmented reality technology to give more information to increase consumer choice as a cognitive response. This significant finding proves that augmented reality technology can bring the on-site shopping experience into virtual reality. With AR technology, consumers can easily make choices to minimize time and energy consumption. This time and energy consumption can also be traced to opportunity costs, significantly reducing marketing costs.

The managerial implication of this research is for marketing managers to continue developing augmented reality application features that, proven statistically, significantly impact consumers' choices. Through the continued development of the AR application, consumers can easily choose products based on the products they want to try as they did on-site shopping.

This research has limitations on men's outwear fashion products, which as glasses. Another limitation is the Covid-19 situation which makes the number of respondents collected relatively small.

Further research should analyze the impact of consumer choice on purchase decisions where AR is the main electronic media advertising. Another suggestion for further research is to analyze the impact of AR on service products such as tourism and education since it is statistically proven that AR can bring real-life experience into a virtual world.

References

Akram, U., Ansari, A. R., Fu, G., & Junaid, M. (2020). Feeling hungry? let's order through mobile! examining the fast food mobile commerce in China. *Journal of Retailing and Consumer Services*, *56*(April), 102142. https://doi.org/10.1016/j.jretconser.2020.102142

Andrews, D. (2016). Product information and consumer choice confidence in multi-item sales promotions. *Journal of Retailing and Consumer Services*, *28*, 45–53. https://doi.org/10.1016/j.jretconser.2015.07.011

Andrews, D., & Allen, A. M. (2016). Information form and level-of-analysis as moderators of the influence of information diagnosticity on consumer choice confidence and purchase readiness. *Academy of Marketing Studies Journal*, *20*(2), 61–84.

Ballantyne, D., & Varey, R. J. (2006). Creating value-in-use through marketing interaction: The exchange logic of relating, communicating and knowing. *Marketing Theory*, *6*(3), 335–348. https://doi.org/10.1177/1470593106066795

Barari, M., Ross, M., & Surachartkumtonkun, J. (2020). Negative and positive customer shopping experience in an online context. *Journal of Retailing and Consumer Services*, *53*(November 2019), 101985. https://doi.org/10.1016/j.jretconser.2019.101985

Baytar, F., Chung, T., & Shin, E. (2020). Evaluating garments in augmented reality when shopping online. *Journal of Fashion Marketing and Management*, *24*(4), 667–683. https://doi.org/10.1108/JFMM-05-2018-0077

Brusch, I., & Rappel, N. (2020). Exploring the acceptance of instant shopping – An empirical analysis of the determinants of user intention. *Journal of Retailing and Consumer Services*, *54*(August 2019), 101936. https://doi.org/10.1016/j.jretconser.2019.101936

Chin, W. W. (1998). Commentary Issues and Opinion on Structural Equation Modeling Clear Reporting. *Modern Methods for Business Research Methodology for Business and Management*, *22*(1), vii–xvi.

Chylinski, M., Heller, J., Hilken, T., Keeling, D. I., Mahr, D., & de Ruyter, K. (2020). Augmented reality marketing: A technology-enabled approach to situated customer experience. *Australasian Marketing Journal*, *28*(4), 374–384. https://doi.org/10.1016/j.ausmj.2020.04.004

Cohen, J. (2013). *Statistical Power Analysis for the Behavioral Sciences*. Routledge. https://doi.org/10.4324/9780203771587

Djalante, R., Lassa, J., Setiamarga, D., Sudjatma, A., Indrawan, M., Haryanto, B., Mahfud, C., Sinapoy, M. S., Djalante, S., Rafliana, I., Gunawan, L. A., Surtiari, G. A. K., & Warsilah, H. (2020). Review and analysis of current responses to COVID-19 in Indonesia: Period of January to March 2020. *Progress in Disaster Science*, *6*(march), 100091. https://doi.org/10.1016/j.pdisas.2020.100091

Fernández del Amo, I., Erkoyuncu, J. A., Roy, R., Palmarini, R., & Onoufriou, D. (2018). A systematic review of Augmented Reality content-related techniques for knowledge transfer in maintenance applications. *Computers in Industry*, *103*, 47–71. https://doi.org/10.1016/j.compind.2018.08.007

Guo, Y., Peeta, S., Agrawal, S., & Benedyk, I. (2022). Impacts of Pokémon GO on route and mode choice decisions: exploring the potential for integrating augmented reality, gamification, and social components in mobile apps to influence travel decisions. In *Transportation* (Vol. 49, Issue 2). Springer US. https://doi.org/10.1007/s11116-021-10181-9

Hair, Joe F., Howard, M. C., & Nitzl, C. (2020). Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. *Journal of Business Research*, *109*(August 2019), 101–110. https://doi.org/10.1016/j.jbusres.2019.11.069

Hair, Joseph F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R*. Springer International Publishing. https://doi.org/10.1007/978-3-030-80519-7

Hair, Joseph F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Hawker, K., & Carah, N. (2021). Snapchat's augmented reality brand culture: sponsored filters and lenses as digital piecework. *Continuum*, *35*(1), 12–29. https://doi.org/10.1080/10304312.2020.1827370

Heitmann, M., Lehmann, D. R., & Herrmann, A. (2007). Choice goal attainment and decision and consumption satisfaction. *Journal of Marketing Research*, *44*(2), 234–250. https://doi.org/10.1509/jmkr.44.2.234

Henseler, J., & Sarstedt, M. (2013). Goodness-of-fit indices for partial least squares path modeling. *Computational Statistics*, *28*(2), 565–580. https://doi.org/10.1007/s00180-012-0317-1

Hidayatullah, D. R., Darmawan, A., & Kallidumban, S. (2020). Finding the strategy after corona crisis: the new normal and resilient economy growth in indonesia. *Internatioal Journal of Economics, Business, and Entrepreneuship*, *3*(1), 64–79.

ICVRT. (2020). *2020 3rd International Conferece on Virtual Reality Technology*. http://icvrt.org/2020.html

Iqbal, M. Z., & Campbell, A. G. (2022). Adopting smart glasses responsibly: potential benefits, ethical, and privacy concerns with Ray-Ban stories. *AI and Ethics*, 7–9. https://doi.org/10.1007/s43681-022-00155-7

Javornik, A. (2016). Augmented reality: Research agenda for studying the impact of its media characteristics on consumer behaviour. *Journal of Retailing and Consumer Services*, *30*, 252–261. https://doi.org/10.1016/j.jretconser.2016.02.004

Kang, H. J., Shin, J. hye, & Ponto, K. (2020). How 3D Virtual Reality Stores Can Shape Consumer Purchase Decisions: The Roles of Informativeness and Playfulness. *Journal of Interactive Marketing*, *49*, 70–85. https://doi.org/10.1016/j.intmar.2019.07.002

Kim, Y., & Krishnan, R. (2015). On product-level uncertainty and online purchase behavior: An empirical analysis. *Management Science*, *61*(10), 2449–2467. https://doi.org/10.1287/mnsc.2014.2063

Kovács, T. Z., David, F., Nagy, A., Szűcs, I., & Nábrádi, A. (2021). An Analysis of the Demand-Side, Platform-Based Collaborative Economy: Creation of a Clear Classification Taxonomy. *Sustainability*, *13*(5), 2817. https://doi.org/10.3390/su13052817

Kovács, T. Z., & Nábrádi, A. (2020). Types of sharing economies and collaborative consumptions. In G. Družić & T. Gelo (Eds.), *Conference Proceedings of the International Conference on the Economics of Decoupling (ICED), Faculty of Economics & Business, University of Zagreb, Croatia* (pp. 530–546).

Kowalczuk, P., Siepmann (née Scheiben), C., & Adler, J. (2021). Cognitive, affective, and behavioral consumer responses to augmented reality in e-commerce: A comparative study. *Journal of Business Research*, *124*(October 2020), 357–373. https://doi.org/10.1016/j.jbusres.2020.10.050

Kusumawati, Y. A., Huda, M. N., Dirgantara, S., & Carvenoriega, O. A. (2021). Architecture Design of Agriculture Marketing Mobile Apps During Pandemic Era. *IOP Conference Series: Earth and Environmental Science*, *794*(1), 012126. https://doi.org/10.1088/1755-1315/794/1/012126

Ling, H. (2017). Augmented Reality in Reality. *IEEE Multimedia*, *24*(3), 10–15. https://doi.org/10.1109/MMUL.2017.3051517

Llewellyn, N. (2021). The Embodiment of Consumer Knowledge. *Journal of Consumer Research*, *48*(2), 212–234. https://doi.org/10.1093/jcr/ucab003

Lu, Y., & Smith, S. (2007). Augmented Reality E-Commerce Assistant System: Trying While Shopping. In *Human-Computer Interaction. Interaction Platforms and Techniques* (pp. 643–652). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-540-73107-8_72

Lv, Z., Halawani, A., Feng, S., Ur Réhman, S., & Li, H. (2015). Touch-less interactive augmented reality game on vision-based wearable device. *Personal and Ubiquitous Computing*, *19*(3), 551–567. https://doi.org/10.1007/s00779-015-0844-1

Mantra, I., Hartawan, M. S., Saragih, H., & Rahman, A. A. (2019). Web Vulnerability Assessment and Maturity Model Analysis on Indonesia Higher Education. *Procedia Computer Science*, *161*, 1165–1172. https://doi.org/10.1016/j.procs.2019.11.229

Meißner, M., Pfeiffer, J., Peukert, C., Dietrich, H., & Pfeiffer, T. (2020). How virtual reality affects consumer choice. *Journal of Business Research*, *117*(May 2019), 219–231. https://doi.org/10.1016/j.jbusres.2020.06.004

Meuter, M. L., Ostrom, A. L., Roundtree, R. I., & Bitner, M. J. (2000). Self-service technologies: Understanding customer satisfaction with technology-based service encounters. *Journal of Marketing*, *64*(3), 50–64. https://doi.org/10.1509/jmkg.64.3.50.18024

Milanova, M., & Aldaeif, F. (2021). Markerless 3D Virtual Glasses Try-On System. In *Smart Innovation, Systems and Technologies* (Vol. 216, Issue April). Springer Singapore. https://doi.org/10.1007/978-981-33-4676-5_7

Nur Amalia Atikah, Siti Zalifah Ramli, Nur Ain Najihah Ibharim, Siti Aishah Zahari, & Muhammad Asyraf Abdullah Zawawi. (2021). Learn Idioms Using Augmented Reality. *International Journal of Multimedia and Recent Innovation*, *3*(1), 11–16. https://doi.org/10.36079/lamintang.ijmari-0301.209

Olivia, S., Gibson, J., & Nasrudin, R. (2020). Indonesia in the Time of Covid-19. *Bulletin of Indonesian Economic Studies*, *56*(2), 143–174. https://doi.org/10.1080/00074918.2020.1798581

Oxenfeldt, A. R. (1950). Consumer Knowledge: Its Measurement and Extent. *The Review of Economics and Statistics*, *32*(4), 300. https://doi.org/10.2307/1925578

Oxford Business Group. (2020). *The Report: Indonesia 2020*. https://oxfordbusinessgroup.com/indonesia-2020#:~:text=Indonesia is the world's 16th,consumer power and regional influence.

Park, C. W., Mothersbaugh, D. L., & Feick, L. (1994). Consumer Knowledge Assessment. *Journal of Consumer Research*, *21*(1), 71. https://doi.org/10.1086/209383

Peterson, D. K., & Pitz, G. F. (1988). Confidence, Uncertainty, and the Use of Information. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *14*(1), 85–92. https://doi.org/10.1037/0278-7393.14.1.85

Purnama, S. G., & Susanna, D. (2020). Attitude to COVID-19 Prevention With Large-Scale Social Restrictions (PSBB) in Indonesia: Partial Least Squares Structural Equation Modeling. *Frontiers in Public Health*, *8*(October), 1–10. https://doi.org/10.3389/fpubh.2020.570394

Ringle, C. M., Wende, S., & Becker, J.-M. (2015). *SmartPLS 3*. https://www.smartpls.com

Romano, B., Sands, S., & Pallant, J. I. (2021). Augmented reality and the customer journey: An exploratory study. *Australasian Marketing Journal*, *29*(4), 354–363. https://doi.org/10.1016/j.ausmj.2020.06.010

Salam, M. T., Imtiaz, H., & Burhan, M. (2021). The perceptions of SME retailers towards the usage of social media marketing amid COVID-19 crisis. *Journal of Entrepreneurship in Emerging Economies*, *13*(4), 588–605. https://doi.org/10.1108/JEEE-07-2020-0274

Sarstedt, M., Hair, J. F., Ringle, C. M., Thiele, K. O., & Gudergan, S. P. (2016). Estimation issues with PLS and CBSEM: Where the bias lies! *Journal of Business Research*, *69*(10), 3998–4010. https://doi.org/10.1016/j.jbusres.2016.06.007

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2017). Partial Least Squares Structural Equation Modeling. In *Handbook of Market Research* (Vol. 21, Issue 1, pp. 1–40). Springer International Publishing. https://doi.org/10.1007/978-3-319-05542-8_15-1

Sepasgozar, S. M. E. (n.d.). *Digital Twin and Web-Based Virtual Gaming Technologies for Online Education: A Case of Construction Management and Engineering*.

Söderström, C. (2021). *Augmented Reality and Artificial Intelligence: The Influence on Behavioral Consumer Responses in E-Commerce* (Issue December). Norwegian University of Science and Technology.

Sujan, M. (1985). Consumer Knowledge: Effects on Evaluation Strategies Mediating Consumer Judgments. *Journal of Consumer Research*, *12*(1), 31. https://doi.org/10.1086/209033

Sun, C., Fang, Y., Kong, M., Chen, X., & Liu, Y. (2022). Influence of augmented reality product display on consumers' product attitudes: A product uncertainty reduction perspective. *Journal of Retailing and Consumer Services*, *64*(January 2021), 102828. https://doi.org/10.1016/j.jretconser.2021.102828

Szilvia, M., & László, S. (2015). Fogyasztási és vásárlási szokások Magyarországon. *Baromfiágazat*, *15*(3), 60–68.

tom Dieck, M. C., & Jung, T. (2018). A theoretical model of mobile augmented reality acceptance in urban heritage tourism. *Current Issues in Tourism*, *21*(2), 154–174. https://doi.org/10.1080/13683500.2015.1070801

Tsai, C. I., & Mcgill, A. L. (2011). No pain, no gain? how fluency and construal level affect consumer confidence. *Journal of Consumer Research*, *37*(5), 807–821. https://doi.org/10.1086/655855

Tumiwa, J. R., Tuegeh, O., Bittner, B., & Nagy, A. (2022). THE CHALLENGES TO DEVELOPING SMART AGRICULTURAL VILLAGE IN THE INDUSTRIAL REVOLUTION 4.0. *Torun International Studies*, *1*(15), 0–2. https://doi.org/10.12775/TIS.2022.002

Ulas, D. (2019). Digital Transformation Process and SMEs. *Procedia Computer Science*, *158*, 662–671. https://doi.org/10.1016/j.procs.2019.09.101

Vyas, P., Ragthaman, K., Chauhan, A., & Rimal, B. (2021). Classification of COVID-19 Cases: An Exploratory Study by Incorporating Transfer Learning with Cloud. *MWAIS 2021 PROCEEDINGS*.

Vyas, P., Reisslein, M., Rimal, B. P., Vyas, G., Basyal, G. P., & Muzumdar, P. (2022). Automated Classification of Societal Sentiments on Twitter With Machine Learning. *IEEE Transactions on Technology and Society*, *3*(2), 100–110. https://doi.org/10.1109/TTS.2021.3108963

Xia, L. (1999). Consumer choice strategies and choice confidence in the electronic environment. *American Marketing Association. Conference Proceedings*, *10*, 270. https://www.proquest.com/scholarly-journals/consumer-choice-strategies-confidence-electronic/docview/199496906/se-2?accountid=15756

Yim, M. Y. C., Chu, S. C., & Sauer, P. L. (2017). Is Augmented Reality Technology an Effective Tool for E-commerce? An Interactivity and Vividness Perspective. *Journal of Interactive Marketing*, *39*, 89–103. https://doi.org/10.1016/j.intmar.2017.04.001

Yovcheva, Z., Buhalis, D., & Gatzidis, C. (2012). Overview of smartphone augmented reality applications for tourism. *E-Review of Tourism Research*, *10*(2), 63–66.