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THE INFLUENCE OF AUGMENTED REALITY FACE FILTER ADDICTION ON ONLINE SOCIAL ANXIETY: A STIMULUS-ORGANISM-RESPONSE PERSPECTIVE

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ABSTRACT

Aim/Purpose	This study aims to analyze the factors that influence user addiction to AR face filters in social network applications and their impact on the online social anxiety of users in Indonesia.
Background	To date, social media users have started to use augmented reality (AR) face filters. However, AR face filters have the potential to create positive and negative effects for social media users. The study combines the Big Five Model (BFM), Sense of Virtual Community (SVOC), and Stimuli, Organism, and Response (SOR) frameworks. We adopted the SOR theory by involving the personality factors and SOVC factors as stimuli, addiction as an organism, and social anxiety as a response. BFM is the most significant theory related to personality.

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Methodology	We used a quantitative approach for this study by using an online survey. We conducted research on 903 Indonesian respondents who have used an AR face filter feature at least once. The respondents were grouped into three categories: overall, new users, and old users. In this study, group classification was carried out based on the development timeline of the AR face filter in the social network application. This grouping was carried out to facilitate data analysis as well as to determine and compare the different effects of the factors in each group. The data were analyzed using the covariance-based structural equation model through the AMOS 26 program.
Findings	The results of this study indicated neuroticism, membership, and immersion influence AR face filter addiction in all test groups. In addition, ARA has a significant effect on online social anxiety.
Contribution	This research fills the gap in previous research which did not discuss much about the impact of addiction in using AR face filters on online social anxiety of users of social network applications.
Recommendations for Practitioners	The findings are expected to be valuable to social network service providers and AR creators in improving their services and to ensure policies related to the list of AR face filters that are appropriate for use by their users as a form of preventing addictive behavior of that feature.
Recommendations for Researchers	This study suggested other researchers consider other negative impacts of AR face filters on aspects such as depression, life satisfaction, and academic performance.
Impact on Society	AR face filter users may experience changes in their self-awareness in using face filters and avoid the latter's negative impacts.
Future Research	Future research might explore other impacts from AR face filter addiction behavior, such as depression, life satisfaction, and so on. Apart from that, future research might investigate the positive impact of AR face filters to gain a better understanding of the impact of AR face filters.

Keywords	augmented reality, face filter, Instagram, social media, Indonesia

INTRODUCTION

One of the highest motives for digital activity is the use of social media as an entertainment source (Siste et al., 2020). The most frequently used social media platforms in Indonesia are Instagram, Facebook, TikTok, and Snapchat (Katadata, 2021). One feature that is widely used on social media is the augmented reality (AR) face filter (Bhatt, 2020). AR is a technology that combines virtual objects with the real world, allowing devices or applications to generate projections in the form of sound, graphics, and video (Hung et al., 2021). AR face filters have several types available on various social networking applications, such as Facebook, Instagram, Snapchat, and Tiktok (Hamilton, 2022). Worldwide more than 600 million people use AR filters on Facebook and Instagram every month (Bhatt, 2020). AR face filters in social network applications have several variants, ranging from color adjustment filters, beautification, quizzes, and games to immersive ones (Hamilton, 2022).

Excessive use of the AR face filter has the potential to create negative effects such as social anxiety (Javornik et al., 2022). Social anxiety is a type of anxiety about possible or actual personal judgement or evaluation in imagined or real contexts (Foroughi et al., 2019). Social anxiety is affected by addiction (Foroughi et al., 2019, 2022). AR face filter addiction (ARA) refers to excessive use of the AR face filter due to dependent psychological factors that can lead to negative outcomes (Moqbel &

Kock, 2018). The definition of excessive use of AR face filters is when users have a high level of dependence on using AR face filters so that cause negative problems for these users. Addiction is influenced by personality (Leong et al., 2019) and sense of virtual community (Naranjo-Zolotov et al., 2021). Furthermore, although the amount of time spent or frequency of application usage using facial filters is a symptom of addiction, the frequency and duration of time do not always indicate addiction to facial filters (Sternlicht & Sternlicht, 2022).

Most of the research on AR is still limited to certain countries, such as the research conducted by Yavuz et al. (2021) in Turkey; S. H.-Y. Hsu et al. (2021) in China, India, and Singapore. The cultural differences in each country affect the behaviors of exploration, exploitation, and innovation (Hubner et al., 2021). Our research question is "What are the factors that influence AR face filters user addiction on online social anxiety of users in Indonesia?" Thus, this research can provide guidance for social network service providers and AR face filter creators in improving their service quality and limiting the level of user addiction to AR face filters.

This study also classifies users into three test groups, namely new users, old users, and all AR face filter users. Classification of new and old users can improve the quality of study recommendations, because the two types of users have different behaviors and are influenced by certain factors (Yu et al., 2019). In this study, user classification was carried out based on the development timeline of the AR face filter in the social network application, which began in 2015 in the Snapchat application (Inde, n.d.). The types of AR face filters can be seen in Appendix A based on Hamilton (2022). In addition, a classification based on all users is also carried out to see the big picture result of all AR face filter users in social network applications.

LITERATURE REVIEW

In recent years, research on AR has focused on its use and adoption (Faqih & Jaradat, 2021; C.-L. Hsu et al., 2021; Hung et al., 2021; Mütterlein et al., 2019; Yavuz et al., 2021). These studies examined AR in various fields, such as education (Faqih & Jaradat, 2021), tourism (Kourouthanassis et al., 2015), and marketing (Rauschnabel et al., 2019). However, most of the AR technologies reviewed in these studies tend to be used as a medium of one-way interaction with users (Hung et al., 2021; López-Faican & Jaen, 2020). One-way communication is a communication method wherein someone provides a stimulus to a particular object without reciprocity (Koukoumelis et al., 2012).

In this study, we adopted the Stimuli, Organism, and Response (SOR) theory by including personality factors and Sense of Virtual Community (SOVC) factors as stimuli, addiction as an organism, and social anxiety as a response. Moon et al. (2014) suggested that personality factors are important predictors in determining the use and adoption of technology. Andreassen et al. (2017) suggested that the Big Five Model (BFM) is the most significant theory related to personality, highlighting that everyone has five components, namely, conscientiousness, openness to experience, neuroticism, extraversion, and agreeableness, which have been found to affect addiction (Leong et al., 2019). Furthermore, the SOVC concept has previously been used in research on addictive behavior in social networks (Naranjo-Zolotov et al., 2021). Social aspects, such as community, are key factors in influencing addiction and the level of use of an application (Naranjo-Zolotov et al., 2021).

STIMULUS, ORGANISM, AND RESPONSE (SOR)

The SOR theory consists of stimulus, organism, and response (Mehrabian & Russell, 1974). Stimulus is the external factor that evokes arousal in an organism (Mehrabian & Russell, 1974). In the context of social networks, stimulus refers to the motivation to take part in community activities that can affect the state of the user (Kamboj et al., 2018). Organisms are mechanisms for internalizing stimuli into information that trigger psychological transformation (Mehrabian & Russell, 1974). This understanding is also supported by other studies stating that the organism is the cognitive and affective condition of the user involved in the whole process that intervenes from a stimulus to a response

(Kamboj et al., 2018). The cognitive aspect plays a role in processing the stimulus into information, which is then used to make decisions, while the affective aspect plays a role in expressing emotions or feelings caused by the stimulus. Response is the behavior that results from the information content of the organism (Mehrabian & Russell, 1974). In the context of social networking, response is a consequence of user involvement in the social networking community in the form of behavior (Kamboj et al., 2018).

Big Five Model (BFM)

The BFM, commonly known as the Big Five Personality Traits, is an idea originally coined by Fiske in 1949 (Cohen & Baruth, 2017). Initially, there were various arguments and contradictions in determining the factors related to a person's personality because these factors were created through the opinions of various experts (de Raad & Mlačić, 2015). The factors used included extraversion, agreeableness, conscientiousness, neuroticism, and openness to experience, which were eventually introduced by Paul Costa and Robert McCrae as the "Big Five" (Ackerman, 2017).

Extraversion is a personality dimension that reflects the comfort level of a person's interactions (Robbins & Judge, 2013). People with high levels of extraversion are energetic, optimistic, and enjoy interacting with people (Watson & Clark, 1997). Agreeableness is referred to as the tendency to be altruistic and cooperative with other individuals (Huang et al., 2018). A person with a high level of agreeableness is easy to sympathize with, likes to help, and can express affection (Patrick, 2011). Conscientiousness is a personality dimension that measures a person's level of reliability (Robbins & Judge, 2013). A high level of conscientiousness reflects someone who is organized, punctual, reliable, trustworthy, and able to determine the target to be addressed (Patrick, 2011). Neuroticism is a personality dimension that describes a person's level of emotional stability in the face of stress (Robbins & Judge, 2013). People with high levels of neuroticism tend to respond negatively to what happens in their lives, such as stress, depression, anxiety, and emotional vulnerability (Emmons et al., 1985). The last factor is openness to experience, which is a personality dimension that represents a person's interest and attraction to learn new things (Robbins & Judge, 2013).

Sense of Virtual Community (SOVC)

SOVC is an individual's perception of sense of ownership, identity, and attachment to a community in the communication process with the help of information and communications technology (Cheng et al., 2012). Virtual communities utilize technology-based communication facilities to overcome limitations in terms of physical proximity to harmony, which is carried out by interactions using text, sound, photos, and videos (Abfalter et al., 2012). The SOVC concept of Koh and Kim (2003) has three dimensions, namely, (1) membership, where individuals are connected and feel part of a virtual community; (2) influence, where the individual influences and is influenced by other individuals or their virtual community; and (3) immersion, where individuals feel immersed during interactions with their virtual community (Koh & Kim, 2003). Therefore, according to Koh and Kim, SOVC is the psychological state of an individual who feels the dimensions of membership, influence, and immersion in his virtual community that come from interactions in online and offline communities.

Conceptual Model

The current study adopted the SOR, BFM, and SOVC frameworks. BFM was adopted because personality is an important predictor in determining technology use and adoption, especially in the context of addiction (Andreassen et al., 2017; Leong et al., 2019; Moon et al., 2014). SOVC was also utilized because the level of interaction in a community is directly proportional to the level of system or technology use that can trigger addiction (J. Kim et al., 2020; Naranjo-Zolotov et al., 2019, 2021). In addition, we included online social anxiety because it has been shown to be a mental health factor influenced by addiction to social network use where Foroughi et al. (2022) found a positive effect of Instagram addiction on social anxiety and depression. As a result, this research model was designed with eight exogenous variables, namely, extraversion, agreeableness, conscientiousness, neuroticism, openness to experience, membership, influence, and immersion in the environment. This research model also has two endogenous variables, namely, ARA as an internal cognition or state of the organism and online social anxiety as a behavioral response. The conceptual model proposed for this research is shown in Figure 1.

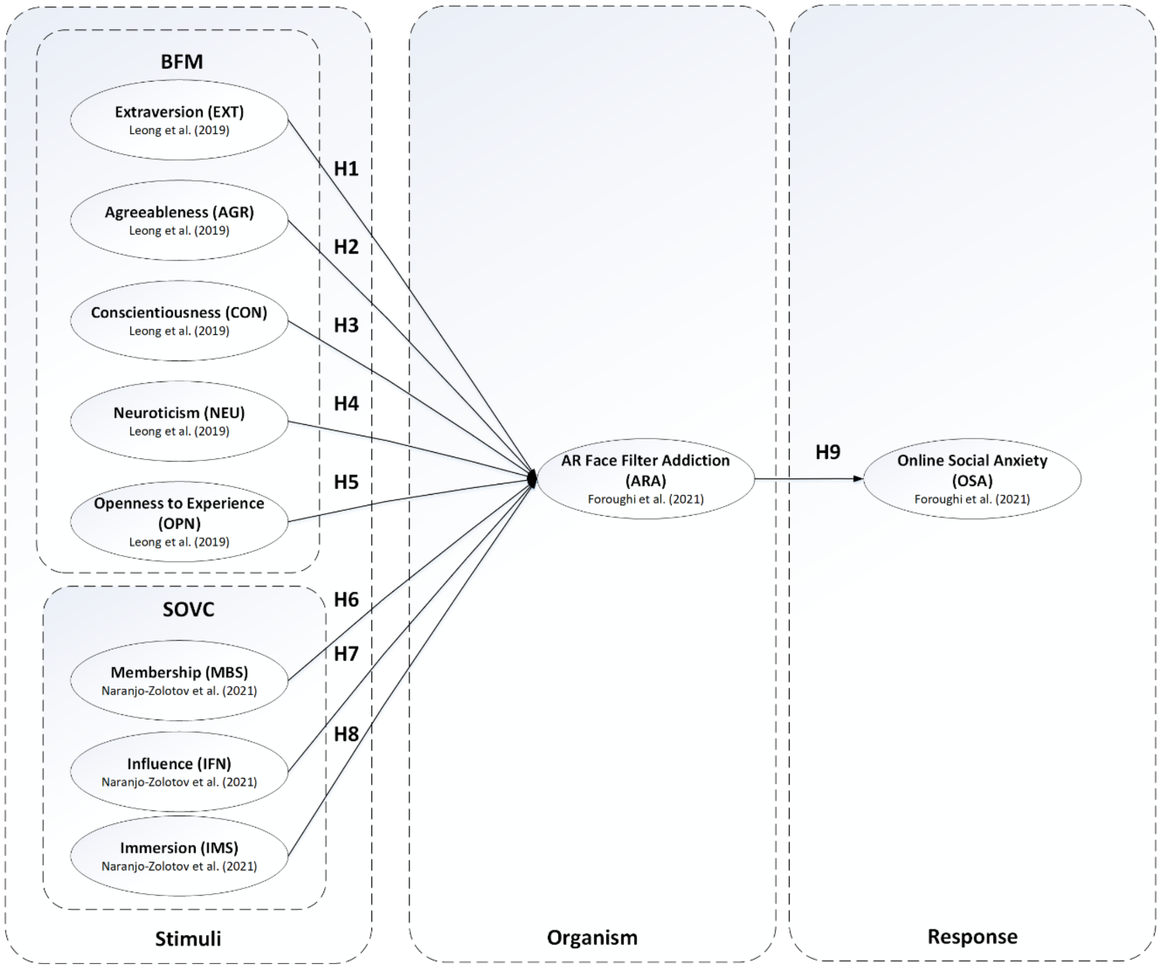

Figure 1. Proposed Conceptual Model

Extraversion is one of the individual personality dimensions in the BFM theory, which refers to the intensity and depth of interpersonal relationships with other people (Ho et al., 2017). People who have high levels of extraversion tend to be extroverted, sociable, talkative, active, assertive, and confident (Leong et al., 2019; Rabaa'i et al., 2015). In this study, the extraversion factor refers to the extent to which individuals or social network users feel confident to upload posts made using AR filters. This is related to the intensity of sharing, which is a feature of the extraversion factor characteristic of a person (Leong et al., 2019). Individuals with high levels of extraversion tend to have high interaction rates, while those with low levels of extraversion tend to limit their interactions with other people (Rabaa'i et al., 2015). Mark and Ganzach (2014) stated that the extraversion factor has a positive significance for Internet use in general. However, Internet use can lead to addiction (Gnisci et al., 2011). Extraversion has also been shown to be a factor driving addictive behavior on social network platforms (Wilson et al., 2010). Individuals with high levels of extraversion have extensive online friendship networks, participate actively in groups on social media, and spend a lot of time on social networking sites (Ho et al., 2017). Therefore, this study proposes the following hypothesis:

H1: Extraversion (EXT) influences ARA on social networks.

Agreeableness is one of the individual personality dimensions in the BFM theory; it refers to the tendency to be altruistic and cooperative (Huang et al., 2018). People who have high levels of agreeableness tend to be flexible, trustworthy, easily forgive, and avoid conflict (Rabaa'i et al., 2015). In this study, the agreeableness factor refers to the extent to which individuals or social network users feel they want to make uploads that do not cause problems for others. This is related to the respectful level, which is a feature of the agreeableness factor characteristic of a person (Leong et al., 2019). Individuals with high levels of agreeableness tend to respect the views of others; conversely, individuals with low levels of agreeableness are more indifferent and tend not to respect the views of others (Leong et al., 2019). Agreeableness has direct and indirect effects on the behavior of addiction to the use of Instagram (Kircaburun & Griffiths, 2018). Individuals who have low agreeableness tend to become pathological users, because they have difficulty building new relationships and maintaining existing relationships (Kircaburun, 2016). Agreeableness has a positive influence on behaviors in terms of group selfie posts, observing other people's selfies, responding to the comments received, and commenting on and liking other people's selfie posts (Choi et al., 2017). Moreover, Rabaa'i et al. (2015) showed that agreeableness levels influence the level of social network platforms use. In the context of addictive behavior towards AR filters, social network users can become active users of AR filters because these users want to make others feel more comfortable when viewing uploaded posts. This action aims to minimize negative responses and avoid conflicts that arise from uploading these posts. This can have repercussions of excessive use of AR filters on social networks leading to addictive behavior. Therefore, we propose the following hypothesis:

H2: Agreeableness (AGR) influences ARA on social networks.

Conscientiousness is one of the individual personality dimensions in the BFM theory; it refers to the extent to which individuals are disciplined, careful, structured, have a strong desire, and work hard to achieve their goals (Leong et al., 2019; Rabaa'i et al., 2015). People who have a high level of conscientiousness tend to be responsible, have an independent attitude, exhibited high willingness, and perseverance, avoid risks, are reliable and organized, and seek long-term relationships (Leong et al., 2019). In this study, conscientiousness refers to the extent to which an individual's internal drive can influence the use of AR face filters on social networks. This is because conscientiousness is the most prominent dimension in showing the correlation of persistence with one's productivity (Rabaa'i et al., 2015). Individuals with high conscientiousness tend to avoid sources of interference in achieving their main goals (Rabaa'i et al., 2015), while individuals with low conscientiousness tend to be negligent, disorganized, and prone to Internet use (Leong et al., 2019). Wilson et al. (2010) found that users with low conscientiousness spend more time surfing social networks and tend to procrastinate on completing tasks (Leong et al., 2019). Individuals who have high conscientiousness are also at higher risk of addiction if the individual is also neurotic and experiences stress (Vaghefi & Qahri-Saremi, 2018). Conscientiousness has been shown to predict Facebook addiction (Błachnio & Przepiorka, 2016; Tang et al., 2016). In addition, Vaghefi and Qahri-Saremi (2018) and Chwaszcz et al. (2018) found that individuals with high conscientiousness are more likely to experience addiction. Therefore, we suggest the following hypothesis:

H3: Conscientiousness (CON) influences ARA on social networks.

Neuroticism is the level of stability and emotional adjustment of individuals, wherein neurotic individuals tend not to be able to control their emotions and are very sensitive, so they easily worry (Ho et al., 2017). People who have high levels of neuroticism tend to experience and display negative influences, such as anxiety, sadness, fear, shame, depression, and guilt, are unable to control their emotions, and tend to isolate themselves to avoid a condition (Leong et al., 2019; Rabaa'i et al., 2015). In this study, neuroticism refers to the level of emotional stability and individual feelings in using AR face filters on social networks. This is because individuals with high neuroticism tend to be more sensitive to stimuli (Leong et al., 2019). Individuals with high neuroticism tend to seek activity diversion to minimize emotional instability, one of which is surfing social networks (Leong et al., 2019). On the other hand, individuals with high neuroticism have the belief that they are unattractive to others and fear rejection (Leong et al., 2019). These thoughts lead to a desire to improve their self-view and can lead to more intense activities through social networks to express their hidden opinions, feelings, and skills (Leong et al., 2019). Mark and Ganzach (2014) found that neuroticism has a positive relationship with Internet use (Rabaa'i et al., 2015). Neuroticism has been shown to predict digital technology addiction (Marciano et al., 2020) and social network addiction (Bowden-Green et al., 2021; Ho et al., 2017; Sindermann et al., 2020). Therefore, we propose the following hypothesis:

H4: Neuroticism (NEU) influences ARA on social networks.

Openness to experience is one of the individual personality dimensions in the BFM theory; it refers to an open-minded pattern in obtaining new experiences (Leong et al., 2019). People who have a high level of openness to experience tend to try new ideas, are creative and imaginative, and have a high level of curiosity (Leong et al., 2019). In this study, the openness to experience factor refers to the extent to which individuals or social network users feel like trying to use AR filters on social networks. This is because a person's level of openness to experience affects their curiosity (Rabaa'i et al., 2015). Individuals with high levels of openness to experience tend to have high curiosity, while individuals with low levels of openness to experience do not have high curiosity and do not feel curious (Rabaa'i et al., 2015). Papastylianou (2013) found that openness to experience is the main predictor of Internet use. Openness to experience has been shown to be positively correlated with general Internet use (Mark & Ganzach, 2014). This is supported by Mostafaei and Khalili (2012), who suggested that users' high levels of openness to experience are associated with their level of addiction to using the Internet. Moreover, the openness to experience factor has been shown to influence social media adoption (Błachnio et al., 2017; Tang et al., 2016; J. L. Wang et al., 2012) and Internet addiction (Błachnio & Przepiorka, 2016; Stieger et al., 2013). Therefore, we recommend the following hypothesis:

H5: Openness to experience (OPN) influences ARA on social networks.

Membership is one of the affective dimensions in the SOVC theory; it refers to the extent to which individuals feel part of a particular community (McMillan & Chavis, 1986). In this study, the membership factor refers to the extent to which individuals or social network users feel they have an attachment and have become a part of their community, namely, their social network friends. Some social network users get to know their social network friends both online and offline, which triggers a stronger sense of belonging (Cheng et al., 2012). This sense of belonging also grows due to feelings of affiliation among individuals in one community, thereby creating clear boundaries between communities (W. G. Kim et al., 2004; Rosenbaum et al., 2005). The higher the sense of belonging between individuals in a community, the higher the level of loyalty and involvement of each individual in the community (Lin, 2008). Membership is also very closely related to the personal investment made by an individual with the aim of having an attachment and being a valuable individual in a community (McMillan & Chavis, 1986). Individuals have a strong and meaningful view of the sense of belonging in a community when they have made more efforts to become a part of and, at the same time, merge into their community (C.-L. Hsu & Liao, 2014). In the context of addictive behavior towards AR filters, social network users tend to become more active when they are emotionally motivated with the aim of joining their virtual community. This can result in excessive use of AR filters on social networks leading to addictive behavior. Therefore, we propose the following hypothesis:

H6: Membership (MBS) influences ARA on social networks.

Influence is defined as the extent to which individuals feel they can influence the decisions or opinions of other members in a virtual community (Koh & Kim, 2003). In this study, the influence factor refers to the extent to which individuals or social network users feel that their views can be influenced and can also influence the views of their community, namely, their social network friends. Influence is a reciprocal or bidirectional factor between individuals in a community that measures each other's impact (McMillan & Chavis, 1986). An individual will feel he has authority in his virtual community when the individual influences others (McMillan & Chavis, 1986). When an individual is actively involved in his community, any influence and openness with other individuals will influence and contribute to increasing the level of individual activity in the community (McMillan & Chavis, 1986). Openness is one of the advantages of virtual communities that allow validation and interaction between individuals within the community 24 hours a day, seven days a week (J. Kim et al., 2020). This allows individuals to share information and emotions without any limitations of space and time, thereby increasing the opportunity to influence each other within the virtual community (J. Kim et al., 2020). In the context of addictive behavior toward AR filters, social network user interactions tend to be more active when they can influence other users' views, one of which is related to facial visualization using filters. This is also supported if the user receives feedback from the community that is in line with posts uploaded on social networks. Individuals also tend to be more receptive to the influence of views from other individuals when they have the same interests (Turel & Osatuyi, 2017). Therefore, we suggest the following hypothesis:

H7: Influence (IFN) affects ARA on social networks.

Immersion is defined as the level of flow felt by individuals when interacting with information technology (Koh & Kim, 2003). Immersion is a flow related to the mental state of an individual when fully involved and enjoying the activities being carried out (Naranjo-Zolotov et al., 2021). In this study, the immersion factor refers to the involvement or immersion of users when interacting with their community, namely, their social networking friends. Social network users can become highly engaged with their social network friends by interacting through uploaded posts. Immersion is one of the basics of addictive behavior because when individuals obtain information that strengthens their views, it will trigger repeated rewards in a safe environment (McMillan & Chavis, 1986). Immersion can also have an impact on biasing information, resulting in the loss of very important information (J. Wang et al., 2019). Both can encourage individuals as social network users to become addicted to the use of face filters when they feel they have support for their views through media posts uploaded to social networks. This will lead to impulsive behavior and neglect of negative impacts (J. Wang et al., 2019). Therefore, we suggest the following hypothesis:

H8: Immersion (IMS) influences ARA on social networks.

Foroughi et al. (2022) showed a positive influence on Instagram addiction on social anxiety and depression where there is also excessive use of Instagram implemented AR face filters. ARA is a subcategory of Internet addiction that applies to excessive AR face filter use on social networks that has a detrimental impact on users' lives (Foroughi et al., 2019; Geng et al., 2021). In this study, ARA behavior refers to the excessive use of face filters on social networks. Individuals with high ARA tend to consider social networking as meeting psychological and social needs (Foroughi et al., 2019). This behavior triggers personal judgment anxiety between expectations and reality (Foroughi et al., 2019). This finding is supported by professional opinions stating that addiction to technology is a symptom of other disorders, one of which is online social anxiety (Sternlicht & Sternlicht, 2022). Foroughi et al. (2022) found that Instagram addiction has a positive relationship with social anxiety. Addictive behavior toward smartphones has also been shown to predict individual anxiety (Alhassan et al., 2018; Geng et al., 2021; Stanković et al., 2021). Therefore, we propose the following hypothesis:

H9: ARA influences online social anxiety (OSA) behavior on social networks.

METHODOLOGY

RESEARCH METHODS

This study has received ethical approval from the Faculty of Computer Science Universitas Indonesia with letter number S-2/UN2.F11.D1.5/PPM.00.00/2024. This study used a quantitative approach employing an online questionnaire. The stages of this research consisted of problem formulation, literature study, model design, instrument preparation, readability testing and a pilot study, quantitative data collection, and data processing and analysis. We defined the measurement items according to previous studies (Akhtar & Azwar, 2019; J. Kim et al., 2020; Naranjo-Zolotov et al., 2021; Zhan et al., 2021). The readability test phase was carried out to determine the quality, readability level, and validity of the questionnaire questions. At this stage, the questionnaire questions were tested for language feasibility and relevance to the research context. The readability test provides an overview to the authors of the extent to which the indicator questions can be understood by the respondents. This stage was carried out by conducting interviews with respondents who met the research criteria, namely, individuals aged 12–35 years and are active users of face filters on social networks (purposive sampling). Interviews with 10 respondents were conducted. The results of the readability test were in the form of criticisms and suggestions regarding sentence equivalents, language rules, selection of diction, and requests for additional explanations on certain questions. Based on the results of the readability test, questions in the questionnaire were revised based on suggestions received to produce the final questionnaire.

Furthermore, the questionnaire questions were tested through the pilot study phase. The pilot study aimed to test the reliability of the research instrument. The pilot study was conducted by distributing research questionnaires to 32 respondents consisting of 25 females and seven males with an age range of 17–25 years. The research instrument is said to be reliable if Cronbach's alpha (CA) is above 0.7 (Hair et al., 2019). From the pilot study respondents' data, a CA value of 0.927 was obtained, which is above 0.7, indicating that the research instrument is reliable and suitable for use (Hair et al., 2019). Thus, we did not need to modify the measurement items in the questionnaire.

Questionnaire links were distributed through posts on several social media channels, such as Line, Facebook, Twitter, and Instagram. These social media platforms have many active users in Indonesia. By reading the general consent and filling out the questionnaire, respondents agreed to participate in this research. Respondents aged 12-16 years old were required to be accompanied by their parents.. Respondent data was collected anonymously and only used for the purposes of this research. The target respondents in this study were individuals who had used an AR face filter feature on social media at least once. We asked several respondents to distribute the questionnaire link (snowball sampling). Quantitative data collection through this online questionnaire lasted for approximately three weeks, from February 16, 2022, to March 7, 2022. As a form of appreciation for respondents who participated in providing valid data, we distributed prizes with a total of IDR 500,0000.00 to ten respondents chosen randomly.

The total number of respondents was 1,201. Only 903 respondents filled out the questionnaire completely. Table 1 presents a summary of the demographics of the respondents. Of the 903 respondents, there were 589 respondents who were new users of AR face filters and 314 respondents who were old users of AR face filters on social networks. We excluded data from respondents aged 12-16 years old because few data were obtained for this age group.

Table 1. Respondent Demographics

Demographics		New User		Old User		Overall	
		N	%	N	%	N	%
Gender	Women	366	62.14%	260	82.80%	626	69.32%
	Men	223	37.86%	54	17.20%	277	30.68%

Demographics		New User		Old User		Overall	
		N	%	N	%	N	%
Age	12–16 years old	23	3.90%	7	2.23%	30	3.32%
	17–25 years old	525	89.13%	289	92.04%	814	90.14%
	26–35 years old	41	6.96%	18	5.73%	59	6.53%
Domicile	Greater Jakarta	217	36.84%	123	39.17%	340	37.65%
	Greater Jakarta in Java Island	269	45.67%	151	48.09%	420	46.51%
	Sumatera	56	9.51%	25	7.96%	81	8.97%
	Kalimantan	19	3.23%	6	1.91%	25	2.77%
	Sulawesi	18	3.06%	2	0.64%	20	2.21%
	Bali / NTT / NTB	10	1.70%	5	1.59%	15	1.66%
	Maluku / Papua	0	0%	2	0.64%	2	0.22%
Education level	Elementary School to High School	121	20.54%	64	20.38%	185	20.49%
	Diploma	46	7.81%	28	8.92%	74	8.19%
	Bachelor	412	69.95%	216	68.79%	628	69.55%
	Master	8	1.36%	4	1.27%	12	1.33%
	Doctoral	2	0.34%	2	0.64%	4	0.44%
Commonly used Social Network Platform (can answer more than one)	Instagram	566	96.10%	297	94.59%	863	95.57%
	Facebook	33	5.60%	24	7.64%	57	6.31%
	TikTok	160	27.16%	131	41.72%	291	32.23%
	Snapchat	106	18%	149	47.45%	255	28.24%

Analysis Methods

We used the Covariance-Based Structural Equation Modeling (CB-SEM) method for processing and analyzing the quantitative data. Confirmatory research was conducted using the CB-SEM method. The CB-SEM analysis was divided into five stages, namely, model specification, model identification, model evaluation and data filtering, measurement model testing, and structural model testing (Kline, 2016). We used several tools to process and analyze research data: AMOS 26 to analyze the data, IBM SPSS Statistics 25 to test variable reliability, and Google Sheets to process data from the research survey results and data analysis results.

In this study, a comparative test was conducted based on the duration of using face filters on social networks. Comparisons were made in three groups, namely, overall, new users, and old users. According to Hung et al. (2021), new users using AR-based filters in social networking apps for less than 3 years are likely to still be in the process of creating interaction and engagement in the app. New users consisted of respondents who have been using face filters on social networks for 0–3 years, while old users consisted of respondents who have been using face filters on social networks for 3–6 years. This group aims to identify and compare the possible differences in behavior between new and old users of AR face filters on social networks.

Research Instruments

The online questionnaire was divided into three parts, namely, validation, general or demographic information, and questions related to research variables based on the research model (measurement items). This study used a five-point Likert scale as the choice for each indicator question. The scale range included strongly disagree (1), disagree (2), neutral (3), agree (4), and strongly agree (5), representing the respondents' views on each indicator question. The results were used to analyze each variable in the research model to address the research problem formulation. The research questionnaire can be seen in Appendix B.

Data Analysis Result

The results of removing outlier data showed that there was still c.r values for several indicators that were outside the range of ±2.58, indicating that the data was not completely normal; thus, a bootstrapping process was needed to normalize the data distribution. Bootstrapping aims to validate the model by resampling and estimating the model on each sample produced (Hair et al., 2019). The results of the multicollinearity test (Appendix C) showed that there are no indicators that correlate ≥ 0.9 so that the research data has met the requirements and can proceed to the next stage. Then, the % of Variance value in all test groups (Appendix D) did not have a value of >50% so that no Common Method Bias was found, and data processing could be continued to the next stage.

Measurement Models

The measurement model test was carried out to ascertain whether each indicator can represent its variables correctly and accurately by conducting validity and reliability tests (Hair et al., 2019). The measurement model meets the requirements of the convergent validity test when the factor loading value (estimated standard loading) is ≥0.7 and the AVE value is ≥0.5 (Hair et al., 2019). Subsequently, a reliability test was carried out by paying attention to the results of the calculation of CA and Composite Reliability (CR), so the value is ≥0.7 (Hair et al., 2019). The AVE, CA, and CR values of this study are presented in Table 2. Table 2 shows that all the results met the requirements.

Table 2. AVE, CA, and CR Values

Variable	AVE			CA			CR		
	New User	Old User	Overall	New User	Old User	Overall	New User	Old User	Overall
EXT	0.59	0.61	0.88	0.85	0.86	0.84	0.85	0.86	0.96
AGR	0.86	0.97	0.97	0.82	0.78	0.81	0.95	0.99	0.99
CON	0.98	0.98	0.98	0.83	0.81	0.82	0.99	0.99	0.99
NEU	0.87	0.99	0.99	0.83	0.80	0.83	0.96	0.99	0.99
OPN	0.97	0.85	0.97	0.76	0.72	0.76	0.99	0.95	0.99
IMS	0.99	0.83	0.99	0.81	0.82	0.81	0.99	0.93	0.99
IFN	0.98	0.98	0.98	0.70	0.70	0.70	0.99	0.99	0.99
MBS	0.98	0.85	0.98	0.82	0.84	0.83	0.99	0.94	0.99
ARA	0.75	0.76	0.76	0.92	0.90	0.91	0.92	0.90	0.90
OSA	0.80	0.80	0.77	0.92	0.92	0.91	0.92	0.92	0.90

Structural Model

The structural model test evaluated the goodness of fit (GoF), which looks at the value of CMIN/df, goodness-of-fit index (GFI), comparative fit index (CFI), normal fit index (NFI), Tucker-Lewis index (TLI), and RMSEA (Hair et al., 2019). The modified version of this research model has a good fit category for the GoF testing, as shown in Table 3.

Table 3. Goodness of Fit (GoF) Values

Goodness of Fit (GoF)	Cut-off Value	Value		
		New User	Old User	Overall
CMIN/df	< 2.00	1.28	1.03	1.77
RMSEA	≤ 0.08	0.02	0.01	0.03
NFI	≥ 0.90	0.95	0.93	0.95
CFI	≥ 0.90	0.99	0.99	0.98

Goodness of Fit (GoF)	Cut-off Value	Value		
		New User	Old User	Overall
GFI	≥ 0.90	0.94	0.92	0.95
TLI	≥ 0.90	0.98	0.99	0.97

Hypothesis Testing

Hypothesis testing in this study was conducted using a two-tailed approach with a significance level of 5%. Testing the hypothesis refers to determining the p-value between the variables, where a hypothesis is accepted if it has a p-value < 0.05 (Hair et al., 2019). The results of this research hypothesis testing are presented in Table 4, which shows seven out of nine accepted hypotheses in the overall group, five out of nine accepted hypotheses in the new user group, and six out of nine accepted hypotheses in the old user group. Finally, Table 5 describes the R^2 results and only the ARA variable has a moderate effect size according to Acock (2013).

Table 4. Hypothesis Testing

Hypothesis				Overall		New User		Old User	
				p-value	Results	p-value	Results	p-value	Results
H1	ARA	←	EXT	0.02	Accepted	0.06	Rejected	0.02	Accepted
H2	ARA	←	AGR	0.40	Rejected	0.84	Rejected	0.83	Rejected
H3	ARA	←	CON	0.02	Accepted	0.01	Accepted	0.07	Rejected
H4	ARA	←	NEU	0.0001	Accepted	0.0001	Accepted	0.0001	Accepted
H5	ARA	←	OPN	0.25	Rejected	0.52	Rejected	0.73	Rejected
H6	ARA	←	MBS	0.0001	Accepted	0.0001	Accepted	0.0001	Accepted
H7	ARA	←	IFN	0.03	Accepted	0.62	Rejected	0.0001	Accepted
H8	ARA	←	IMS	0.0001	Accepted	0.0001	Accepted	0.0001	Accepted
H9	OSA	←	ARA	0.0001	Accepted	0.0001	Accepted	0.0001	Accepted

Table 5. R^2 Results

Variable	New User		Old User		Overall	
	Mean	Description	Mean	Description	Mean	Description
ARA	0.25	Moderate	0.30	Moderate	0.24	Moderate
OSA	0.69	Kuat	0.78	Kuat	0.77	Kuat

DISCUSSION

THE INFLUENCE OF EXTRAVERSION ON AR FACE FILTER ADDICTION ON SOCIAL NETWORKS

This study found that the influence of extraversion on ARA behavior in social networking is accepted by the old user group and the overall data group. Therefore, social networking is a means to continue to interact with family, friends, and other people, resulting in an increase in the intensity of social media use during the pandemic. According to Bowden-Green et al. (2020), extroverted individuals use social media actively. The pattern of active use of social media reflects the individual's behavior when interacting offline (Bowden-Green et al., 2020), so it is prone to excessive Internet use (Przepiorka et al., 2019). Adolescents with an extroverted nature have the urge to establish social relationships online (Przepiorka et al., 2019) to have a wide network of friends (Ho et al., 2017). In addition, Eftekhar et al. (2014) revealed a relationship between extroversion and the number of images uploaded to social media. Extroverted individuals tend to upload images of (1) people and objects and (2) faces that show a variety of emotions, except for natural expressions (Bowden-Green et al., 2020). Individuals with an extroverted nature also often do selfie editing (D. Wang, 2019).

However, the results of the H1 test were rejected in the new user group. This finding relates to the motivation of extroverted individuals described by Bowden-Green et al. (2021), who stated that the motivation of extroverted individuals in using social networks is to maintain relationships that they already have in the real world. However, extroverted individuals tend to use technology by initially conducting a thorough exploration (Frison & Eggermont, 2020; Gadekar & Ang, 2020). In the context of social networking, extroverted individuals are not focused on exploring only one feature but all the interactive features that exist in the social networking application (Frison & Eggermont, 2020). The more often and the longer an extroverted individual uses the features on social networks, the more they will become attached to these features and trigger their overuse. New users tend to be in the exploration stage and have not yet entered the overuse stage (Gadekar & Ang, 2020).

THE INFLUENCE OF AGREEABLENESS ON AR FACE FILTER ADDICTION ON SOCIAL NETWORKS

The effect of agreeableness on ARA behavior in social networking (H2) was rejected in this study. Individuals who agree easily tend to have empathy in their real-world friendships (Chang et al., 2022; Getzmann et al., 2021; Jeon et al., 2018). Agreeable individuals also have good personal relationships in social networks, as well as in real life (Chang et al., 2022). Therefore, the individual does not consider social networking as the only way to fulfill one's social needs (Chang et al., 2022). This type of individual tends to use social networks only as a supporting medium in maintaining the social relationships they already have in the real world (Chang et al., 2022; Getzmann et al., 2021; Jeon et al., 2018). In addition, individuals who agree easily also have a tendency not to upload content considered inappropriate or potentially deceptive (Miller, 2020). This is because the individual has the characteristics of avoiding conflict and trying not to offend others (Miller, 2020). Demographic data in this study shows 80.81% of new users, 61.46% of old users, and 74.09% of all users only use AR face filters less than eight times per week. This result shows that the intensity of use is not high because AR face filters are also one of the supporting media in maintaining social relations. Therefore, this study shows that agreeableness does not affect addictive behavior in using AR face filter in social networking applications for all user groups in Indonesia.

The Influence of Conscientiousness on AR Face Filter Addiction on Social Networks

The influence of conscientiousness on ARA behavior in social networking (H3) was accepted for the new user group and the whole group. This finding is in line with that of Vaghefi and Qahri-Saremi (2018), who revealed that individuals who are careful tend to experience addiction to the use of information technology. Chwaszcz et al. (2018) also revealed that individuals who are careful tend to experience addiction to Internet use. Vaghefi and Qahri-Saremi (2018) and Chwaszcz et al. (2018) found several correlations between personalities that can increase the risk of addiction. Both studies revealed that the strongest correlation is found between conscientiousness and emotional (neurotic) instability. This combination is highly conducive to the risk of developing addiction (Chwaszcz et al., 2018; Vaghefi & Qahri-Saremi, 2018) because one of the risks of a very conscientious individual is focusing on perfection, meeting unrealistic expectations, and being frustrated by failure or high levels of stress for the individual. High conscientiousness fully compensates for the high risk of emotional instability. Notably, the various changes that occur in people's lives exacerbate people's susceptibility to stress and may cause cognitive disorders that reduce productivity. This is supported by data from this study survey, in which we found that among 565 respondents with a cautious nature and 537 respondents with a neurotic nature, 362 respondents, or around 64.07%, had both traits.

H3 result was rejected for the old user group. Rettner (2018) states that individuals with very cautious traits control strong impulses and urges to achieve certain goals; thus, they tend not to develop social media addiction. Although cautious and neurotic traits are the perfect combination for the risk of developing addiction, this cautious nature is also a drug to cure addiction and even applies to neurotic individuals (Smiddy, 2020). Cautious nature provides individual awareness of experiences that become uninteresting (Smiddy, 2020). The more often a behavior is repeated, and the effects felt are the same, the individual will become tolerant which causes the pleasure of use to be reduced (Hartney, 2023). This awareness makes it easier for old users to quit their addiction (Hartney, 2023). Therefore, it can be said that the nature of conscientiousness provides a change in the satisfaction of the face filter experience between the test group of new users and old users of social networks in Indonesia which causes a decrease in the level of addiction behavior over time.

The Influence of Neuroticism on AR Face Filter Addiction on Social Networks

The effect of neuroticism on the behavior of ARA in social networking applications (H4) was accepted in this study. This finding is in line with Ho et al. (2017) and Bowden-Green et al. (2021), who revealed that neurotic individuals tend to experience addiction to the use of social networks. Other studies also revealed the influence of neurotic traits on addictive behavior in various contexts, such as addiction to digital technology (Marciano et al., 2020) and Facebook (Sindermann et al., 2020). The virtual world, which is easily accessible via the Internet, offers a unique environment for neurotic individuals to escape the negative emotions they feel (Marciano et al., 2022). The habit of running away negatively affects the quality of relationships in the real world and increases addiction to the virtual world (Marciano et al., 2022). Neurotic individuals seek to reduce stress in the real world by impersonating themselves in social networks (Bowden-Green et al., 2021; Marciano et al., 2020).

The Influence of Openness to Experience on AR Face Filter Addiction on Social Networks

The influence of openness to experience on ARA behavior in social networking applications (H5) was rejected in this study. Survey data showed that as many as 66.56% of the respondents have a personality that is open to experience. A total of 71.88% of the respondents with this personality trait stated that the reason they used face filters was out of curiosity. This finding confirms that the intention of individuals opens to experience using AR face filters is curiosity. Silvia and Christensen (2020) stated that curiosity is a major component of openness and represents one of its core attributes. In addition, the research survey data show that 76.39% of respondents who are open-minded and use face filters out of curiosity only use face filters less than eight times a week. The curiosity experienced by an individual will disappear when the individual already knows everything he wants to know. Individuals who are open to experience are less likely to become addicted to social networks when they no longer perceive everything on the social network as a unique and new experience (Patel et al., 2021).

The Influence of Membership on AR Face Filter Addiction on Social Networks

The effect of membership on ARA behavior in social networking applications (H6) was accepted in this study. This finding is in line with Lin (2008) and C.-L. Hsu and Liao (2014), who revealed that if the sense of belonging between individuals in a virtual community is high, the loyalty and involvement of everyone in the community concomitantly increase, enabling merging into the community. Naranjo-Zolotov et al. (2019) supported these findings by positing that high levels of a sense of community are associated with higher levels of system use. This finding also strengthens the membership variable in the SOVC theory, which is directly related to personal investment by an individual with the aim of being able to have an attachment and become a valuable individual for his community (Koh & Kim, 2003; McMillan & Chavis, 1986). In a previous study, Naranjo-Zolotov et al. (2021) stated that individuals with a strong sense of belonging in a virtual community tend to exhibit addictive behavior on social networks when they want to express themselves to others in the community.

The Effect of Individual Influence on AR Face Filter Addiction on Social Networks

The effect of influence on ARA behavior in social networking applications (H7) is accepted by the old user group and the data for the whole group. This result is in line with the SOVC theory on the influence variable, which reveals that an individual will feel he has authority in his community when he influences others in the community (Koh & Kim, 2003; McMillan & Chavis, 1986;). This addictive behavior can occur supported by openness to virtual communities that allow validation and interaction between individuals in the community to share information and emotions without any limitations of space and time (J. Kim et al., 2020).

However, the results of the H7 test were rejected in the new user group. J. Kim et al. (2020) found that influence in virtual communities requires a process to create effective interaction and engagement with social network friends in sharing information and emotions. Influence occurs when individuals feel they have authority in their community in a two-way manner (Koh & Kim, 2003; McMillan & Chavis, 1986). The average time required by social network users to go through this process is 1–2 years (Snow, 2015). New users of AR-based filters in social networking applications for less than 3 years tend to still go through the process of creating interaction and engagement to build a two-way influence. This finding is in line with Hung et al. (2021), who stated that the motivation of individuals in using AR filters tends to come from their own desires and not from social influences or people around them; thus, there is no two-way influence on new users. Demographic data on the reasons for using face filters in the new user group also indicate that 69.61% are due to curiosity and only 14.43% are due to a friend's invitation.

The Influence of Immersion on AR Face Filter Addiction on Social Networks

The influence of immersion on ARA behavior in social networking applications (H8) was accepted in this study. This result is in line with the findings of previous studies, which revealed that immersion is one of the basics of addictive behavior because it can trigger repeated rewards when an individual obtains information that reinforces his views to allow the individual to drift in a safe environment (Koh & Kim, 2003; Naranjo-Zolotov et al., 2021). This finding is supported by the fact that face filter users on social networks often get compliments or affirmations related to appearance when uploading posts using face filters (Josephs, 2022). Seo and Ray (2019) stated that individuals who experience strong immersion in social networks tend to be addicted because they get a higher level of pleasure than before. This level of pleasure can make an individual obsessed, which eventually turns into addiction over time (Seo & Ray, 2019).

The Influence of AR Face Filter Addiction on Online Social Anxiety on Social Networks

Finally, the effect of ARA behavior on online social anxiety in social networking applications (H9) was accepted in this study. This result is in line with Alhassan et al. (2018) and Foroughi et al. (2019, 2022), who revealed that smartphone addiction and social networking applications have a positive relationship with social anxiety. This phenomenon occurs owing to the large number of social interactions diverted to social networks due to physical distancing and quarantine, causing an increase in the use of social networks, which have a negative impact on social welfare (Brailovskaia et al., 2021). Individuals who have been addicted to a feature in social networks tend to consider social networking as psychological and social needs. This behavior triggers personal judgment anxiety between expectations and reality (Foroughi et al., 2019). This is supported by the overall survey data, which showed that 40.42% of the respondents stated that they felt insecure about their own faces as one of the negative impacts of using AR face filter.

Implications

Theoretical Implications

This study succeeded in proving that there is a significant influence between extraversion, conscientiousness, and neuroticism on the tendency to experience AR face filter addiction on social networks. However, this study was unable to prove the effect of agreeableness and openness to experience on addictive behavior in each test group, as suggested by Rabaa'i et al. (2015) in Kuwait and Leong et al. (2019). This study adds the finding that grouping the characteristics of AR face filter users can influence the significance of the variables in the big five personality models to the addiction variable.

The results of this study also contribute by expanding the research of Naranjo-Zolotov et al. (2021) which has not been able to prove the influence of membership variables and influence on the sense of virtual community on addiction behavior on social networks directly. The research also enriches this by validating it into the context of a specific social networking feature, the AR face filter. Furthermore, the results of this study also found differences in characteristics in the addictive behavior of AR face filters on social networks that were influenced by the sense of virtual community between user groups obtained through comparative analysis.

Moreover, this study found that addiction to AR face filters on social networks has an impact on online social anxiety. These findings confirm the research conducted by Foroughi et al. (2019, 2022) regarding the relationship between social networking addiction behavior and social anxiety and validating it in the context of a more specific social networking feature, namely AR face filters. This study also contributes to the expansion of AR addiction research conducted by Hung et al. (2021) into the context of using AR face filters on social networks. In addition, these findings contribute to the expansion of research on the impact of using facial filters, such as research by Javornik et al. (2022) which only examined the positive impact of using facial filters so that these findings succeeded in complementing the negative impact of using facial filters.

PRACTICAL IMPLICATIONS

Social network service providers can minimize users' addiction to using AR face filters by providing a personality test feature before users use AR face filters. It aims to provide personalization of features according to the user's personality to prevent addiction from occurring based on the risk level of each personality type in the three groups of users. Individuals with extroverted traits may experience addiction to a feature for a long period of time. This can be used as an indicator of self-control when using the AR face filter feature to minimize the negative impact caused. Another insight gained by users is the use of conscientious traits that exist in users as a healer of addiction behavior as experienced by old users of AR face filters in this study.

The results of this study found that AR face filter addiction was shown to affect online social anxiety in all test groups. Online social anxiety is a negative impact resulting from excessive use of AR face filters. Therefore, AR service providers and creators can consider strategies to limit the use of AR face filters by users so as not to increase anxiety rates in Indonesia. Users can also pay more attention and be aware of the effects resulting from excessive behavior that occurs on them. This research provides insight into how excessive use of AR face filters can have adverse effects on users so cooperation between parties involved is needed to avoid the adverse effects of online social anxiety. Thus, social network service providers must be able to ensure policies related to the list of AR face filters that are appropriate for use by their users as a form of preventing addictive behavior on that feature. Social network service providers may limit the use of facial filters to certain levels. First, by providing a warning notification if the user has used a facial filter excessively. Second, AR service providers and creators can spread campaigns to limit the use of facial filters to maintain users' mental health. In the long term, social network service providers can develop features that can limit access for users who have used the AR face filter feature excessively.

CONCLUSION, CONTRIBUTION, AND FUTURE WORKS.

This study found that the factors affecting ARA are extraversion, conscientiousness, neuroticism, membership, influence, and immersion. Agreeableness and openness to experience do not affect ARA. In addition, it was found in the new user test group that extraversion and influence do not have a significant effect on ARA. The old user test group demonstrated that conscientiousness has no significant effect on ARA. Furthermore, ARA affects online social anxiety. This study has some limitations. Approximately 90% of the respondents are dominated by individuals aged 17–25 years, and 84% of the respondents live in Java which has a good Internet connection. Also, this study found that approximately 70% of the respondents are women. Further research can consider other negative impacts of AR face filters on aspects such as depression, life satisfaction, and academic performance. Finally, The R^2 value of the ARA variable in this study only produces a moderate effect size; thus, future research can use other variables as antecedent variables for ARA. Finally, future research can conduct research regarding the positive impact of AR face filters to get better understanding on the impact of AR face filter.

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REFERENCES

Abfalter, D., Zaglia, M. E., & Mueller, J. (2012). Sense of virtual community: A follow up on its measurement. *Computers in Human Behavior*, *28*(2), 400–404. https://doi.org/10.1016/j.chb.2011.10.010

Ackerman, C. E. (2017). *Big five personality traits: The OCEAN model explained*. Positive Psychology. https://positivepsychology.com/big-five-personality-theory/

Acock, A. (2013). Discovering structural equation modeling using Stata. Stata Press. https://www.stata.com/bookstore/discovering-structural-equation-modeling-using-stata/

Akhtar, H., & Azwar, S. (2019). Indonesian adaptation and psychometric properties evaluation of the big five personality inventory: IPIP-BFM-50. *Jurnal Psikologi, 46*(1), 32. https://doi.org/10.22146/jpsi.33571

Alhassan, A. A., Alqadhib, E. M., Taha, N. W., Alahmari, R. A., Salam, M., & Almutairi, A. F. (2018). The relationship between addiction to smartphone usage and depression among adults: A cross-sectional study. *BMC Psychiatry*, *18*(1). https://doi.org/10.1186/s12888-018-1745-4

Andreassen, C. S., Pallesen, S., & Griffiths, M. D. (2017). The relationship between addictive use of social media, narcissism, and self-esteem: Findings from a large national survey. *Addictive Behaviors*, *64*, 287–293. https://doi.org/10.1016/j.addbeh.2016.03.006

Bhatt, S. (2020). The big picture in the entire AR-filter craze. *The Economic Times*. https://economictimes.indiatimes.com/internet/brands-seethe-big-picture-in-ar-filter-craze/articleshow/78266655.cms?from=mdr

Błachnio, A., & Przepiorka, A. (2016). Personality and positive orientation in Internet and Facebook addiction. An empirical report from Poland. *Computers in Human Behavior*, *59*, 230–236. https://doi.org/10.1016/j.chb.2016.02.018

Błachnio, A., Przepiorka, A., Senol-Durak, E., Durak, M., & Sherstyuk, L. (2017). The role of personality traits in Facebook and Internet addictions: A study on Polish, Turkish, and Ukrainian samples. *Computers in Human Behavior*, *68*, 269–275. https://doi.org/10.1016/j.chb.2016.11.037

Bowden-Green, T., Hinds, J., & Joinson, A. (2020). How is extraversion related to social media use? A literature review. *Personality and Individual Differences*, *164*, 110040. https://doi.org/10.1016/j.paid.2020.110040

Bowden-Green, T., Hinds, J., & Joinson, A. (2021). Understanding neuroticism and social media: A systematic review. *Personality and Individual Differences*, *168*, 110344. https://doi.org/10.1016/j.paid.2020.110344

Brailovskaia, J., Truskauskaite-Kuneviciene, I., Margraf, J., & Kazlauskas, E. (2021). Coronavirus (COVID-19) outbreak: Addictive social media use, depression, anxiety and stress in quarantine – An exploratory study in Germany and Lithuania. *Journal of Affective Disorders Reports*, *5*, 100182. https://doi.org/10.1016/j.jadr.2021.100182

Chang, K., Li, X., Zhang, L., & Zhang, H. (2022). A double-edged impact of social smartphone use on smartphone addiction: A parallel mediation model. *Frontiers in Psychology*, *13*. https://doi.org/10.3389/fpsyg.2022.808192

Cheng, S.-Y., Tsai, M.-T., Cheng, N.-C., & Chen, K.-S. (2012). Predicting intention to purchase on group buying website in Taiwan: Virtual community, critical mass and risk. *Online Information Review*, *36*(5), 698–712. https://doi.org/10.1108/14684521211275984

Choi, T. R., Sung, Y., Lee, J. A., & Choi, S. M. (2017). Get behind my selfies: The big five traits and social networking behaviors through selfies. *Personality and Individual Differences*, *109*, 98–101. https://doi.org/10.1016/j.paid.2016.12.057

Chwaszcz, J., Lelonek-Kuleta, B., Wiechetek, M., Niewiadomska, I., & Palacz-Chrisidis, A. (2018). Personality traits, strategies for coping with stress and the level of internet addiction—A study of Polish secondary-school students. *International Journal of Environmental Research and Public Health*, *15*(5), 987. https://doi.org/10.3390/ijerph15050987

Cohen, A., & Baruth, O. (2017). Personality, learning, and satisfaction in fully online academic courses. *Computers in Human Behavior*, *72*, 1–12.

de Raad, B., & Mlačić, B. (2015). Big five factor model, theory, and structure. *International Encyclopedia of the Social & Behavioral Sciences*, 559–566. https://doi.org/10.1016/b978-0-08-097086-8.25066-6

Eftekhar, A., Fullwood, C., & Morris, N. (2014). Capturing personality from Facebook photos and photo-related activities: How much exposure do you need? *Computers in Human Behavior*, *37*, 162–170. https://doi.org/10.1016/j.chb.2014.04.048

Emmons, R. A., Diener, E., & Larsen, R. J. (1985). Choice of situations and congruence models of interactionism. *Personality and Individual Differences*, *6*, 693-702. https://doi.org/10.1016/0191-8869(85)90080-7

Faqih, K. M. S., & Jaradat, M.-I. R. (2021). Integrating TTF and UTAUT2 theories to investigate the adoption of augmented reality technology in education: Perspective from a developing country. *Technology in Society*, *67*, 101787. https://doi.org/10.1016/j.techsoc.2021.101787

Foroughi, B., Griffiths, M. D., Iranmanesh, M., & Salamzadeh, Y. (2022). Associations between Instagram addiction, academic performance, social anxiety, depression, and life satisfaction among university students. *International Journal of Mental Health and Addiction*, 20(4), 2221-2242. https://doi.org/10.1007/s11469-021-00510-5

Foroughi, B., Iranmanesh, M., Nikbin, D., & Hyun, S. S. (2019). Are depression and social anxiety the missing link between Facebook addiction and life satisfaction? The interactive effect of needs and self-regulation. *Telematics and Informatics*, *43*, 101247. https://doi.org/10.1016/j.tele.2019.101247

Frison, E., & Eggermont, S. (2020). Toward an integrated and differential approach to the relationships between loneliness, different types of Facebook use, and adolescents' depressed mood. *Communication Research*, *47*(5), 701–728. https://doi.org/10.1177/0093650215617506

Gadekar, R., & Ang, P. H. (2020). Is social media use socially enhancing or compensating? *Journal of Creative Communications*, *15*(3), 269–288. https://doi.org/10.1177/0973258620943705

Geng, Y., Gu, J., Wang, J., & Zhang, R. (2021). Smartphone addiction and depression, anxiety: The role of bedtime procrastination and self-control. *Journal of Affective Disorders*, *293*, 415–421. https://doi.org/10.1016/j.jad.2021.06.062

Getzmann, S., Digutsch, J., & Kleinsorge, T. (2021). Covid-19 pandemic and personality: Agreeable people are more stressed by the feeling of missing. *International Journal of Environmental Research and Public Health*, *18*(20), 10759. https://doi.org/10.3390/ijerph182010759

Gnisci, A., Perugini, M., Pedone, R., & Di Conza, A. (2011). Construct validation of the use, abuse and dependence on the Internet inventory. *Computers in Human Behavior*, *27*(1), 240–247. https://doi.org/10.1016/j.chb.2010.08.002

Hair, J., Black, W., Babin, B., & Anderson, R. (2019). *Multivariate data analysis* (8th ed.). Cengage.

Hamilton, J. (2022, February 9). *Insight. AR Filters – Everything You Need to Know!*. https://eon-media.com/insights/ar-filters/

Hartney, E. (2023). *Why quitting an addiction can be so challenging*. Verywell Mind. https://www.verywellmind.com/how-can-i-quit-my-addiction-22390

Ho, S. S., Lwin, M. O., & Lee, E. W. J. (2017). Till logout do us part? Comparison of factors predicting excessive social network sites use and addiction between Singaporean adolescents and adults. *Computers in Human Behavior*, *75*, 632–642. https://doi.org/10.1016/j.chb.2017.06.002

Hsu, C.-L., & Liao, Y.-C. (2014). Exploring the linkages between perceived information accessibility and microblog stickiness: The moderating role of a sense of community. *Information & Management*, *51*(7), 833–844. https://doi.org/10.1016/J.IM.2014.08.005

Hsu, S. H.-Y., Tsou, H.-T., & Chen, J.-S. (2021). "Yes, we do. Why not use augmented reality?" Customer responses to experiential presentations of AR-based applications. *Journal of Retailing and Consumer Services*, *62*, 102649. https://doi.org/10.1016/j.jretconser.2021.102649

Huang, H.-C., Cheng, T. C. E., Huang, W.-F., & Teng, C.-I. (2018). Impact of online gamers' personality traits on interdependence, network convergence, and continuance intention: Perspective of social exchange theory. *International Journal of Information Management*, *38*(1), 232–242. https://doi.org/10.1016/j.ijinfomgt.2017.08.009

Hubner, S., Frese, M., Song, Z., Tripathi, N., Kaschner, T., & Le Kong, X. (2021). An Asia-centric approach to team innovation: Cultural differences in exploration and exploitation behavior. *Journal of Business Research*, *138*, 408–421. https://doi.org/10.1016/j.jbusres.2021.09.009

Hung, S.-W., Chang, C.-W., & Ma, Y.-C. (2021). A new reality: Exploring continuance intention to use mobile augmented reality for entertainment purposes. *Technology in Society*, *67*, 101757. https://doi.org/10.1016/j.techsoc.2021.101757

Inde. (n.d.). *The brief history of social media AR filters*. https://www.indestry.com/blog/the-brief-history-of-social-media-ar-filters

Javornik, A., Marder, B., Barhorst, J. B., McLean, G., Rogers, Y., Marshall, P., & Warlop, L. (2022). What lies behind the filter?' Uncovering the motivations for using augmented reality (AR) face filters on social media and their effect on well-being. *Computers in Human Behavior, 128*(3), 107126. https://doi.org/10.1016/j.chb.2021.107126.

Jeon, H. J., Kim, S., Chon, W.-H., & Ha, J. H. (2018). Is Internet overuse associated with impaired empathic ability in Korean college students? *Medicine*, *97*(39). https://doi.org/10.1097/md.0000000000012493

Josephs, M. (2022, January 26). *How teens actually feel about Instagram filters.* Teen Vogue. https://www.teenvogue.com/story/7-teens-on-instagram-filters-social-media-and-mental-health

Kamboj, S., Sarmah, B., Gupta, S., & Dwivedi, Y. (2018). Examining branding co-creation in brand communities on social media: Applying the paradigm of stimulus-organism-response. *International Journal of Information Management*, *39*, 169–185. https://doi.org/10.1016/j.ijinfomgt.2017.12.001

Katadata. (2021, November 9). *Inilah Negara Pengguna Instagram Terbanyak, Indonesia Urutan Berapa?* [This is the country with the most Instagram users, in what order is Indonesia?]. https://databoks.katadata.co.id/datapublish/2021/08/03/inilah-negara-pengguna-instagram-terbanyak-indonesia-urutan-berapa

Keng, S. L., Smoski, M. J., & Robins, C. J. (2011). Effects of mindfulness on psychological health: a review of empirical studies. *Clinical Psychology Review, 31*(6), 1041-1056. https://doi.org/10.1016/j.cpr.2011.04.006

Kim, J., Kim, H.-M., & Kim, M. (2020). The impact of a sense of virtual community on online community: Does online privacy concern matter? *Internet Research*, *31*(2), 519–539. https://doi.org/10.1108/intr-01-2020-0015

Kim, W. G., Lee, C., & Hiemstra, S. J. (2004). Effects of an online virtual community on customer loyalty and travel product purchases. *Tourism Management*, *25*(3), 343–355. https://doi.org/10.1016/s0261-5177(03)00142-0

Kircaburun, K. (2016). Effects of gender and personality differences on twitter addiction among Turkish undergraduates. *Journal of Education and Practice, 7*(24), 33–42. https://www.researchgate.net/publication/307512980_Effects_of_Gender_and_Personality_Differences_on_Twitter_Addiction_among_Turkish_Undergraduates

Kircaburun, K., & Griffiths, M. D. (2018). Instagram addiction and the big five of personality: The mediating role of self-liking. *Journal of Behavioral Addictions*, *7*(1), 158–170. https://doi.org/10.1556/2006.7.2018.15

Kline, R. (2016). *Principles and practice of structural equation modeling* (4th ed.). The Guilford Press.

Koh, J., & Kim, Y.-G. (2003). Sense of virtual community: A conceptual framework and empirical validation. *International Journal of Electronic Commerce*, *8*(2), 75–94. https://doi.org/10.1080/10864415.2003.11044295

Koukoumelis, A., Levati, M. V., & Weisser, J. (2012). Leading by words: A voluntary contribution experiment with one-way communication. *Journal of Economic Behavior & Organization*, *81*(2), 379–390. https://doi.org/10.1016/j.jebo.2011.11.007

Kourouthanassis, P., Boletsis, C., Bardaki, C., & Chasanidou, D. (2015). Tourists responses to mobile augmented reality travel guides: The role of emotions on adoption behavior. *Pervasive and Mobile Computing*, *18*, 71–87. https://doi.org/10.1016/j.pmcj.2014.08.009

Leong, L.-Y., Hew, T.-S., Ooi, K.-B., Lee, V.-H., & Hew, J.-J. (2019). A hybrid SEM-neural network analysis of Social Media Addiction. *Expert Systems with Applications*, *133*, 296–316. https://doi.org/10.1016/j.eswa.2019.05.024

Lin, H.-F. (2008). Determinants of successful virtual communities: Contributions from system characteristics and social factors. *Information & Management*, *45*(8), 522–527. https://doi.org/10.1016/j.im.2008.08.002

López-Faican, L., & Jaen, J. (2020). Emofindar: Evaluation of a mobile multiplayer augmented reality game for primary school children. *Computers & Education*, *149*, 103814. https://doi.org/10.1016/j.compedu.2020.103814

Marciano, L., Camerini, A.-L., & Schulz, P. J. (2020). Neuroticism in the digital age: A meta-analysis. *Computers in Human Behavior Reports*, *2*, 100026. https://doi.org/10.1016/j.chbr.2020.100026

Marciano, L., Camerini, A.-L., & Schulz, P. J. (2022). Neuroticism and internet addiction: What is next? A systematic conceptual review. *Personality and Individual Differences*, *185*, 111260. https://doi.org/10.1016/j.paid.2021.111260

Mark, G., & Ganzach, Y. (2014). Personality and internet usage: A large-scale representative study of young adults. *Computers in Human Behavior*, *36*, 274–281. https://doi.org/10.1016/j.chb.2014.03.060

McMillan, D. W., & Chavis, D. M. (1986). Sense of community: A definition and theory. *Journal of Community Psychology*, *14*(1), 6–23. https://doi.org/10.1002/1520-6629(198601)14:1

Mehrabian, A., & Russell, J. A. (1974). *An approach to environmental psychology*. The MIT Press.

Miller, R. E. (2020). College students and inappropriate social media posting: Is it a question of personality or the influence of friends? *Personality and Individual Differences*, *158*, 109857. https://doi.org/10.1016/j.paid.2020.109857

Moon, Y. J., Kim, W. G., & Armstrong, D. J. (2014). Exploring neuroticism and extraversion in flow and user generated content consumption. *Information and Management*, *51*(3), 347–358. https://doi.org/10.1016/j.im.2014.02.004

Moqbel, M., & Kock, N. (2018). Unveiling the dark side of social networking sites: Personal and work-related consequences of social networking site addiction. *Information & Management, 55*(1), 109-119. https://doi.org/10.1016/j.im.2017.05.001.

Mostafaei, A., & Khalili, M. (2012). The relationship between internet addiction and mental health in male and female university students. *Annals of Biological Research*, *3*(9), 4362–4366.

Mütterlein, J., Kunz, R. E., & Baier, D. (2019). Effects of lead-usership on the acceptance of media innovations: A mobile augmented reality case. *Technological Forecasting and Social Change*, *145*, 113–124. https://doi.org/10.1016/j.techfore.2019.04.019

Naranjo-Zolotov, M., Oliveira, T., Casteleyn, S., & Irani, Z. (2019). Continuous usage of e-participation: The role of the sense of virtual community. *Government Information Quarterly*, *36*(3), 536–545. https://doi.org/10.1016/j.giq.2019.05.009

Naranjo-Zolotov, M., Turel, O., Oliveira, T., & Lascano, J. E. (2021). Drivers of online social media addiction in the context of public unrest: A sense of virtual community perspective. *Computers in Human Behavior*, *121*, 106784. https://doi.org/10.1016/j.chb.2021.106784

Papastylianou, A. (2013). Relating on the internet, personality traits and depression: Research and implications. *The European Journal of Counselling Psychology*, *2*(1), 65–78. https://doi.org/10.5964/ejcop.v2i1.6

Patel, N., Kadavala, B., Chanpa, N., Tiwari, D., & Patel, V. (2021). Social media addiction: Role of social media use characteristics and personality factors among medical undergraduates. *International Journal of Current Research, 13*(8), 18480-18484. https://doi.org/10.24941/ijcr.42051.08.2021

Patrick, C. (2011). Student evaluations of teaching: Effects of the big five personality traits, grades and the validity hypothesis. *Assessment & Evaluation in Higher Education*, *36*(2), 239e249. http://dx.doi.org/10.1080/02602930903308258

Przepiorka, A., Blachnio, A., & Cudo, A. (2019). The role of depression, personality, and future time perspective in internet addiction in adolescents and emerging adults. *Psychiatry Research, 272*(1), 340-348. https://doi.org/10.1016/j.psychres.2018.12.086

Rabaa'i, A. A., Zogheib, B., & AlJamal, E. (2015). Personality traits as predictors of social networks addiction among university students. *Journal of Emerging Trends in Engineering and Applied Sciences*, *6*(3), 182-195. https://www.scholarlinkinstitute.org/jeteas/articles/Personality%20Traits%20as%20Predictors.pdf

Rauschnabel, P. A., Felix, R., & Hinsch, C. (2019). Augmented reality marketing: How mobile AR-apps can improve brands through inspiration. *Journal of Retailing and Consumer Services*, *49*, 43–53. https://doi.org/10.1016/j.jretconser.2019.03.004

Rettner, R. (2018, March 12). *These personality traits could put you at risk for Social Media Addiction*. LiveScience. https://www.livescience.com/61996-personality-social-media-addiction.html

Robbins, S., & Judge, T. (2013). *Organizational behavior*. Prentice Hall.

Rosenbaum, M. S., Ostrom, A. L., & Kuntze, R. (2005). Loyalty programs and a sense of community. *Journal of Services Marketing*, *19*(4), 222–233. https://doi.org/10.1108/08876040510605253

Seo, D. B., & Ray, S. (2019). Habit and addiction in the use of social networking sites: Their nature, antecedents, and consequences. *Computers in Human Behavior*, *99*, 109–125. https://doi.org/10.1016/j.chb.2019.05.018

Silvia, P. J., & Christensen, A. P. (2020). Looking up at the curious personality: Individual differences in curiosity and openness to experience. *Current Opinion in Behavioral Sciences*, *35*, 1–6. https://doi.org/10.1016/j.cobeha.2020.05.013

Sindermann, C., Elhai, J. D., & Montag, C. (2020). Predicting tendencies towards the disordered use of Facebook's social media platforms: On the role of personality, impulsivity, and Social Anxiety. *Psychiatry Research*, *285*, 112793. https://doi.org/10.1016/j.psychres.2020.112793

Siste, K., Hanafi, E., Sen, L. T., Christian, H., Adrian, Siswidiani, L. P., Limawan, A. P., Murtani, B. J., & Suwartono, C. (2020). The impact of physical distancing and associated factors towards internet addiction among adults in Indonesia during COVID-19 pandemic: A nationwide web-based study. *Frontiers in Psychiatry*, 11. https://doi.org/10.3389/fpsyt.2020.580977

Smiddy, C. (2020, March 3). *Can someone really have an addictive personality?* Hired Power. https://www.hiredpower.com/blog/can-someone-really-have-an-addictive-personality/

Snow, S. (2015, September 21). *How long does it take for social media marketing to start paying off?* Social Media Today. https://www.socialmediatoday.com/marketing/sarah-snow/2015-09-21/how-long-does-it-take-social-media-marketing-start-paying

Stanković, M., Nešić, M., Čičević, S., & Shi, Z. (2021). Association of smartphone use with depression, anxiety, stress, sleep quality, and internet addiction. Empirical evidence from a smartphone application. *Personality and Individual Differences*, *168*, 110342. https://doi.org/10.1016/j.paid.2020.110342

Sternlicht, L., & Sternlicht, A. (2022). *The 6 most common types of technology addiction*. Family Addiction Specialist: Addiction Counselor. https://www.familyaddictionspecialist.com/blog/the-6-most-common-types-of-technology-addiction

Stieger, S., Burger, C., Bohn, M., & Voracek, M. (2013). Who commits virtual identity suicide? Differences in privacy concerns, internet addiction, and personality between Facebook users and quitters. *Cyberpsychology, Behavior, and Social Networking*, *16*(9), 629–634. https://doi.org/10.1089/cyber.2012.0323

Tang, J.-H., Chen, M.-C., Yang, C.-Y., Chung, T.-Y., & Lee, Y.-A. (2016). Personality traits, interpersonal relationships, online social support, and Facebook addiction. *Telematics and Informatics*, *33*(1), 102–108. https://doi.org/10.1016/j.tele.2015.06.003

Turel, O., & Osatuyi, B. (2017). A peer-influence perspective on compulsive social networking site use: Trait mindfulness as a double-edged sword. *Computers in Human Behavior, 77*, 47-53. https://doi.org/10.1016/j.chb.2017.08.022

Vaghefi, I., & Qahri-Saremi, H. (2018). Personality predictors of IT addiction. *Proceedings of the 51st Hawaii International Conference on System Sciences.* https://doi.org/10.24251/hicss.2018.657

Wang, D. (2019). A study of the relationship between narcissism, extraversion, body-esteem, social comparison orientation and selfie-editing behavior on social networking sites. *Personality and Individual Differences*, *146*, 127–129. https://doi.org/10.1016/j.paid.2019.04.012

Wang, J., Wang, P., Yang, X., Zhang, G., Wang, X., Zhao, F., Zhao, M., & Lei, L. (2019). Fear of missing out and procrastination as mediators between sensation seeking and adolescent smartphone addiction. *International Journal of Mental Health and Addiction*, *17*(4), 1049–1062. https://doi.org/10.1007/s11469-019-00106-0

Wang, J. L., Jackson, L. A., Zhang, D. J., & Su, Z. Q. (2012). The relationships among the big five personality factors, self-esteem, narcissism, and sensation-seeking to Chinese University students' uses of social networking sites (SNSs). *Computers in Human Behavior*, *28*(6), 2313–2319. https://doi.org/10.1016/j.chb.2012.07.001

Watson, D., & Clark, L. A. (1997). Extraversion and its positive emotional core. In R. Hogan, J. Johnson, & S. Brigs (Eds.), *Handbook of personality psychology* (pp. 767–793). https://doi.org/10.1016/b978-012134645-4/50030-5

Wilson, K., Fornasier, S., & White, K. M. (2010). Psychological predictors of young adults' use of social networking sites. *Cyberpsychology, Behavior, and Social Networking*, *13*(2), 173–177. https://doi.org/10.1089/cyber.2009.0094

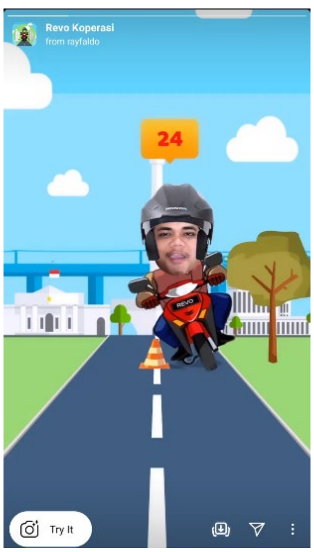
Yavuz, M., Çorbacıoğlu, E., Başoğlu, A. N., Daim, T. U., & Shaygan, A. (2021). Augmented reality technology adoption: Case of a mobile application in Turkey. *Technology in Society*, *66*, 101598. https://doi.org/10.1016/j.techsoc.2021.101598

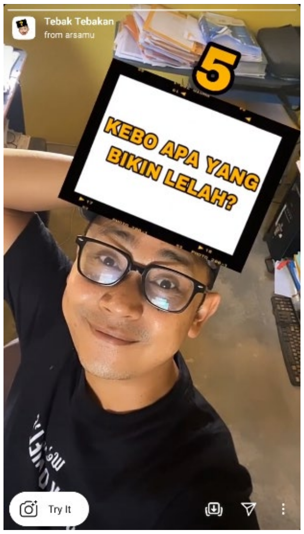
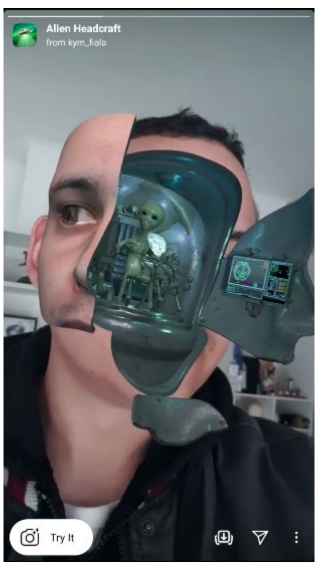
Yu, Z., Lian, J., Mahmoody, A., Liu, G., & Xie, X. (2019). Adaptive user modeling with long and short-term preferences for personalized recommendation. *Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence* (pp 4213-4219). https://doi.org/10.24963/ijcai.2019/585

Zhan, Z., Wei, Q., & Hong, J.-C. (2021). Cellphone addiction during the COVID-19 outbreak: How online social anxiety and cyber danger belief mediate the influence of personality. *Computers in Human Behavior, 121,* 106790. https://doi.org/10.1016/j.chb.2021.106790

APPENDIX A. AR FACE FILTERS

AR Face Filter	Description
 *Colour Adjustment Filter*	A face filter that changes the camera's color settings in real-time, resulting in more attractive color tones.
 *Beautifying Filter*	Face filters that provide AR-based virtual makeup such as face softening/whitening, virtual eyelashes, virtual eye shadows, blushes, and lipsticks.

AR Face Filter	Description
 *Random Filter*	A face filter that generates random results based on a given question, such as the "Animal What Am I?" filter.
 *Game Filter*	A face filter that allows users to act as if they are playing a game when using it.

AR Face Filter	Description
 *Quiz Filter*	Face filters that provide different types of questions for users to answer.
 *Immersive Filter*	Face filters that allow users to transform their faces or parts of their bodies into three-dimensional shapes.

APPENDIX B. RESEARCH QUESTIONNAIRE

1. Validation

Have you ever used the AR face filter feature available on social networking apps like Instagram, Facebook, TikTok or Snapchat? Yes/No

2. Demographic Information

a. Gender : Women/Men
b. Age : 12–16 years old/17–25 years old/26–35 years old
c. Domicile : Greater Jakarta/ Greater Jakarta in Java Island/ Sumatera/Others
d. Education level: Elementary School to High School/ Diploma/Bachelor/ Master/ Doctoral
e. Commonly used Social Networking: Instagram/ Facebook/ TikTok/ Snapchat

3. Measurement Items

Code	Measurement Items	References
EXT1	I like to liven up the atmosphere in an event	Akhtar and Azwar (2019)
EXT2	I feel comfortable around other people	
EXT3	I like to start a conversation	
EXT4	I like interacting with many people in an event	
EXT5	I don't mind being the center of attention	
AGR1	I care about other people	
AGR2	I sympathize with other people's feelings	
AGR3	I like to make time for other people	
AGR4	I like to understand other people's feelings	
AGR5	I like to make other people feel comfortable	
CON1	I always prepare everything	
CON2	I like to pay attention to things in detail	
CON3	I immediately do the assigned task	
CON4	I like regularity	

Code	Measurement Items	References
CON5	I do activities according to schedule or agenda	
CON6	I am diligent in doing my work	
NEU1	I get depressed easily	
NEU2	I worry easily	
NEU3	I have a mood that often changes quickly	
NEU4	I get irritated easily	
NEU5	I often feel upset	
OPN1	I have a very strong imagination	
OPN2	I have brilliant ideas	
OPN3	I'm quick to understand things	
OPN4	I take time to reflect on things	
OPN5	I have lots of ideas	
MBS1	I know most of my friends on my social network	J. Kim et al. (2020)
MBS2	I feel friends in my social network are my close friends	Naranjo-Zolotov et al. (2021)
MBS3	I feel comfortable when I'm with friends on my social network	J. Kim et al. (2020)
MBS4	I like friends on my social networks	Naranjo-Zolotov et al. (2021)
IFN1	I often interact with friends on my social networks	J. Kim et al. (2020)
IFN2	I care about what my friends on social networks think about my posts	

Code	Measurement Items	References
IFN3	I feel I can influence friends on my social network	Naranjo-Zolotov et al. (2021)
IFN4	I noticed that my activity posts are often seen by friends on my social networks	
IMS1	I spend a lot of time online with friends on my social networks	Naranjo-Zolotov et al. (2021)
IMS2	I spend more time than I expected interacting with friends on my social networks	
IMS3	I really need interaction with friends on my social networks	
IMS4	I feel that interactions with friends on social networks can interfere with other activities	Keng et al. (2011)
ARA1	I feel less confident when interacting in the real world because I am used to using face filters on social networks	Turel & Osatuyi (2017)
ARA2	I feel uncomfortable when posting my face without a filter on social networks	
ARA3	I feel too dependent on face filters on social networks	
ARA4	I will definitely use filters before uploading my face posts on social networks	Zhan et al. (2021)
OSA1	I feel uneasy when no one responds to my posts using face filters on social networks	
OSA2	I'm worried about the negative feedback from other people about my posts using face filters on social networks	
OSA3	I will feel uneasy if someone criticizes my posts using face filters on social networks	
OSA4	I am afraid of getting verbal attacks from others when I often share my posts using face filters on social networks	

APPENDIX C. MULTICOLLINEARITY TEST

	ARA3	ARA2	OSA1	OSA2	MBS1	MBS2	MBS3	MBS4	IFN1	IFN2
ARA3	1.00									
ARA2	0.79	1.00								
OSA1	0.65	0.67	1.00							
OSA2	0.69	0.70	0.65	1.00						
MBS1	0.08	0.04	0.07	0.06	1.00					
MBS2	0.35	0.32	0.39	0.32	0.31	1.00				
MBS3	0.31	0.32	0.33	0.30	0.33	0.68	1.00			
MBS4	0.25	0.23	0.23	0.23	0.39	0.57	0.61	1.00		
IFN1	0.16	0.12	0.20	0.13	0.58	0.49	0.45	0.47	1.00	
IFN2	0.31	0.33	0.37	0.36	0.26	0.56	0.56	0.47	0.36	1.00
IFN3	0.27	0.23	0.32	0.21	0.34	0.51	0.55	0.51	0.43	0.45
IFN4	0.18	0.15	0.21	0.15	0.38	0.33	0.39	0.45	0.39	0.35
IMS1	0.34	0.31	0.35	0.33	0.36	0.66	0.61	0.51	0.62	0.49
IMS2	0.38	0.40	0.42	0.37	0.27	0.63	0.67	0.51	0.43	0.56
IMS3	0.34	0.32	0.40	0.37	0.28	0.53	0.56	0.54	0.42	0.53
IMS4	0.25	0.23	0.32	0.23	0.15	0.22	0.23	0.22	0.14	0.23
OPN1	0.09	0.10	0.12	0.13	0.19	0.25	0.24	0.22	0.26	0.17
OPN2	0.13	0.13	0.18	0.11	0.26	0.27	0.27	0.28	0.30	0.21
OPN3	0.13	0.10	0.17	0.09	0.27	0.19	0.16	0.24	0.24	0.19
OPN4	0.12	0.13	0.15	0.12	0.20	0.19	0.21	0.26	0.27	0.22
OPN5	0.14	0.16	0.20	0.14	0.29	0.29	0.27	0.30	0.32	0.21
NEU1	0.26	0.27	0.26	0.34	-0.04	0.17	0.16	0.11	0.01	0.20
NEU2	0.26	0.26	0.24	0.33	0.06	0.22	0.20	0.19	0.11	0.21
NEU3	0.27	0.24	0.28	0.29	0.03	0.18	0.15	0.16	0.10	0.16

	ARA3	ARA2	OSA1	OSA2	MBS1	MBS2	MBS3	MBS4	IFN1	IFN2
NEU4	0.28	0.24	0.29	0.26	0.06	0.22	0.20	0.18	0.11	0.18
NEU5	0.37	0.35	0.34	0.39	0.05	0.26	0.24	0.19	0.16	0.25
CON1	0.08	0.07	0.10	0.06	0.21	0.17	0.15	0.22	0.21	0.15
CON2	0.05	0.05	0.08	0.07	0.22	0.14	0.13	0.21	0.17	0.17
CON3	0.16	0.17	0.22	0.12	0.19	0.22	0.18	0.20	0.20	0.22
CON4	0.08	0.10	0.07	0.09	0.25	0.20	0.23	0.28	0.24	0.24
CON5	0.11	0.10	0.16	0.07	0.22	0.18	0.16	0.23	0.25	0.17
CON6	0.17	0.19	0.17	0.15	0.26	0.26	0.25	0.28	0.25	0.24
AGR1	0.05	0.07	0.04	0.10	0.20	0.19	0.21	0.31	0.27	0.24
AGR2	0.09	0.11	0.09	0.13	0.26	0.22	0.26	0.39	0.29	0.30
AGR3	0.11	0.09	0.14	0.08	0.29	0.25	0.31	0.36	0.30	0.24
AGR4	0.14	0.12	0.12	0.11	0.28	0.24	0.31	0.37	0.31	0.28
AGR5	0.05	0.04	0.05	0.10	0.31	0.20	0.26	0.36	0.29	0.25
EXT1	0.03	-0.02	0.12	-0.01	0.31	0.24	0.17	0.25	0.37	0.17
EXT2	0.06	0.02	0.13	0.04	0.31	0.25	0.25	0.32	0.37	0.20
EXT3	0.04	0.03	0.13	0.02	0.29	0.22	0.22	0.25	0.33	0.22
EXT4	0.10	0.06	0.21	0.05	0.37	0.29	0.25	0.33	0.42	0.23
EXT5	0.16	0.08	0.23	0.04	0.27	0.24	0.24	0.23	0.32	0.19
OSA3	0.71	0.69	0.65	0.78	0.07	0.37	0.33	0.28	0.17	0.40
OSA4	0.65	0.63	0.60	0.75	0.04	0.36	0.30	0.25	0.15	0.38
ARA1	0.71	0.72	0.63	0.61	0.06	0.33	0.31	0.26	0.15	0.29
ARA4	0.75	0.74	0.57	0.56	0.08	0.32	0.30	0.27	0.18	0.33

	IFN3	IFN4	IMS1	IMS2	IMS3	IMS4	OPN1	OPN2	OPN3
ARA3									
ARA2									
OSA1									
OSA2									
MBS1									
MBS2									
MBS3									
MBS4									
IFN1									
IFN2									
IFN3	1.00								
IFN4	0.45	1.00							
IMS1	0.47	0.34	1.00						
IMS2	0.49	0.33	0.68	1.00					
IMS3	0.56	0.36	0.51	0.56	1.00				
IMS4	0.32	0.20	0.22	0.28	0.22	1.00			
OPN1	0.25	0.20	0.27	0.24	0.17	0.14	1.00		
OPN2	0.33	0.25	0.26	0.21	0.23	0.24	0.43	1.00	
OPN3	0.26	0.23	0.19	0.19	0.19	0.16	0.25	0.41	1.00
OPN4	0.26	0.21	0.23	0.22	0.24	0.18	0.26	0.40	0.24
OPN5	0.31	0.27	0.31	0.25	0.27	0.23	0.44	0.72	0.38
NEU1	0.13	0.07	0.22	0.25	0.13	0.15	0.28	-0.02	0.00
NEU2	0.15	0.11	0.25	0.29	0.19	0.19	0.22	0.07	0.04
NEU3	0.13	0.10	0.27	0.27	0.19	0.17	0.22	0.10	0.12
NEU4	0.19	0.07	0.25	0.27	0.18	0.23	0.17	0.04	0.05

	IFN3	IFN4	IMS1	IMS2	IMS3	IMS4	OPN1	OPN2	OPN3
NEU5	0.22	0.15	0.33	0.36	0.23	0.20	0.20	0.04	0.03
CON1	0.21	0.26	0.12	0.13	0.19	0.12	0.24	0.36	0.32
CON2	0.17	0.19	0.14	0.12	0.18	0.17	0.22	0.36	0.36
CON3	0.18	0.20	0.17	0.18	0.22	0.16	0.14	0.34	0.36
CON4	0.22	0.27	0.19	0.16	0.23	0.14	0.19	0.33	0.28
CON5	0.22	0.27	0.15	0.14	0.19	0.13	0.16	0.37	0.32
CON6	0.26	0.27	0.22	0.21	0.25	0.17	0.22	0.38	0.39
AGR1	0.13	0.20	0.17	0.15	0.16	0.10	0.18	0.21	0.20
AGR2	0.23	0.26	0.21	0.20	0.21	0.12	0.23	0.25	0.21
AGR3	0.28	0.27	0.21	0.23	0.29	0.13	0.11	0.29	0.22
AGR4	0.25	0.26	0.24	0.24	0.25	0.15	0.20	0.27	0.30
AGR5	0.19	0.29	0.21	0.20	0.25	0.10	0.25	0.24	0.23
EXT1	0.25	0.27	0.21	0.14	0.22	0.18	0.21	0.36	0.27
EXT2	0.30	0.31	0.23	0.19	0.26	0.18	0.19	0.26	0.26
EXT3	0.30	0.25	0.17	0.17	0.21	0.20	0.13	0.35	0.22
EXT4	0.37	0.31	0.27	0.21	0.29	0.26	0.18	0.33	0.32
EXT5	0.36	0.33	0.21	0.12	0.25	0.20	0.17	0.36	0.29
OSA3	0.28	0.17	0.39	0.41	0.39	0.24	0.14	0.10	0.09
OSA4	0.25	0.14	0.39	0.42	0.36	0.24	0.13	0.09	0.11
ARA1	0.30	0.19	0.33	0.40	0.37	0.31	0.14	0.16	0.11
ARA4	0.24	0.22	0.34	0.38	0.33	0.18	0.11	0.15	0.16

	OPN4	OPN5	NEU1	NEU2	NEU3	NEU4	NEU5	CON1	CON2
ARA3									
ARA2									
OSA1									
OSA2									
MBS1									
MBS2									
MBS3									
MBS4									
IFN1									
IFN2									
IFN3									
IFN4									
IMS1									
IMS2									
IMS3									
IMS4									
OPN1									
OPN2									
OPN3									
OPN4	1.00								
OPN5	0.34	1.00							
NEU1	0.15	0.03	1.00						
NEU2	0.23	0.05	0.67	1.00					
NEU3	0.24	0.15	0.49	0.52	1.00				
NEU4	0.21	0.09	0.53	0.51	0.54	1.00			

	OPN4	OPN5	NEU1	NEU2	NEU3	NEU4	NEU5	CON1	CON2
NEU5	0.21	0.13	0.54	0.51	0.48	0.51	1.00		
CON1	0.37	0.29	0.11	0.17	0.07	0.08	0.10	1.00	
CON2	0.31	0.30	0.03	0.15	0.09	0.09	0.06	0.47	1.00
CON3	0.28	0.27	-0.02	0.10	0.07	0.05	0.08	0.45	0.35
CON4	0.36	0.29	0.08	0.16	0.12	0.19	0.08	0.51	0.43
CON5	0.32	0.32	0.00	0.05	0.03	0.06	0.08	0.54	0.36
CON6	0.33	0.38	0.03	0.12	0.11	0.06	0.09	0.46	0.35
AGR1	0.21	0.19	0.10	0.19	0.10	0.08	0.08	0.31	0.26
AGR2	0.30	0.24	0.13	0.22	0.12	0.10	0.13	0.33	0.37
AGR3	0.24	0.27	-0.04	0.08	0.07	0.04	0.10	0.22	0.23
AGR4	0.34	0.25	0.09	0.15	0.15	0.12	0.16	0.31	0.30
AGR5	0.32	0.23	0.09	0.20	0.19	0.14	0.12	0.27	0.29
EXT1	0.24	0.34	-0.06	0.01	0.02	0.01	0.01	0.29	0.20
EXT2	0.16	0.25	-0.05	0.00	0.00	0.01	0.05	0.19	0.20
EXT3	0.20	0.28	-0.10	0.01	-0.01	0.04	-0.02	0.24	0.13
EXT4	0.24	0.30	-0.07	0.00	0.07	0.08	0.03	0.25	0.19
EXT5	0.22	0.32	-0.05	-0.04	0.07	0.02	0.06	0.19	0.15
OSA3	0.12	0.16	0.32	0.33	0.34	0.30	0.38	0.09	0.07
OSA4	0.12	0.13	0.36	0.32	0.32	0.30	0.42	0.10	0.04
ARA1	0.15	0.19	0.29	0.28	0.30	0.28	0.37	0.07	0.07
ARA4	0.13	0.17	0.23	0.24	0.22	0.22	0.30	0.11	0.08

	CON3	CON4	CON5	CON6	AGR1	AGR2	AGR3	AGR4	AGR5
ARA3									
ARA2									
OSA1									
OSA2									
MBS1									
MBS2									
MBS3									
MBS4									
IFN1									
IFN2									
IFN3									
IFN4									
IMS1									
IMS2									
IMS3									
IMS4									
OPN1									
OPN2									
OPN3									
OPN4									
OPN5									
NEU1									
NEU2									
NEU3									

	CON3	CON4	CON5	CON6	AGR1	AGR2	AGR3	AGR4	AGR5
NEU4									
NEU5									
CON1									
CON2									
CON3	1.00								
CON4	0.38	1.00							
CON5	0.52	0.52	1.00						
CON6	0.53	0.44	0.51	1.00					
AGR1	0.26	0.23	0.23	0.22	1.00				
AGR2	0.30	0.27	0.25	0.23	0.59	1.00			
AGR3	0.32	0.21	0.22	0.24	0.40	0.44	1.00		
AGR4	0.28	0.33	0.28	0.25	0.45	0.57	0.46	1.00	
AGR5	0.16	0.30	0.28	0.22	0.47	0.53	0.41	0.53	1.00
EXT1	0.27	0.21	0.24	0.23	0.37	0.33	0.40	0.33	0.35
EXT2	0.23	0.20	0.24	0.19	0.32	0.38	0.46	0.35	0.37
EXT3	0.31	0.22	0.21	0.19	0.28	0.32	0.51	0.39	0.30
EXT4	0.31	0.26	0.31	0.23	0.29	0.32	0.47	0.41	0.33
EXT5	0.22	0.18	0.21	0.21	0.16	0.22	0.35	0.31	0.26
OSA3	0.12	0.10	0.07	0.14	0.09	0.17	0.07	0.13	0.11
OSA4	0.15	0.08	0.07	0.18	0.09	0.16	0.06	0.11	0.08
ARA1	0.18	0.09	0.15	0.18	0.07	0.10	0.10	0.11	0.06
ARA4	0.19	0.11	0.15	0.23	0.10	0.13	0.14	0.17	0.12

	EXT1	EXT2	EXT3	EXT4	EXT5	OSA3	OSA4	ARA1	ARA4
ARA3									
ARA2									
OSA1									
OSA2									
MBS1									
MBS2									
MBS3									
MBS4									
IFN1									
IFN2									
IFN3									
IFN4									
IMS1									
IMS2									
IMS3									
IMS4									
OPN1									
OPN2									
OPN3									
OPN4									
OPN5									
NEU1									
NEU2									
NEU3									
NEU4									

	EXT1	EXT2	EXT3	EXT4	EXT5	OSA3	OSA4	ARA1	ARA4
NEU5									
CON1									
CON2									
CON3									
CON4									
CON5									
CON6									
AGR1									
AGR2									
AGR3									
AGR4									
AGR5									
EXT1	1.00								
EXT2	0.50	1.00							
EXT3	0.59	0.50	1.00						
EXT4	0.61	0.60	0.65	1.00					
EXT5	0.47	0.44	0.47	0.53	1.00				
OSA3	0.02	0.02	0.05	0.06	0.08	1.00			
OSA4	0.02	0.02	0.02	0.04	0.03	0.78	1.00		
ARA1	0.00	0.02	0.03	0.07	0.10	0.61	0.59	1.00	
ARA4	0.09	0.11	0.11	0.15	0.18	0.60	0.59	0.59	1.00

APPENDIX D. COMMON METHOD BIAS TEST RESULT

Extraction Sums of Squared Loadings		
Total	*% of Variance*	*Cumulative %*
12.21	26.55	26.55

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