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Article

Determinants of Behavioral Intention in Augmented Reality Filter Adoption: An Integrated TAM and Satisfaction–Loyalty Model Approach

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Abstract

This study dives into what drives people to use AR filters in the catering industry, focusing on the Hong Kong market. The main idea is to determine how "perceived value" shapes users' intentions to engage with these filters. To do this, the research combines concepts from two popular models—the extended Technology Acceptance Model (TAM) and the Satisfaction–Loyalty Model (SLM)—to understand what influences perceived value. The survey data were then analyzed with Structural Equation Modeling (SEM) to see how perceived usefulness, enjoyment, satisfaction, and value connect to users' intentions. The results showed that "perceived value" is a big deal—the main factor driving whether people want to use AR filters. Things like how useful or enjoyable the filters are and how satisfied users feel all play a role in shaping this perceived value. These findings are gold for marketing teams and AR developers, especially in the catering world. Combining TAM and the Satisfaction–Loyalty Model offers a fresh perspective on how AR technology influences consumer behavior. On top of that, it gives practical advice for businesses looking to make the most of AR filters in their marketing and customer experience strategies.

Keywords: augmented reality; structural equation model; behavioral intention; technology acceptance model

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1. Introduction

In the 21st century, the swift advancement of information and communication technologies has brought about profound transformations in the business landscape. The widespread use of social media platforms has connected users from diverse backgrounds, transforming how global citizens access information online. Mobile social media (MSM) apps have become an essential part of people's daily routines, prompting businesses to leverage these platforms to promote their brands. This has led to the emergence of a new type of commerce known as social commerce. The integration of advanced technologies, such as augmented reality (AR), into MSM apps enhances user experiences, leading to increased engagement [1–4]. AR effects, such as AR 3D object filters and face masks, combine the user's face or natural environment with AR elements, enabling interactive experiences [5]. The usage of AR technology has been on the rise, with an estimated 0.81 billion active AR users worldwide in 2021 and an expected growth to 1.73 billion users by 2024 [6]. Marketing managers have recognized the potential of AR technology in their activities on social media apps, leading to the emergence of AR marketing [7–10]. Various brands across industries have already applied AR technology to provide immersive experiences for promotional purposes and to influence purchase decisions [11,12]. However, there has been a lack of successful examples of AR experiences explicitly developed for different products and services in recent years. This dearth of information and insights hinders the development of immersive AR filters and limits our understanding of user behavior and motivations behind their usage. This study seeks to investigate the reasons behind users' engagement with AR filters and offer valuable insights and recommendations for AR filter developers aiming to design immersive marketing tools to promote catering products and services [13–18]. E-commerce has become a prevalent trend, with enterprises across various industries adopting strategies to develop their businesses. Brands providing catering services follow suit by establishing e-commerce operations to enhance their sales performance [7–10,19]. AR technology has provided real-time product information to potential customers, enhancing their purchase decisions. These examples can serve as references for catering products and service providers looking to create AR experiences for their potential customers. In this context, utilizing mobile social media (MSM) with AR filters can be useful for promoting catering brands, including product and restaurant information. MSM offers convenience and low-cost access to potential customers while stimulating awareness and discussions through user sharing. Therefore, developing AR filters for promotional purposes can be a viable direction for marketing catering products and services, including social media.

1.1. Mobile Social Media (MSM) and Augmented Reality Filter

The integration of MSM and AR filters has emerged as a major trend in recent years. The widespread adoption of mobile devices and the growing popularity of social media platforms have driven the evolution of MSM. As of January 2021, there were 4.15 billion active MSM users, representing over 98% of all active social media users [20]. This phenomenon indicates the immense potential of MSM as a future direction for social media platforms. Social media platforms offer various functions and features to cater to user preferences, such as the ability to watch videos and view photos rather than just reading text messages [21]. This multimedia nature of social media has contributed to its rapid growth. Users increasingly follow brand accounts on social media platforms to gain more information about the products and services they are interested in. Businesses have recognized the importance of social media as an effective marketing tool, as it can significantly influence customer loyalty and purchase behavior, as Ceyhan [21] mentioned. With the growth of e-commerce and social commerce, businesses are dedicating more resources to crafting marketing strategies that promote their brands via social media platforms, resulting in the development of innovative marketing approaches. A key feature of MSM is "Stories," which enables users to capture, record, and share multiple photos and videos through their mobile device's camera. Several popular social networks have adopted the Stories feature [22]. To provide a premium user experience and increase user satisfaction, MSM platforms have incorporated innovative technologies into their mobile applications, including AR technology embedded in the Stories feature in the digital space.

AR refers to the overlay of digital objects onto the real-world environment in real time, creating an interactive and synchronized experience [23]. With the widespread availability of AR technology, its applications have expanded, and one emerging trend is the integration of AR technology into the camera functions of social media platforms to create AR filters [24–28]. Snapchat was the first MSM platform to introduce AR effects to its Stories feature, and Instagram and Facebook followed suit to stay competitive [29].

Research forecasted that the global revenue from the mobile AR market will increase from USD 3.99 billion in 2019 to USD 26.06 billion in 2025 [30]. This market information highlights the potential of AR development in MSM applications, driving the intense competition in the AR technology market. AR filters, also known as AR lenses or effects, allow MSM users to use their device's camera to capture photos and videos with virtual effects or superimposed content on real-life images. These augmented images or videos can then be shared in Stories, enabling users to interact more and communicate with others. AR filters provide unique and interesting experiences, which contribute to their popularity [13–18]. The success of AR filters has led MSM platforms to open up the creation of filters to all users, including active users, artists, and creators, to develop a wide range of AR filters and attract more users. This openness also enables brands to develop their own AR filters for marketing purposes, turning AR filters into a valuable marketing tool for promotion [31]. Overall, AR filters provide unique and engaging experiences, contributing to their widespread adoption and usage for marketing [32].

1.2. Augmented Reality Marketing

AR marketing is a modern marketing concept that incorporates computer-generated content or objects into the audience's real-world environment to convey organizational messages and benefits [23]. It offers an immersive experience to customers, enabling them to understand products and services better and make informed purchase decisions [33]. The use of AR in marketing is on the rise, with the number of mobile AR active users projected to reach 1.73 billion in 2024 [6]. Studies also indicate that a significant percentage of consumers are interested in retailers that provide AR experiences and are more likely to engage and make purchases in such environments [34]. These insights highlight the growing importance of AR technology in marketing [14,27,28,35–42]. Marketing managers are increasingly embracing innovative technologies like AR as marketing tools to promote their brands [16,43–49]. Advertising agencies also report increased AR use in their campaigns [50]. AR marketing has the potential to become a prominent trend in the business world, with AR technology being widely applied in various marketing activities. AR technology can be employed in different forms in marketing, such as offering AR product trials and preview experiences. AR filters in MSM applications can also serve as effective marketing tools, delivering brand information interactively and engagingly to a large user base. Therefore, designing compelling AR filters to promote brand information is crucial, as the user base of social media platforms can amplify the reach of marketing activities through the sharing of brand content among users [51–57]. Therefore, researching the reasons behind AR filters' usage can provide valuable insights for AR filter developers and marketing managers, guiding them in leveraging this technology effectively for marketing purposes. However, despite the potential of AR filters in marketing, there seems to be a lack of research on their effectiveness, leading to businesses investing fewer resources in designing branded AR filters than expected.

1.3. Research Questions

1. What is the influence of AR filters on customer behavior in online shopping?

The purpose of this research is to investigate the effect of AR filters on customer behaviour and online shopping. As an advanced technology, AR overlays the digital content with the physical world by electronically blending devices realistically. AR filters are an excellent example of a unique feature integrated within MSM platforms with various applications [58–61], as they facilitate users' creative interaction with brands and content. AR filters have not yet been widely accepted in widespread use, and users' perceptions of usefulness and ease of use play key roles in determining both behavioral intentions and adoptive behavior. With the diffusion of AR filters, MSM users are incorporating them into their mundane lives, and they are reshaping not only how users interact with digital content but also the mediatization of MSM platforms. To tap into this growing trend, companies are now using AR filters as marketing instruments to increase brand exposure and reach potential customers. However, the utility of AR filters for prompting engagement and activation remains underexamined due to earlier stages of their life cycle. This study aims to determine the major motivations of AR filter usage and to examine their influence on marketing tactics and on managerial decision making. In doing so, it hopes to provide some valuable insights for the complex interplay between AR technology, consumer behaviour, and MSM platforms.

2. How will customer expectations be satisfied through the current marketing approaches?

In this research, we investigate research on how to solve customer demand using different marketing strategies of the catering industry in the changing market environment under social commerce. More and more good cuisine companies have abandoned the traditional MSM platform, and use appealing content for marketing (for example, photos and videos) to attract the attention of potential customers. However, with the rise of AR technology, particularly AR filters, MSM usage is changing, and user behavior is being influenced [19–22]. Despite being both immersive and interactive, AR filters are confirmed to be part of users' daily routine, challenging the power and influence level of traditional marketing campaigns and strategies. Consumers prefer going to the shop to obtain an AR-improved service by word of mouth because hands-on shopping is more appealing in stores that can enhance the shopping experience with augmented reality, and consumers are showcased through empirical studies to have a greater trust that increases positive perceptions [34]. While the potential is there, AR filters' use on the marketing side is limited, and it is not often that managers are using AR filters effectively in a way that satisfies the expectations of the audience. By doing so, the present study aims to provide a better understanding of why companies may want to adopt AR filters, consequently improving how these services can be strategically employed to help companies fill the void between customer expectations and companies' current marketing efforts. The conclusions contribute to offering actionable recommendations for the craft of AR-based strategies' formation and implementation, ensuring the coherence with customers' requirements, and increasing the overall effectiveness of marketing in catering.

3. How does the effectiveness of AR filter marketing affect the current situation?

The impact of AR filter marketing has changed the game in marketing today and provided companies with new techniques to improve brand promotion. With the development of e-commerce and the emergence of mobile commerce, digital marketing has been promoted. AR filters that are free on MSM platforms based in reality can be used as an effective tool for spreading the branding among its colossal number of subscribers. Despite the booming popularity, little research can be found that investigates the marketing potential of AR filters, as they are still at their preliminary stage of adoption. ATM usage continues to exist, and thus, the factors influencing user acceptance and satisfaction with AR filters warrant investigation. Knowledge of these factors is really important for the creation and optimization of brand AR filters and for guaranteeing their use as an effective marketing tool. The results of this research are expected to identify critical factors that will enable companies to improve marketing and exploit the potential of AR in enhancing the engagement of consumers and increasing brand exposure. This paper intends to examine antecedents that impact the intention and behavior of MSM users to use AR filters in MSM apps. Though AR filters have been rapidly developed, their adoption varies widely among demographics, and the perceived value from users also varies. For businesses to best take advantage of AR filters as a marketing tool, it is important to understand the factors that increase the adoption of these objects. This in turn enables the creation of customized branded AR filters that genuinely connect with users, thus optimizing the degree of user satisfaction and the impact on marketing. In order to fulfill these objectives, in this research, a literature review of theoretical frameworks is carried out in order to analyze internal and external factors that affect consumer intention and behavior. By pinpointing the most important factors affecting user acceptance and satisfaction, the study contributes insight into the adoption of and, in particular, the effectiveness of AR filters. More specifically, this study targets the catering industry in Hong Kong, in which conventional content marketing, such as editing of photos and videos, generally fails to satisfy the expectations of customers. These traditional approaches often fall short of accurately visualizing the food and beverage service and have shown promise in projecting the look of catered offerings via AR filter settings before they exist in reality. Although there is a lot of potential, AR filters are not currently marketing tools often seen in use, especially in the Hong Kong market. The examination of AR filters' use as marketing tools in this context is the focus of this research and offers important implications for catering service providers. From bridging the divide between customer expectations and marketing results, and improving customer engagement and satisfaction, AR filters can be applied by enterprises to propel the growth of any business.

The paper is structured as follows: Section 2 presents the hypothesis model, which establishes the theoretical framework based on the Technology Acceptance Model (TAM) and Satisfaction–Loyalty Model with an extension. In Section 3, the methodology employed for survey development is elucidated. This session includes a detailed explanation of the sampling strategy, the process of data collection, and the measurement scales employed. Section 4 provides a comprehensive presentation of the results and findings derived from the empirical analysis conducted. The ensuing discussion and implications of the findings are expounded upon in Section 5. This section also encompasses a concluding summary that encapsulates the main insights gleaned from the study. Finally, Section 6 critically examines the limitations of the research and suggests avenues for future inquiry, aimed at further advancing our understanding of the topic.

2. Hypothesis Model

This section primarily focuses on elucidating the underlying reasons for formulating the hypothesis model. It describes two fundamental models: the Technology Acceptance Model and the Satisfaction–Loyalty Model. Furthermore, a summary of the research gap is provided, highlighting the existing knowledge deficit in the field.

2.1. Technology Acceptance Model (TAM)

TAM was widely applied to investigate and explain the reason behind users' behavioral intention toward a system or technology through their acceptance level. It is a theoretical framework for measuring user behavioral intention of adopting products and services with newly invented technology applied, and is appropriate for evaluating users' acceptance level and behavioral intention toward new systems and technologies [62–64]. Davis [65] first proposed TAM, which concerns the Theory of Reasonable Action, as a theoretical framework to explain user behavior and acceptance of information systems or technologies, including four constructs: Perceived Usefulness (PU), Perceived Ease of Use (PEU), Attitude toward Using, and Actual System Use. Davis [62] found that intention had a significant correlation with usage, which led to Davis et al. [64] modifying the original TAM to a new version of TAM in which a new construct, Intention to Use, was added into the modified version of TAM for the purpose of explaining the user behavior of the computer. In further research, the construct of Attitude toward Using was removed from the model as the attitude construct did not fully mediate the effect of PU on behavioral intention. However, the PU and PEU constructs were investigated as the determinants directly affecting behavior intention [66]. After further research, more determinants of PU and PEU, as well as the factors affecting the effect of constructs, were added to TAM [67,68], and other different forms of extended TAM and integrated model were built based on the development of the final version of TAM such as the Unified Theory of Acceptance and Use of Technology (UTAUT) and TAM for a hedonic information system [69].

The extended TAM for a hedonic information system was developed by adding the Perceived Enjoyment (PE) construct as an intrinsic motivation, which was found to have a significant effect on the users' behavior intention of the system and technology, to the TAM to study the usage intention of the system and technology that generated a hedonic value to the users [63,69,70]. The developed TAM for the hedonic information system was widely used to investigate the effect of hedonic value on behavioral intention, such as accessing the World Wide Web context and online shopping [71,72]. The studied system or technology usually could generate hedonic value to the users or the entertaining purposes, while the AR filter function also has an entertaining effect on users, which supports it being suitable for being studied with the extended TAM for hedonic information [32,69]. Moreover, the three primary constructs, which have a significant effect on the usage behavior but exclude the effect of the factors regardless of the system or technology development itself such as social influences or incident impact [69], can help focus on the specific factors to give meaningful insights to the developer for building an AR filter. Therefore, the proposed model can be built based on the extended TAM for hedonic information systems and to investigate the new determinants and factors to understand deeply and clearly the mediating effect of the three main constructs on behavior intention, and to study the reason behind the usage of AR filters. The TAM is normally connected with the satisfaction–loyalty model by different researchers in different fields.

2.2. Satisfaction–Loyalty Model (SLM)

The concepts of customer satisfaction and loyalty were investigated and introduced in 1997, and the Satisfaction–Loyalty Model was developed in later research [73,74]. It was a theoretical model explaining the reason behind the purchase behavior and repurchase behavior toward a brand through the concept of customer satisfaction and loyalty. The model is widely applied to the marketing field to find out the factors affecting customer satisfaction and loyalty to improve the performance of firms and retain customers [75–77]. Customer satisfaction and loyalty play a significant role in purchase behavior, as it is customers' perception of the products and services [74].

The quality and performance of products and services were found to have a significant impact on customer satisfaction and loyalty [75], while other research found that the perceived value was the factor affecting them [76,77], which assisted in developing different forms of the research framework with the application of the Satisfaction–Loyalty Model. As information technology advances and online services become increasingly popular, some researchers have integrated the Satisfaction–Loyalty Model with TAM to better understand users' overall behavioral intentions toward new technologies or systems [78–81]. This study investigates behavioral intention toward AR filters using an integrated model that combines the Satisfaction–Loyalty Model and the extended TAM. It is particularly significant to examine users' perceptions and feelings toward AR filters, as this emerging technology provides hedonic value. Consequently, the proposed model incorporates the Satisfaction–Loyalty Model to identify the factors influencing AR filter usage and analyze the mediating effects of user satisfaction and loyalty on behavioral intention.

In the field of justice AR filters, it is important to note the differences between satisfaction and loyalty as they represent a specific user response. Satisfaction is defined as the user's affective response to the AR filter being used at that specific moment, and it is reached only if the interaction is at least as enjoyable as the user expected it. This includes the innovation, and additionally the comparison of if it was what was expected and what the user found engaging. On the other hand, loyalty is solely the user's willingness to use the AR filter longer, and to recommend it, which indicates an attitudinal and behavioral commitment. However, despite the fact that is it is most typical to find the three of them being discussed simultaneously in the service and technology adoption literature, the situation is different in the case of hedonic AR filters, where the precedence of the factors is linked to the strong emphasis on experiential value and social influence. The articulation of these metrics was primarily driven by the literature but was intentionally formed to align with the playful, entertainment-oriented structure of AR filters in the context of social media. In this sense, the differentiation of the two exposes the entrapment of the digital channels by positive user experiences, which in turn result in their engagement and advocacy behaviors.

The current research combines TAM with the SLM in order to deal with the multidimensional user engagement using AR filters. Although TAM has been extensively used to predict technology adoption as a function of constructs such as perceived usefulness, perceived ease of use, and attitude toward use, there is recent evidence that "attitude" does not completely account for the affective and post-adoption aspects important in experiential and hedonic digital environments. In the domain of AR filters—where sustained engagement, emotional appeal, and repeated usage are key—user satisfaction and loyalty are more tangible, direct outcomes than a generic attitude measure. Accordingly, this research modifies the TAM by including satisfaction and loyalty, as opposed to attitude toward use, to accommodate recent calls to harmonize acceptance models with the requisites of digital consumer experiences. This hybrid model can have some theoretical advantages over models like UTAUT2. Second, it enables a more fine-grained investigation into the initial acceptance (through TAM constructs) as well as the continuous interaction between users and AR filters (through constructs relating to SLM), bridging the adoption and post-adoption behaviors. Second, due to modelling satisfaction and loyalty explicitly (as opposed to via satisfaction to the former as is performed in the TR model), the framework can capture the affective and behavioral antecedents of continued use and advocacy (which are more pertinent in SM and AR contexts). Finally, this integration of perspectives allows a broader view of the underpinnings of user engagement, combining explanation depth with practical applicability for the design and management of AR filter experiences.

2.3. Research Gap

Although the study of AR and its applications has been growing in popularity, there are still many areas lacking in the existing literature that need further examination. First, little has been studied in relation to AR filter usage behavioral intention. Previous studies have mainly examined the benefits of AR technology in the retail and construction sectors—e.g., AR-based retailing and the use of AR in building design—leaving the antecedents of the adoption and use of AR filters unexplored. Furthermore, the internal design characteristics that have an impact on the users' use and intention in the case of AR filters have not been fully investigated, which represents a lack of knowledge in relation to how these features may affect the way users interact. Second, the vast majority of papers on AR marketing have mainly examined the retailing field, and have extremely rarely taken into consideration the catering industry. Although the impact of AR on consumer purchasing behavior has been studied in retail stores, only a few studies have centered on factors influencing the behavioral intention of AR filter use in the catering environment. Since catering facilities are unique as they are strongly associated with experience engagement, among other industry-specific attributes, we need to know how AR filters can meet the challenges faced by the catering industry. Finally, there is a lack of work in terms of evaluating the effectiveness of AR filter marketing campaigns. While prior studies have explored AR applications in mobile-based retail settings, scant effort has been made to investigate operational implications and the strategic significance of AR filter marketing. This includes knowledge about the impact of AR filters on consumer engagement, satisfaction, and loyalty, especially in non-retail environments, such as catering. The answers to these questions will not only contribute to the current knowledge on AR but also support academic investigation and industry-oriented exploitation. Exploring the behavior-strategy dimension of AR filter use, this research aims to provide insights into the creation and promotion of effective AR filter marketing strategies and insights to give actionable advice for both academia and industry practitioners.

1. Limited investigation about the behavioral intention of AR filters

In recent years, AR technology has been designed to assist workers and influence purchasing behavior. Much of the research has examined the factors impacting user behavior in contexts like AR retail applications and AR construction tools [12,82]. However, there has been limited research into the behavioral intention behind AR filter usage. Only a few studies have explored the impact of AR filters on social media platforms and brand engagement [32], but these did not investigate the reason behind AR filters' usage. Moreover, the internal design factors of AR filters that affect the behavioral intention of AR filter users have not been examined. Therefore, this research is going to study the factors affecting the behavioral intention of AR filters to provide a comprehensive view of AR filter usage.

2. Most research focuses on retailing but not on catering

In recent research regarding AR marketing, most of the investigation focused on the retail industry. The AR technology is able to visualize the products in three-dimensional content to demonstrate the product details to customers. The motivational impact of AR technology on purchasing behavior in the retailing industry was studied [12,82]. However, for the catering industry, the application of AR technology for marketing purposes is still in the beginning stage, and scarcely any of the research regarding the catering industry has found factors affecting the behavioral intention of users using AR filters. Therefore, this paper will explore the variables affecting AR filter usage with a background of the catering industry.

3. Limited research on the effectiveness of AR filter marketing

As most of the research has studied the AR technology embedded in mobile applications for retailing purposes, the investigation of the application of AR technology for marketing purposes is limited, and the effectiveness of AR filter marketing has not been reviewed. The clues and implications for managers are not clear and sufficient, which hinders the development of AR technology and AR filters in the catering industry, meaning managers refuse to invest in AR technology due to unclear results provided. Therefore, the effectiveness of AR filter marketing is studied to provide implications for managers when establishing marketing strategies.

2.4. Hypothesis Model

To increase the theoretical base for our predictions, we ground the relationships among the proposed constructs in established psychological and marketing theories like cognitive appraisal theory and flow theory. One theoretical approach that can explain the relationship between PE and satisfaction is the cognitive appraisal theory, according to which the cognitive evaluations users make on system effort and the system's ease of use impact their emotions and the extent of their satisfaction. Flow theory also reinforces the difference between the intrinsic enjoyment during system use (perceived enjoyment) and the evaluative judgment after use (satisfaction). The fun factor is operationalized in this research as the perception of using the AR filter (i.e., perceived enjoyment) and satisfaction as the global assessment of the AR filter immediately following its use. Unpacking these differences while systematically linking our hypotheses to theory will minimize ambiguity in definitions and enhance the predictive value of our model.

Echoing these ideas, flow theory states that when users are able to devote their full concentration, act to the full extent, and enjoy the activity they are doing, they transition into a psychological condition called "flow", which is particularly related to the perceived enjoyment in interactive digital environments like AR filters. This flow state not only promotes the current enjoyment but also has a long-term effect on satisfaction through the positive affect and the sense of achievement it caters to. Additionally, the cognitive appraisal theory underlines the point that the users' assessments of the AR filter's characteristics, such as ease of use, novelty, and interactivity, are factors that govern their emotional responses and overall satisfaction. By the combined use of these two theoretical schemes, our model obtains the AR filter use pleasure that people receive instantaneously, as well as the reflective assessment that comes later; thus, the satisfaction of magnetic technology is explained comprehensively. The method of embedding these theories in our research ensures that our hypotheses are rooted solidly in the well-established principles of science and thus make our study more conceptually rigorous.

TAM is widely applied in measuring the behavioral intention of new systems or technology; however, it still has its drawbacks in that it cannot provide the whole picture of user behavior intention that needs to be solved. Some research investigated that the TAM cannot fully explain all of the user's behavioral intentions, and some of the relevant factors affecting behavioral intention are not studied within the model [81]. Venkatesh et al. [83] noticed the weakness of TAM, such that the Unified Theory of Acceptance and Use of Technology (UTAUT) model was developed to explain all the effects on the behavioral intention of the system or technology. However, the insight provided through UTAUT is fragmented with little coherent integration; the independent variables were too many to predict intention and behavior [84]. Moreover, UTAUT measured the social impact and incident influences, which is not a focus point in this study [83]. Therefore, TAM for hedonic systems or technology is better than UTAUT when applied to the proposed model development in the investigation. To address the limitation of TAM, it is extended and integrated with the Satisfaction–Loyalty Model to investigate a better explanation for the reason behind the behavioral intention of a hedonic system or technology [78–81].

According to Davis et al. [64], the modified TAM was built where the construct, the attitude toward using intention, was included inside the model. However, the construct (the attitude toward using intention) was taken out of the TAM as it was found that the factor was a weak determinant of behavioral intention in the final version of TAM [67]. In terms of the hedonic system or technology, it is appropriate to study the attitude toward behavior intention to explain the behavior intention of a hedonic system or technology, as the hedonic system or technology is closely related to the feelings and perceptions of users so that attitude can be a significant factor to be measured [69,79,81]. With the situation of the weak effect of the attitude construct on behavioral intention, satisfaction and loyalty are found to be attitudinal factors [73–75,85,86], and thus are used to replace the attitude toward the behavioral intention construct to provide a comprehensive understanding of the reason behind AR filter usage behavior. Some research studied satisfaction and loyalty acting as attitudinal factors with the purpose of investigating how the perceived value or perception of users affects their behavior [74,76,77], which can support the replacement of the attitude toward behavior intention construct of TAM. Perceived value was also found to influence satisfaction and loyalty. Additionally, TAM has been applied to explain satisfaction and loyalty, as perceived usefulness (PU), perceived enjoyment (PE), and perceived ease of use (PEU) are considered forms of perceived value. As a result, these three key constructs (PU, PE, and PEU) can effectively replace the perceived value construct in the Perceived Value–Satisfaction–Loyalty Model [62,64,69,76,77].

Moreover, it has been found that satisfaction is a determinant of loyalty, and loyalty is a predictor of behavioral intention, as noted in previous literature reviews [78,80,81,85], which also supports the proposed model construction. Therefore, along with the AR filter as a technology providing hedonic value [32], the model is built and expanded through the integration of the TAM model and the Satisfaction–Loyalty model so that the attitude toward using intention is replaced by satisfaction and loyalty constructs, to offer a more comprehensive perspective on understanding the reasons behind the behavioral intention to use AR filters and to examine the impact of determinants and mediating factors on their usage. Along with studying the impact of determinants on the perceived value of TAM constructs with the extension, the structure framework relationship of the study is shown in Figure 1.

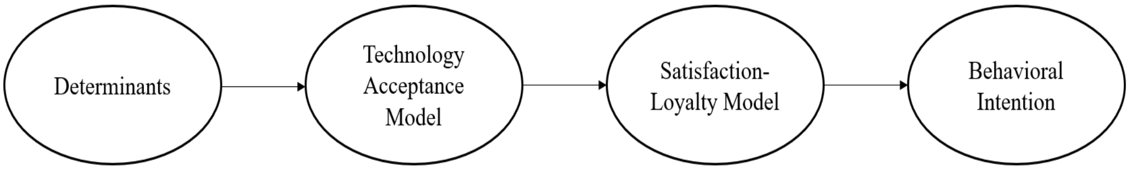

Figure 1. Structure framework relationship of the study.

Behavioral Intentions: Davis (1985) [65] found that behavioral intention reflects the desire or possibility of a person to perform a specific behavior, which supports the definition of behavioral intention in this study as the willingness of the user to use AR filters. In the previous literature view, the Technology Acceptance Model and the Satisfaction–Loyalty model are discussed. Along with some added determinants of the three main constructs, a hypothesis model integrating the two models is proposed in this research for conducting the Structural Equation Model (SEM) and Confirmatory Factor Analysis (CFA), shown in Figure 2.

The decision to operationalize aesthetic quality within multiple dimensions—color, text, music, and animation—reflects the various dimensions of users' aesthetic experiences in multimedia. Each of these components has been found independently in previous studies to affect how users perceive design quality as well as emotion-related responses. By separately modeling these factors, the model captures the unique contributions of visual and auditory cues to the overall aesthetic impression. This approach makes it possible to conduct a more fine-tuned analysis of how particular design characteristics influence user attitudes and behavioral intentions than would be possible based on a single aggregate measure of aesthetics. The necessity of these dimensions in the model and the measurements can be supported by previous research, and it was confirmed by the confirmatory factor analysis that each factor has a significant impact on the construct aesthetic quality.

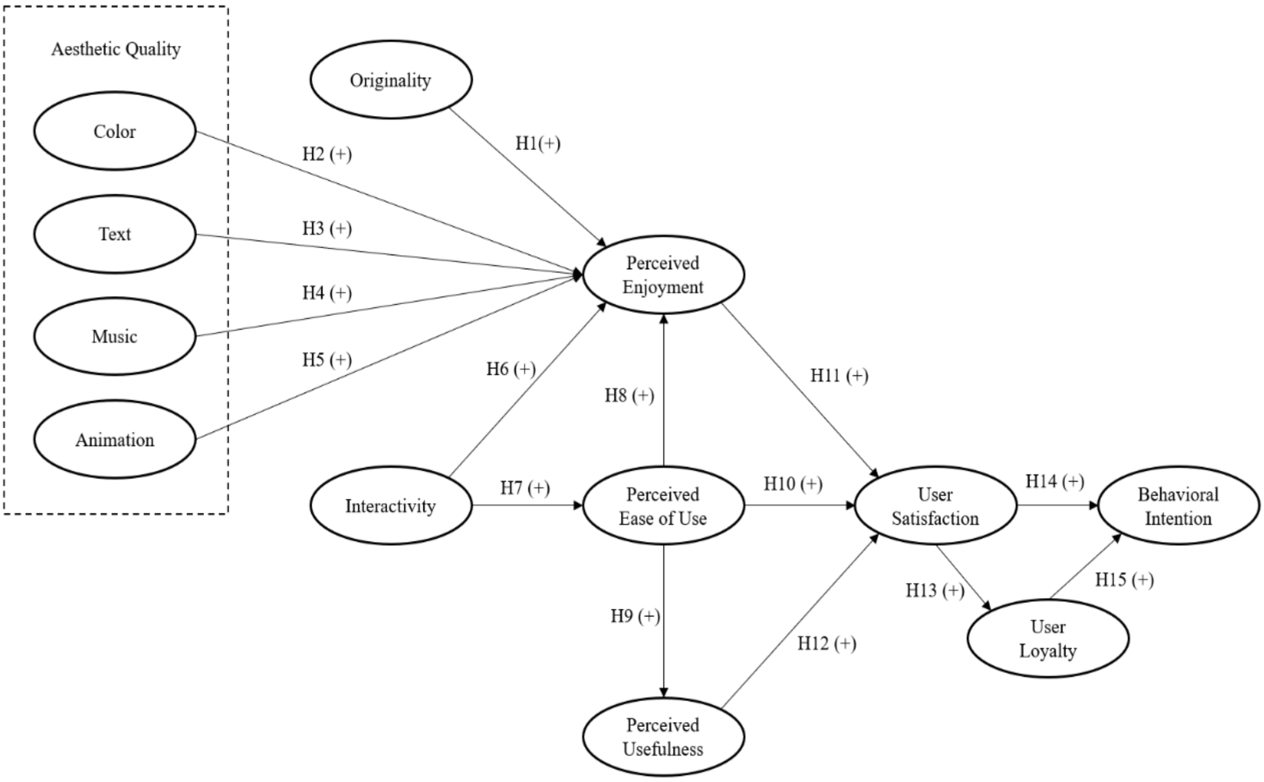

Figure 2. The hypothesis model.

2.5. Determinants of Perceived Enjoyment and Perceived Ease of Use

A. Originality

Originality is the degree to which the contents are not standard, inventive, and contemporary to the audience [32]. In this research, the originality construct developed is defined as the degree to which the AR filter contents presented to the users are designed to be uncommon, unique, and leading-edge. As the trial of a new content experienced by the audience and user can provoke an interesting perception of the user and draw their attention, it will further enhance the perception of enjoyment. Flavián et al. [32] also found that originality can predict users' perceived enjoyment and usefulness, which supports the argument. Thus, the hypothesis that originality affects perceived enjoyment is suggested as follows:

H1: *Originality has a positive effect on perceived enjoyment.*

B. Aesthetic quality

Aesthetic quality is the extent of digital content of graphic and cinematic appearance generated by the technology [32]. Aesthetic quality can also be divided into four main components: color, text, music, and animation. Cyr et al. [87] stated that color, text, music, and animation could be mediums used to present the visual design of content. Color, text, music, and animation are some of the essential components used to construct and present the content of an AR filter to users, and it can be divided into four components to measure the effect of aesthetic quality. Therefore, the aesthetic quality can be defined as the degree of 4 elements: color, text, music, and animation of the vivid and visual appearance of the AR filter. According to Cyr et al. [87], aesthetic quality is a predictor of perceived enjoyment, ease of use, and usefulness. It is backed by the literature in that people can receive pleasure from aesthetic objects such as music and graphics [88]. Some research also found that the

AR content's quality positively affects satisfaction [78]. Therefore, the hypotheses that the four components of aesthetic quality predict perceived enjoyment are made as below:

H2: *Color has a positive effect on perceived enjoyment.*

H3: *Text has a positive effect on perceived enjoyment.*

H4: *Music has a positive effect on perceived enjoyment.*

H5: *Animation has a positive effect on perceived enjoyment.*

C. Interactivity

Interactivity refers to the extent to which users and the content within a medium can influence one another through interactions in a mediated environment [79]. It is also defined as the degree of the user being able to alter and control the content that is shown in the technology-mediated environment [12]. In this study, interactivity is defined as the extent of the users' ability to affect and control the AR content inside the mobile phone's display. With the attributes of the AR filter, it has a large potential for providing hedonic value to users by enhancing the interaction between them and the AR filter's content in terms of interactivity. The users can receive joy and enjoyment while using the AR filter with an interactive design such as games or through displayed content. The literature supported that interactivity is a determinant of perceived enjoyment and ease of use in AR filter technology [32]. Therefore, the hypothesis that interactivity affects perceived enjoyment is suggested as below:

H6: *Interactivity has a positive effect on perceived enjoyment.*

H7: *Interactivity has a positive effect on perceived ease of use.*

2.6. Integration and Extension of the Technology Acceptance Model (TAM) and the Satisfaction–Loyalty Model

A. Perceived Ease of Use

Davis [62] defined ease of use as the extent to which a person perceives using a certain system or technology without difficulty. Other research shared the same idea as Davis [62] and applied it to other systems or technology research [71,72,80]. In this study, the perceived ease of use of AR filter for users is defined as the extent to which users perceive AR filters as simple and straightforward to use.

The original TAM identified ease of use as a prerequisite for perceptions of usefulness [62,64], and furthermore, other studies have confirmed that perceived usefulness mediates the relationship between perceived ease of use and the attitude toward using a system or technology. [71,72]. Moreover, in the extended TAM for hedonic systems proposed by Van der Heijden [69], it was demonstrated that perceived enjoyment and perceived usefulness mediate the effect of perceived ease of use on behavioral intention. Moon and Kim [71] also found that perceived ease of use predicts both perceived enjoyment and perceived usefulness, which, in turn, influence the attitude toward using technologies in the context of the World Wide Web. Similarly, the application of AR filters, as a newly developed mobile social media feature, can be complex, making it difficult for users to navigate. This complexity may discourage users from adopting and learning how to use it [62,64]. The characteristics of AR filters, that they are easy to use, can improve the accessibility of AR filters to users, which further assists the users in receiving information and obtaining enjoyment and entertainment while using them [64,67,69].

Moreover, the easy-to-use characteristics of AR filters help users generate positive feelings and attitudes toward using them [69,71]. This argument is supported by applying the findings from other utilitarian and hedonic systems discussed earlier, highlighting the relationships between perceived ease of use, perceived usefulness, perceived enjoyment, attitude toward usage, and behavioral intention within the TAM framework. Consequently, with the replacement of the constructs from attitude to satisfaction and loyalty, as proposed in the previous section, the perceived ease of use of AR filters for users is expected to predict their perceived enjoyment, perceived usefulness, and satisfaction. Based on this, the following hypotheses are proposed:

H8: *Perceived ease of use has a positive effect on perceived enjoyment.*

H9: *Perceived ease of use has a positive effect on perceived usefulness.*

H10: *Perceived ease of use has a positive effect on user satisfaction.*

B. Perceived Enjoyment

Perceived enjoyment refers to the degree to which an individual perceives a system or technology as providing pleasure and fun during use, independent of any expected performance outcomes [63,69]. Supported by later works of literature [32,72,79], the perceived enjoyment of AR filter users is defined as the degree to which they obtain fun and pleasure from the experiences of AR filters, excluding the user's perception of its expected performance. In the early stages of TAM, it was proposed that perceived usefulness and perceived ease of use are key determinants of information technology adoption and usage [62,64,65]. The study examined the impacts of extrinsic and intrinsic motivation on workplace computer usage and intention, defining perceived usefulness as a form of extrinsic motivation and perceived enjoyment as a form of intrinsic motivation [70]. Van der Heijden [69] found that perceived enjoyment has a significant effect on behavioral intention, and other researchers had the same result in other systems or technologies [32,71,72,87]. Meanwhile, it was revealed that perceived enjoyment determines the attitude toward using technology and satisfaction in the other systems and technology acceptance research [71,79], which provides a basis for exploring the relationship between perceived enjoyment and user satisfaction as an attitudinal factor among AR filter users. As a hedonic technology, AR filters deliver hedonic value, enjoyment, and entertainment, which can foster positive feelings and attitudes toward their usage [32,69,89]. In the previous section, it was discussed that user satisfaction and loyalty replace the attitude construct since they better explain the mediating effect on behavior intention for AR filters as a hedonic system and technology [90,91]. Thus, the perceived enjoyment affecting user satisfaction is proposed with the following hypothesis:

H11: *Perceived enjoyment has a positive effect on user satisfaction.*

C. Perceived Usefulness

Davis [62] defined perceived usefulness as the degree to which an individual believes that using a particular system or technology will enhance their job performance. One of the major purposes of a system or technology is to provide useful information to users, but it is also defined as the extent to which users conveniently obtain helpful information when using a certain technology or system [89]. Along with one of the functions of AR filters being to contain and spread useful information [32], the perceived usefulness of AR filters by users refers to the degree to which they obtain useful and convenient information from their experiences of using the AR filter for a better user perception.

The previous section discussed the investigation of perceived usefulness, including perceived ease of use and perceived enjoyment, as key user perceptions that predict attitudes toward using a new system or technology, as well as behavioral intention. This relationship has also been supported by recent studies examining other new systems and technologies [32,67,69,71,72,80]. AR filters can be used as a technology to spread information, such as brand and product information, to users, contributing to positive feelings and attitudes toward using AR filters when they receive useful or desired information [32,69,89]. Therefore, with the change of the constructs from attitude to satisfaction and loyalty in the proposed model, the perceived usefulness of AR filters for users is identified as one of the key predictors of user satisfaction. Based on this, the following hypothesis is proposed:

H12: *Perceived usefulness has a positive effect on user satisfaction.*

D. User Satisfaction

Satisfaction is a concept primarily used in marketing studies and is defined as the "fulfillment response or judgment of a consumer that a product or service feature provides a pleasurable degree of consumption-related fulfillment, including levels of under- or over-fulfillment" [74]. Some studies shared the exact definition of satisfaction with Oliver [74,79,80,92], and other researchers have also defined satisfaction as the extent of an individual's perception related to their experience, which generates positive value or feelings [78]. The investigation regarding the new system or technology supports the definition of the user satisfaction construct in this research in that it refers to the extent of the evaluation and affective response of AR filter users to the experiences provided by the AR filter.

Oliver [73] stated that consumer loyalty comes after consumer satisfaction. The Satisfaction–Loyalty Model was then built and was used to investigate other topics related to marketing, in which the results showed that satisfaction significantly affects loyalty [75–77]. Moreover, Oliver [86] found that satisfaction is positively correlated to future intention, facilitating the application of the satisfaction and loyalty concept from another perspective. Some researchers built the model with the satisfaction and loyalty constructs to study the new system or technology, which also had the result that satisfaction predicts loyalty and behavioral intention [78–81,89,93]. It is proposed that the AR filter, as a technology providing AR experience, generates a positive feeling in the users, which can further affect their loyalty and behavioral intention [94,95]. Therefore, the effect of user satisfaction on user loyalty and behavioral intention is going to be investigated with the hypotheses shown below:

H13: *User Satisfaction has a positive effect on User Loyalty.*

H14: *User Satisfaction has a positive effect on Behavioral Intentions.*

E. User Loyalty

In the past marketing literature, loyalty has been defined as a multidimensional concept encompassing both attitudinal and behavioral perspectives. From an attitudinal perspective, loyalty is described as the extent to which an individual desires to maintain a relationship with a product or service provider. In contrast, from a behavioral perspective, loyalty refers to the tendency to repurchase a product or the willingness to recommend it to others [73,74,76,77]. Loyalty is also defined as the strong commitment of consumers to remain with a brand and resist switching to competitors [73]. A similar definition of loyalty was used to study the intention of new technology or systems [87,92], which supported that the user loyalty of AR filter users is defined as the strong commitment of the users not to switch to an alternative AR filter within mobile social media. It was found that attitudinal loyalty significantly influences behavioral loyalty, supporting the consideration of behavioral loyalty as behavioral intention [73,85]. The strong commitment of users not to switch further enhances their behavioral intention to use AR filters. Therefore, with loyalty mediating the effect of satisfaction on behavioral intention, the following hypothesis is proposed [96–98]:

H15: *Loyalty has a positive effect on behavioral intention.*

While existing research has built a firm base, investigating the adoption of AR in retail and beyond, our work contributes to this literature by combining and developing these existing results in a number of important directions. Unlike prior studies which solely focus on one separate or adapted construct of the AR acceptance not in connection with the context of the application in practice, we take a perspective based on TAM and SLM and apply them to the hedonic and experiential context of AR filters within the serve-with-a-smile approach in the catering industry. Prior work has considered the joint use of TAM and SLM in other fields (e.g., e-commerce, mobile applications), which have, however, tended to either ignore the idiosyncratic affective and design-driven influence factors of AR filter use and consumption patterns of consumers in the catering context. Through taking into account elements like originality, aesthetic quality, and interactivity—properties particularly relevant in AR filters but largely ignored in former models—the present work not only bridges theoretical lacunae but also offers practical answers to a field that had been largely neglected by the academic community. More importantly, our proposed methodology transcends mere mechanistic abstraction by contrasting the predictive power and weaknesses of existing models, showing how our extended framework reflects the intricate relationships between consumers' perceptions, satisfaction, loyalty, and behavioral intention in a manner that is both coherent with the specific domain of interest and empirically trustworthy. In this respect, this study contributes an innovative and more holistic view of the AR filter adoption, contributing to theory and practice.

Although the TAM and its extensions have been widely used in explaining user behavioral intentions to use new technology, there are some limitations, particularly in hedonic and experiential systems such as AR filters. Although the original TAM is a strong model, it does not account for the complete range of determinants or drivers that affect user behaviour, as many subjective and affective determinants are left out, which play an important role in the use of hedonic technology [32–35]. While meant to fill some of these gaps, it brought a certain complexity in terms of constructs and emphasized social and organizational influences that are less relevant in explaining individual, hedonic technology acceptance. Moreover, TAM and UTAUT have been criticized for their lack of explaining post-adoption behaviors, including satisfaction, loyalty, and continued use, which are particularly critical in the dynamic and competitive nature of social media and AR applications. Existing work has also neglected the role played by aesthetic and interactive aspects, which are key aspects of the user experience with AR filters. These lacunae suggest that an integrative model that not only extends TAM with satisfaction–loyalty constructs but also includes crucial determinants such as originality, aesthetic appeal, and interactivity will lead to better insights into the users' behavioral intention in hedonistic technology contexts. This work fills these gaps by developing a research framework and empirically testing it in an extended way, to suit the special features and user motivation of AR filters.

3. Experimental Methods

The survey aims to examine users' acceptance of AR filters and identify the factors influencing their usage on social media platforms. It is divided into two sections: demographic information and participants' opinions on the constructs of interest. To ensure adequate data for conducting SEM in the subsequent analysis, the sample size is set at approximately 1200 respondents. Informed consent was obtained from all participants, and the study was approved by the DRP.

The first part of the questionnaire utilizes multiple-choice questions to gather demographic information from the respondents, such as age, gender, education status, occupation, and monthly salary. Multiple-choice questions provide predefined answer options, and respondents are required to select a single answer that best represents their demographic characteristics. The second part of the questionnaire utilizes a 7-point Likert-type scale to collect more precise data. The scale includes the options: strongly disagree, disagree, somewhat disagree, neutral, somewhat agree, agree, and strongly agree. This approach requires respondents to indicate their level of agreement or disagreement with specific statements or questions. The Likert scale is particularly effective for measuring latent variables in the proposed model and supports data collection for Structural Equation Modeling (SEM) analysis. By capturing respondents' opinions along a continuum of preferences, the Likert scale enhances the accuracy and depth of the data collected [99,100]. It is widely used in social science research and is particularly relevant for studying concepts related to TAM. Bollen [99] states that direct observation cannot analyze the latent variable, while the 7-point Likert-type scale helps indicate personal expression and perception [101]. Moreover, it is widely used in social science, and it analyzes studies related to TAM [102]. Therefore, the 7-point Likert-type scale is recommended for analyzing the latent variables in this study.

The second part of the questionnaire focuses on participants' views and opinions regarding the latent variables outlined in the proposed model. It consists of 12 latent variables and 58 observed variables. The measurement items for these constructs have been adapted from relevant literature sources to suit the specific context of this study. For instance, the originality of the AR filter design (5 items) was adapted from past studies by Moldovan et al. [103] and Flavián et al. [32]. Color (5 items), text (5 items), music (5 items), and animation (5 items) as aesthetic qualities were adapted from Blijlevens et al. [88] and Cyr et al. [87]. Interactivity (5 items) was adapted from Pantano et al. [12] and Flavián et al. [32]. Perceived enjoyment (5 items) was adapted from Cheema et al. [72]. Perceived ease of use (5 items) was adapted from Chiu et al. [80] and Moon and Kim [71]. Perceived usefulness (5 items) was adapted from Chiu et al. [80]. User satisfaction (5 items) was adapted from Chiu et al. [80] and Jung et al. [78]. User loyalty (5 items) was adapted from Candan et al. [104]. Behavioral intention was adapted from Moon and Kim [71] and Cheema et al. [72].

In summary, the survey comprises demographic information and opinions on the constructs of interest. Multiple-choice questions are used to gather demographic data, while a 7-point Likert-type scale is employed to assess respondents' opinions. The second part of the questionnaire includes 12 latent variables with their corresponding measurement items adapted from the existing literature.

For a comprehensive overview of the measurement sources for each construct, please refer to Table 1.

Table 1. The measurement items of the hypothesis model.

Items	Measurements	References
Color	I find that the color design of the AR Filter looks attractive.	Blijlevens, et al. [88] and Cyr, et al. [87] and Xu, et al. [105].
	It is nice to see the color design of the AR Filter.	
	I like the color design of the AR Filter.	
	The color design of the AR Filter is beautiful.	
	I am pleased to see the color design of the AR Filter.	
Text	I find that the text design of the AR Filter looks attractive.	Blijlevens, et al. [88] and Cyr, et al. [87] and Yousefi, et al. [106].
	It is nice to see the text design of the AR Filter.	
	I like the text design of AR Filter.	
	The text design of the AR Filter is beautiful.	
	I am pleased to see the text design of the AR Filter.	
Music	I find that the music of AR Filter is attractive.	Blijlevens, et al. [88], Cyr, et al. [87], and Xu, et al. [107].
	It is nice to listen to the music of AR Filter.	
	I like the music of AR Filter.	
	The music of AR Filter is wonderful.	
	I am pleased to listen to the music of AR Filter.	
Animation	I find that the animation of the AR Filter is attractive.	Blijlevens, et al. [88] and Cyr, et al. [87].
	It is nice to watch the animation of the AR Filter.	
	I like the animation of the AR Filter.	
	The animation of the AR Filter is wonderful.	
	I am pleased to watch the animation of the AR Filter.	
Originality	I think it is unique.	Moldovan, et al. [103] and Flavián, et al. [32].
	I think it is innovative.	
	It is novel to me.	
	I am curious about the newly designed AR Filter.	
	It gives me the feeling of freshness.	
Interactivity	The interaction with the AR Filter can provide me with an enjoyable experience.	Pantano, et al. [12] and Flavián, et al. [32].
	I like the interaction mode with the AR Filter.	
	I enjoy interacting with the AR Filter.	
	Interacting with the AR Filter makes me willing to use the AR Filter.	
	I always desired to receive a response from AR Filter when I am using it.	
Perceived Enjoyment	Using the AR Filter is fun.	Cheema, et al. [72].
	Using the AR Filter can provide me with excitement.	
	I have enjoyment while I am using the AR Filter.	
	I find it interesting to use the AR Filter.	
	I feel joyful using the AR Filter.	

Table 1. *Cont.*

Items	Measurements	References
Perceived Ease of Use	AR Filter is easy to use.	Chiu et al. [80] and Moon and Kim [71].
	It is easy for me to learn to use the AR Filter.	
	It is easy to remember how to use the AR Filter.	
	My interaction with the AR Filter is clear and understandable.	
	It is easy for me to become skillful at using the AR Filter.	
Perceived Usefulness	AR Filter makes it easier to deliver brand information (products, place, promotion, etc.) to me.	Chiu, et al. [80].
	To receive brand information (products, place, promotion, etc.), using an AR Filter is an effective way.	
	It is useful for me to use AR Filter to receive brand information (products, place, promotion, etc.).	
	I think AR Filter is convenient to receive brand information (products, place, promotion, etc.).	
	I think using AR Filter is an effective way to receive brand information (products, place, promotion, etc.).	
User Satisfaction	I am satisfied with the AR Filter.	Chiu, et al. [80] and Jung, et al. [78].
	I feel satisfied with using the AR Filter.	
	I am pleased with the experience of receiving brand information from the AR Filter.	
	Using the AR Filter provides me with satisfaction.	
	Overall, I am satisfied with the experience of receiving brand information from the AR Filter.	
User Loyalty	I feel better when I use the AR Filter.	Candan, et al. [104].
	Using AR Filter will be my first choice when using a mobile social media application in the future.	
	I like the entertainment provided by AR Filter more than other functions and features of the mobile social media application.	
	I think the brand information delivered by AR Filter is better than other functions and features of a mobile social media application.	
Behavioral Intention	I intend to continue using AR Filter in the future.	Moon and Kim [71] and Cheema et al. [72].
	I will frequently use the AR Filter in the future.	
	I will recommend using AR Filter to my friends.	
	I have the intention to use AR Filter for receiving brand information.	

3.1. Data Collection Method

The survey employed an online questionnaire created using Google Forms as the primary method for data collection. This approach facilitated the efficient collection of accurate data and results through the respondents' responses and explanations. Moreover, it provided the interviewees with the convenience of trying out the designed AR filters by accessing a designated link before proceeding to answer the questionnaire. Additionally, the utilization of an online survey offered the advantage of gathering a substantial amount of data through targeted online promotion to the intended audience on various social media platforms.

3.1.1. Pilot Study

A pilot study, a preliminary quantitative investigation conducted on a smaller scale, is widely utilized in social science research to lay the groundwork for future larger-scale studies and to test the research instruments [108]. As proposed by Van Teijlingen and Hundley [108], the pilot study serves several purposes, including acquiring preliminary data, assessing the feasibility of the main research, determining the appropriate and sufficient research instruments, establishing sampling and recruitment methods, providing guidance to assistant researchers, and developing and refining the protocols for future large-scale studies. The pilot study serves as an exploratory investigation on a smaller scale and a valuable guide for subsequent research endeavors. It allows researchers to gain a deeper understanding of the intricacies involved in the research process and helps identify and address any unforeseen challenges before data collection [109,110].

In the pilot study, a multi-stage procedure was conducted to establish the validity and relevance of the measurement items in the AR filter setting. Firstly, all survey items (both new and adapted) were assessed for content validity by a panel of three AR and user experience design experts. Items were rated by the experts for clarity, relevance of content, and relevance for the intended construct. When necessary, descriptions of items were tailored for AR filter features. Concerning the operationalization of "originality", "animation" [109,110], and "music", these were identified as potential first-order constructs, but we also checked for their conceptual fit as perceivable aspects of a higher "aesthetic quality" factor reflected in the literature review. We created a series of self-built AR filters, which were systematically varied with regard to their visual and interactive characteristics, to conduct a pilot study. These filters were pre-tested with a participant test sample of 20 people rating quality, usability, and realism using a standardized scale. Feedback of experts and users on filters and survey items was used to revise the survey and filters, adding to the experiment, and strengthening the reliability and ecological validity of our measures.

In order to enhance the research approach, a pilot study was conducted before the main research. The pilot study involved a sample of 150 participants, whose feedback was collected to refine the survey design and research process. Valuable insights were obtained from the pilot study, prompting necessary adjustments to improve the clarity and effectiveness of the research instruments. Specifically, participants expressed confusion regarding the usage of the designed filters, which led to the incorporation of more precise instructions within the filter interface itself. Additionally, concerns were raised about the length of the questionnaire, necessitating the removal of unnecessary and insignificant questions to streamline the instrument. Furthermore, it was identified that participants encountered difficulties comprehending certain complex concepts, potentially affecting the accuracy of their responses. To address this issue, comprehensive explanations accompanied by supporting visuals were added before relevant questions, ensuring a thorough understanding of the underlying concepts. The findings and feedback from the pilot study provide valuable insights into the refinement of the research instruments and methodology, thereby enhancing the overall rigor and validity of the study. While the primary focus of the analysis should be on the main research data, incorporating relevant descriptive statistics or qualitative insights from the pilot study can provide contextual information and support the rationale behind specific modifications made during the research process.

Some participants indicated a lack of clarity regarding the usage of the designed filters, which necessitated clearer instructions. Consequently, instructions for using the filters were incorporated within the filter itself to provide explicit guidance and enhance participants' comprehension. Another concern raised during the pilot study was the length of the questionnaire, with participants expressing the need for a more time-efficient instrument.

To address this, unnecessary and insignificant questions were eliminated, ensuring that participants could complete the questionnaire without compromising the integrity of the study. Additionally, it was discovered that participants encountered difficulties in comprehending certain complex concepts, leading to potential inaccuracies in their responses. To mitigate this issue, clear explanations accompanied by supporting visuals were added before relevant questions, offering participants a comprehensive understanding of the underlying concepts.

3.1.2. Self-Designed AR Filters

In order to facilitate a better understanding of the abstract constructs and address the issue of respondents' limited comprehension, four AR filters were designed using Spark AR Studio software (version 173), developed by Facebook. These AR filters were closely related to the research and aimed to provide visual references for respondents when answering the 7-point scale questions. A new Instagram account was created to publish the AR filters, making them accessible to participants. The AR filters incorporated various elements representing different constructs within the proposed model. During the online questionnaire, participants were presented with captured images of the AR filters. This visual representation is aimed at enhancing their understanding and perception of the AR filters. By providing a clearer understanding of the AR filters, participants were expected to provide more accurate and informed responses to select the most appropriate answers.

The development of the AR filters was based on the research's focus on the catering industry. The AR filters were designed to showcase a restaurant's marketing mix components (product, price, place, and promotion). Each element within the AR filters represented different constructs developed in the previous section, thereby aligning with the research framework. The utilization of AR filters as visual aids in the questionnaire aimed to bridge the gap between abstract constructs and respondents' understanding. By providing a tangible and interactive experience, the AR filters served as valuable references for participants when responding to the questionnaire, ultimately enhancing the accuracy and reliability of their answers. The AR filters are shown in the following, and the Appendix A session will further discuss the filters' details.

3.2. Data Collection

One thousand five hundred questionnaires were distributed to social media users in Hong Kong from July 2024 to December 2024. The respondents were requested to finish the questionnaire about their perceptions of the behavior of users of the AR filters. Participation in the survey was voluntary and anonymous, and the data were kept confidential. The participants filled out the questionnaires using the Google Forms we created in different areas of Hong Kong. One thousand three hundred and fifty-seven questionnaires were collected. During the analysis phase, it was discovered that specific results were deemed inappropriate for answering the questionnaire and were subsequently deleted from the dataset. The decision to remove these responses was made to ensure the integrity and validity of the study. The inappropriate results may have included incomplete or inconsistent responses, outliers, or responses that did not adhere to the study's guidelines or criteria for participation. As the research focuses on AR filter usage, only AR filter users were considered rather than social media users with no understanding of AR filters. The participants with less understanding of the questions and who answered questions with difficulty were also excluded. In total, 1251 questionnaires were valid for further data analysis. Table 2 shows respondents' demographic information and their usage of AR filters. Most respondents' education level (1126 frequency, 90.01%) was tertiary or above. The majority of respondents had a monthly income level of was USD 10,000–USD 24,999

(623 frequency, 49.8%), followed by USD 25,000–USD 49,999 (356 frequency, 28.46%). Most respondents were full time (698 frequency, 55.80%) in terms of employment status, while the second largest group preferred not to say (311 frequency, 24.86%). In terms of the usage of AR filters, 1152 respondents used mobile social media applications daily (92.09%). For the active use of mobile social media, almost all of the respondents actively used Instagram (1195, 95.52%), while YouTube (1217 responses, 97.28% of respondents) and Facebook (897 responses, 71.10% of respondents) were in second and third place, respectively. The responses in terms of the usage of AR filters was close. One thousand and eleven respondents (82.02%) used AR filters weekly. One hundred and fifty-one respondents (12.07%) used AR filters daily. The result was reasonable, as most of the respondents were relatively young.

Table 2. Descriptive statistics of the demographic information and the usage of AR filters by respondents.

Attributes	Responses	
	Frequency	Percent
Education System (Hong Kong, China)		
Primary or lower	15	1.20%
Secondary	47	3.76%
University or above	1126	90.01%
Prefer not to say	63	5.04%
Personal Monthly Income Level (Hong Kong dollars)		
Less than USD 10,000	69	5.52%
USD 10,000–USD 24,999	623	49.80%
USD 25,000–USD 49,999	356	28.46%
USD 50,000–USD 99,999	105	8.39%
USD 100,000 or above	23	1.84%
Prefer not to say	6	0.48%
Employment Status		
Self-employed	31	2.48%
Full time	698	55.80%
Part time	105	8.39%
Homemaker	23	1.84%
Student	66	5.28%
Unemployment	15	1.20%
Retired	2	0.16%
Unable to work	31	2.48%
Prefer not to say	311	24.86%
Frequency of using mobile social media applications		
Use daily	1152	92.09%
Use weekly	82	6.55%
Use monthly	17	1.36%

Table 2. *Cont.*

Attributes	Responses	
	Frequency	Percent
Actively using a social mobile social media application. (Use multiple times monthly.)		
Facebook	897	71.70%
X	394	31.49%
Youtube	1217	97.28%
Instagram	1195	95.52%
Snapchat	152	12.15%
Wechat	912	72.90%
MeWe	275	21.98%
LinkedIn	583	46.60%
Frequency of using AR Filter		
Use daily	151	12.07%
Use weekly	1011	80.82%
Use monthly	55	4.40%
Haven't used before	34	2.72%

4. Results and Findings

By measuring latent variables related to behavioral intention, the SEM (Structural Equation Modeling) approach is adopted in this study to analyze the proposed theoretical model. This includes testing data reliability and validity, as well as examining the relationships between independent variables and dependent variables [111,112]. Moreover, it is conducted to analyze the causal relationships between latent variables in the hypothesized model [112]. The software IBM SPSS Statistics 26 and IBM SPSS AMOS 26.0.0 are used to perform analyses for measuring the reliability and validity of the data, as well as evaluating the model fit. The reliability and validity of the data are assessed through standardized factor loadings, Cronbach's alpha (α), Composite Reliability (CR), and Average Variance Extracted (AVE). According to Hair (2021) [103], the following thresholds are used. Standardized factor loading is excellent when greater than 0.7; Cronbach's alpha should be higher than 0.7; Composite Reliability being greater than 0.8 is acceptable; and Average Variance Extracted should be greater than 0.5 [113]. The standardized factor loading and Cronbach's alpha (α) data can be collected in the SPSS software. In terms of CR and AVE, it has to be calculated manually.

Table 3 shows the results of the reliability and validity measurements. As all of the measurement items passed the standard that the standardized factor loading is larger than 0.7, no items were removed from the model. The range of the standardized factor loading of all measurement items was between 0.730 and 0.871; the range of the Cronbach's alpha of factors was between 0.856 and 0.918; the range of the Composite Reliability of factors was between 0.857 and 0.919; and the range of the Average Variance Extracted of factors was between 0.586 and 0.695. Therefore, the testing of the data is acceptable, and the data is reliable and valid. The variance inflation factors are also checked. The results indicate that all VIF values fall well below the commonly accepted threshold, suggesting that multicollinearity is not a significant concern in our model.

Table 3. The testing results of the standardized factor loading, Cronbach's alpha (α), Composite Reliability (CR), variance inflation factors (VIFs), and Average Variance Extracted (AVE) of the data.

Factors	No. of Items	No. of Items Deleted	Standardized Factor Loading	*VIF*	α	CR	AVE
Color	5	0			0.894	0.895	0.631
COL1			0.807	2.833			
COL2			0.799	2.158			
COL3			0.821	3.087			
COL4			0.773	2.385			
COL5			0.770	2.316			
Text	5	0			0.918	0.919	0.695
TEX1			0.790	2.836			
TEX2			0.853	2.572			
TEX3			0.860	2.376			
TEX4			0.871	3.114			
TEX5			0.790	2.174			
Music	5	0			0.913	0.914	0.680
MUS1			0.821	2.485			
MUS2			0.840	2.195			
MUS3			0.833	2.274			
MUS4			0.804	2.538			
MUS5			0.824	3.114			
Animation	5	0			0.898	0.898	0.638
ANI1			0.812	3.127			
ANI2			0.771	2.635			
ANI3			0.820	2.241			
ANI4			0.792	2.797			
ANI5			0.799	2.636			
Interactivity	5	0			0.896	0.904	0.653
INT1			0.787	2.266			
INT2			0.807	2.213			
INT3			0.822	2.336			
INT4			0.846	2.254			
INT5			0.775	2.947			
Originality	5	0			0.876	0.876	0.586
ORI1			0.762	3.15			
ORI2			0.802	2.847			
ORI3			0.761	2.351			
ORI4			0.742	2.278			
ORI5			0.760	3.042			

Table 3. *Cont.*

Factors	No. of Items	No. of Items Deleted	Standardized Factor Loading	*VIF*	α	CR	AVE
Perceived Enjoyment	5	0			0.904	0.910	0.668
PE1			0.847	2.98			
PE2			0.842	3.144			
PE3			0.781	2.76			
PE4			0.811	2.37			
PE5			0.804	3.043			
Perceived Ease of Use	5	0			0.893	0.897	0.635
PEU1			0.780	2.669			
PEU2			0.805	3.141			
PEU3			0.775	3.172			
PEU4			0.797	3.116			
PEU5			0.826	2.558			
Perceived Usefulness	5	0			0.879	0.879	0.592
PU1			0.730	2.606			
PU2			0.771	2.819			
PU3			0.810	2.439			
PU4			0.771	2.372			
PU5			0.762	2.702			
User Satisfaction	5	0			0.881	0.892	0.624
US1			0.858	3.095			
US2			0.742	2.546			
US3			0.744	2.995			
US4			0.772	2.684			
US5			0.828	2.510			
User Loyalty	4	0			0.856	0.857	0.600
UL1			0.795	2.293			
UL2			0.753	3.191			
UL3			0.778	2.756			
UL4			0.773	2.938			
Behavioral Intention	4	0			0.860	0.865	0.615
BI1			0.840	3.071			
BI2			0.756	3.014			
BI3			0.785	2.18			
BI4			0.754	2.267			

α: Cronbach's Alpha; CR: Composite Reliability; AVE: Average Variance Extracted.

4.1. Measurement and Structural Model

The model's goodness of fit was estimated to show an exemplary data fit. In terms of measuring the goodness of fit of the model, three absolute fit indices, including the goodness of fit index (GFI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR); and two model incremental fit indices, including the Normed Fit Index (NFI) and Comparative Fit Index (CFI), were employed; as well as three parsimonious fit indices including Relative Chi-Square (x^2/df), the Parsimonious Goodness of Fit Index (PGFI), and Parsimonious Normed Fit Index (PNFI). The acceptable level of the goodness-of-fit indices is recommended as follows: the p-value is recommended to be below 0.05 [114]; the GFI is suggested to be 0.80 when the parameter is large [115]; the RMSEA is excellent if below 0.05 [113]; the SRMR is recommended with the value below 0.05 [102]; the NFI is acceptable with a value larger than 0.90 [116] and the CFI is recommended with a value higher than 0.90 [116]; the Relative Chi-Square (x^2/df) is recommended to be acceptable when the value is below 3 [102]; the PGFI is suggested with a value under 0.05 [117]; and the PNFI is recommended to be acceptable when the value is under 0.05 [117]. The summary of the acceptance level of goodness-of-fit indices is shown in Table 4.

Table 4. Acceptance levels of goodness-of-fit indices with references.

Goodness of Fit Indices		Acceptance Level	Reference
Chi-Square Test	x^2	$p < 0.05$	Hoyle [114]
Absolute Fit Indices			
Goodness of Fit Index	GFI	>0.80	Doll, et al. [115]
Root Mean Square Error of Approximation	RMSEA	<0.05	Hair [113]
Standardized Root Mean Square Residual	SRMR	<0.05	Kline [102]
Relative Fit Indices			
Normed Fit Index	NFI	>0.90	Bentler and Bonett [116]
Comparative Fit Index	CFI	>0.90	Bentler and Bonett [116]
Parsimonious Fit Indices			
Relative Chi-Square	x^2/df	1–3	Kline [102]
Parsimonious Goodness of Fit Indices	PGFI	>0.05	Mulaik, et al. [117]
Parsimonious Normed Fit Indices	PNFI	>0.05	Mulaik, et al. [117]

As with the findings of Doll et al. [115], as the research has a small sample size and more measurement items, it could be concluded that the fitness of the hypothesis model could be underestimated when measuring the GFI. For the Root Mean Square Error of Approximation (RMSEA), the value is 0.049, which is lower than the recommended level, meaning that the model fits. The Standardized Root Mean Square Residual (SRMR) value is 0.040, which is perfect compared with the acceptance level. The value of the Normed Fit Index (NFI) is 0.906, which is higher than the acceptance level of 0.900 [111]. As with the finding of Ullman [111], as the research has a small sample size, it could be concluded that the fitness of the hypothesis model could be underestimated when measuring the NFI. The value of the Comparative Fit Index (CFI) is 0.932, which is higher than the acceptance level of 0.900, meaning that the model is a perfect fit. For Relative Chi-Square, the value is 1.426, which is between the acceptance level of 1 and 3, meaning that the model fits. For the Parsimonious Goodness of Fit Index (PGFI), the value is 0.670, which is higher than the acceptance level of 0.500, meaning the complexity of the model is a good fit. For the Parsimonious Normed Fit Index (PNFI), the value is 0.763, which is higher than the acceptance level of 0.500, meaning the complexity of the model is a good fit. Due to the small sample size and the number of measurement items, the value of the test could be affected as the calculation of some of the tests was under the consideration of the sample size and the number of measurement items. Therefore, it is concluded that in terms of the model's fitness, it is not a perfect fit but is adequate and valid.

4.2. Hypothesis Testing

The path analysis result of the model is shown in Table 5. The testing was accepted for all the hypotheses. The impact of originality on perceived enjoyment was positive and significant ($\beta = 0.799$, $p < 0.05$), supporting hypothesis H1. The effect of color on perceived enjoyment was positive and significant ($\beta = 0.751$, $p < 0.05$), such that the hypothesis H2 was supported. The prediction of text on perceived enjoyment was positive and significant ($\beta = 0.732$, $p < 0.05$), such that the hypothesis H3 was supported. The effect of music on perceived enjoyment was positive and significant ($\beta = 0.714$, $p < 0.05$), such that the hypothesis H4 was supported. The impact of animation on perceived enjoyment was positive and significant ($\beta = 0.763$, $p < 0.05$), such that the hypothesis H5 was supported. The prediction of interactivity on perceived enjoyment was positive and significant ($\beta = 0.900$, $p < 0.001$), supporting hypothesis H6. The impact of interactivity on perceived ease of use was positive and significant ($\beta = 0.852$, $p < 0.001$), supporting hypothesis H7. The effect of perceived ease of use on perceived enjoyment was positive and significant ($\beta = 0.925$, $p < 0.001$), such that the hypothesis H8 was supported. The prediction of perceived ease of use on perceived usefulness was positive and significant ($\beta = 0.871$, $p < 0.001$), supporting hypothesis H9. The effect of perceived ease of use on user satisfaction was positive and significant ($\beta = 919$, $p < 0.001$), supporting hypothesis H10. The impact of perceived enjoyment on user satisfaction was positive and significant ($\beta = 0.913$, $p < 0.001$), supporting hypothesis H11. The prediction of perceived usefulness on user satisfaction was significant and positive ($\beta = 0.853$, $p < 0.001$), such that the hypothesis H12 was supported. The impact of user satisfaction on user loyalty was positive and significant ($\beta = 0.973$, $p < 0.001$), supporting hypothesis H13. The effect of user satisfaction on behavioral intention was positive and significant ($\beta = 0.962$, $p < 0.001$), supporting hypothesis H14. The prediction of user loyalty on behavioral intention was positive and significant ($\beta = 0.911$, $p < 0.001$), such that the hypothesis H15 was supported. The analysis also includes Harman's single-factor test for each construct. The results indicate that the first unrotated factor accounts for less than 40% of the total variance, suggesting that common method bias is unlikely to be a significant issue in our study. Table 6 shows the Fornell–Larcker criterion of the first-order factor model. It results in a proper value under the model development.

Table 5. Hypothesis testing result.

Hypothesis	Path	β	Significant	Result
H1	Originality → Perceived Enjoyment	0.799	<0.05	Accepted
H2	Color → Perceived Enjoyment	0.751	<0.05	Accepted
H3	Text → Perceived Enjoyment	0.732	<0.05	Accepted
H4	Music → Perceived Enjoyment	0.714	<0.05	Accepted
H5	Animation → Perceived Enjoyment	0.763	<0.05	Accepted
H6	Interactivity → Perceived Enjoyment	0.900	<0.001	Accepted

Table 5. *Cont.*

Hypothesis	Path	β	Significant	Result
H7	Interactivity → Perceived Ease of Use	0.852	<0.001	Accepted
H8	Perceived Ease of Use → Perceived Enjoyment	0.925	<0.001	Accepted
H9	Perceived Ease of Use → Perceived Usefulness	0.871	<0.001	Accepted
H10	Perceived Ease of Use → User Satisfaction	0.919	<0.001	Accepted
H11	Perceived Enjoyment → User Satisfaction	0.913	<0.001	Accepted
H12	Perceived Usefulness → User Satisfaction	0.853	<0.001	Accepted
H13	User Satisfaction → User Loyalty	0.973	<0.001	Accepted
H14	User Satisfaction → Behavioral Intentions	0.962	<0.001	Accepted
H15	User Loyalty → Behavioral Intentions	0.911	<0.001	Accepted

Table 6. Fornell–Larcker criterion of the first-order factor model.

COL	TEX	MUS	ANI	INT	ORI	PE	PEU	PU	US	UL	BI
0.515											
0.564	0.645										
0.725	0.598	0.782									
0.680	0.523	0.653	0.691								
0.752	0.527	0.533	0.748	0.761							
0.642	0.680	0.693	0.549	0.722	0.762						
0.698	0.602	0.636	0.551	0.530	0.574	0.600					
0.559	0.662	0.735	0.559	0.755	0.639	0.527	0.598				
0.684	0.782	0.698	0.535	0.771	0.505	0.626	0.792	0.568			
0.654	0.616	0.744	0.716	0.647	0.687	0.588	0.674	0.772	0.627		
0.746	0.593	0.550	0.579	0.563	0.618	0.616	0.588	0.689	0.735	0.696	
0.733	0.546	0.776	0.682	0.744	0.708	0.707	0.669	0.583	0.500	0.568	0.582

The complete model validation is thoroughly described to ensure the absolute robustness and transparency of the SEM analysis. Each construct was demonstrated to be reliable through the calculation of Cronbach's alpha (ranging between 0.856 and 0.918) and CR (ranging between 0.857 and 0.919), with all exceeding the Chris Daker and Lilia Fedotova38 recommended thresholds. Convergent validity was established through AVE values ranging from 0.586 to 0.695, and standardized factor loadings of all measurement items, which in turn ranged from 0.730 to 0.871. Discriminant validity was established using the Fornell–Larcker criterion which indicated that the square root of the AVEs of each construct was higher than its correlation with other constructs. Moreover, all VIF values were far lower than the widely accepted threshold, so multicollinearity was not an issue here. To prove the model even more, a complete list of the indices' model fit was submitted (GFI, RMSEA, SRMR, NFI, CFI, relative chi-square, PGFI, and PNFI); all of these achieved or exceeded the acceptable criteria. These findings are presented in Tables 3 and 4 and demonstrate the robustness, validity, and sufficiency of the measurement and structural models. This approach guarantees the robustness and replicability of the SEM model applied here in that the study reports these validation criteria.

5. Discussion

This study explores how various factors influence the behavioral intentions of mobile social media users who engage with AR filters in the catering industry. The primary aim is to identify the key motivators driving the use of AR filters and to address gaps in marketing research regarding their application as a promotional tool in the catering sector. The results provide valuable insights into how AR filters are used in real-life settings and the behaviors of their users.

The hybrid approach proposed by this study contributes to the current knowledge about AR filters as products by considering both fun and functional aspects simultaneously, so that the complexity of users' experience can be taken into account in this new context. The model integrates constructs from technology acceptance, aesthetic quality, and user satisfaction models, which makes it a more comprehensive determination of factors underlying user engagement in the AR setting. This not only fills gaps in extant research that has often studied those dimensions in isolation, but also allows for a more nuanced perspective on how use-contributing and use-restricting aspects jointly affect user attitudes and behaviour. Accordingly, our model provides a solid basis for further research in the field of AR technology acceptance and UX design. While adopted and the acceptance of AR technologies have been examined in other domains, the current study stands out by looking at the implementation of AR filters in the Hong Kong catering business—a context typified by a strong consumer culture and high pace of digital transformation. The Hong Kong catering industry, with its competitive environment, diverse cuisines, and tech-savvy customers, provides ample opportunity to cater innovative marketing and engagement solutions and ideas. Unlike many existing studies that focus on retail, tourism, or general entertainment contexts, this study contributes to an understudied area and empirically investigates how AR filters are utilized in the food and beverage context to facilitate user experience, brand attitude, and social sharing behavior.

One of the core contributions of this study is a deep dive into the aesthetic and interactivity elements relevant to AR filters for both design and user experience. Although previous studies have recognized the centrality of visual (or entertainment) appeal to AR applications, few have broken such notions down into measurable entities, such as creativity (in terms of originality), animation and music (overall aesthetic quality), and interactivity features. By operationalizing them as first-order versus second-order constructs, our study offers an enhanced insight into how certain design elements affect user perceptions and behavioral intentions in an actual commercial setting. This method helps promote the theoretical growth of AR user experiences, and also provides practical guidance for designers and advertisers who wish to leverage filter functionality to increase interaction. In addition, the special cultural, social atmosphere in Hong Kong gives an extra dimension to our results. The city's consumers spend a lot of time on social media and value new digital experiences that combine physical and digital experiences. In such an environment, AR filters function not for mere functionality, but as an outlet for self-expression, socialization, and brand narrative. Our study illustrates how aesthetic and interactive factors of AR filters can exacerbate these effects, stretching into elevated satisfaction, enjoyment, and willingness to recommend. By locating our study in the Hong Kong catering industry, we are interested in identifying culturally bound technology adoption and digital engagement patterns that might not be visible in Western or other Asian markets.

5.1. User Behaviour of AR Filter

Participants in this study demonstrate frequent use of mobile social media platforms, with Instagram, Facebook, and YouTube emerging as the most popular. Among these, Instagram and Facebook are recognized for offering AR filter functionalities, while Snapchat also provides similar features. These findings highlight the growing importance of AR filters within mobile social media environments. Additionally, the results show that a large portion of participants use AR filters at least once a week, emphasizing their relevance in users' everyday activities. This regular engagement reflects the value users derive from

AR filters, which motivates them to incorporate these features into their routines. These findings are consistent with previous studies, which have shown that the interactive design and immersive experiences offered by AR filters effectively capture user interest [32].

5.1.1. The Effect of Determinants on the Perceived Value of Users

The findings of this study provide important insights into the relationships between key factors, including aesthetic quality, interactivity, originality, and perceived value (measured as perceived enjoyment and perceived ease of use) among AR filter users. The analysis shows that interactivity has a positive impact on both perceived enjoyment and perceived ease of use. This highlights the central role of interactivity in enhancing user experiences, which is consistent with prior studies that identify interactivity as a critical component of AR experiences that boosts enjoyment and usability.

The study also confirms that aesthetic quality and originality positively influence perceived enjoyment. These findings align with earlier research, which has established strong connections between these factors and user satisfaction. Furthermore, the results demonstrate that interactivity and aesthetic quality significantly contribute to perceived enjoyment, reinforcing the strength of these relationships. Interactivity, in particular, emerges as a key factor in shaping users' hedonic experiences and immersive interactions with AR filters. Its positive effect on perceived ease of use can be attributed to the dynamic user-filter interface, which simplifies user engagement and reduces the effort required to interact with AR filters. Additionally, originality and aesthetic quality are shown to be important predictors of perceived enjoyment, highlighting their role in creating engaging and satisfying user experiences. Overall, this study underscores the importance of interactivity, originality, and aesthetic quality in influencing users' enjoyment and ease of use when engaging with AR filters.

5.1.2. The Relationship Between Perceived Values and User Satisfaction

The findings of this study highlight significant relationships among perceived values, including perceived enjoyment, perceived ease of use, perceived usefulness, and user satisfaction, in the context of AR filter users. The results demonstrate that perceived ease of use not only positively impacts perceived usefulness but also significantly influences perceived enjoyment. Among these factors, perceived enjoyment is identified as the strongest predictor of user satisfaction, followed by perceived ease of use. Additionally, perceived usefulness is shown to have a meaningful impact on user satisfaction. These outcomes align with prior research, which suggests that the strength of these relationships may vary depending on the type of technology or system being studied [69].

Perceived usefulness, reflecting the practical value users associate with a new system or technology [62], is recognized for its strong role in predicting system adoption. However, given that AR filters provide both utilitarian and hedonic value, perceived enjoyment—defined as the pleasure and fun experienced by users [69]—is found to be a more robust determinant of user satisfaction [32,71,72], which emphasizes the importance of hedonic value in driving user engagement with AR filters. In conclusion, this study establishes significant associations among perceived values, emphasizing the primary role of perceived enjoyment as a predictor of user satisfaction with AR filters. At the same time, the influence of perceived usefulness on user satisfaction is also noteworthy, further supporting the relevance of both hedonic and utilitarian factors in shaping user experiences with AR technologies.

5.1.3. The Relationship Between User Satisfaction, User Loyalty, and Behavioral Intention

This study shows that user satisfaction strongly impacts both user loyalty and behavioral intention when it comes to AR filters. In other words, when users are happy with their experience, they will stay loyal to the filters and continue using them. This can be explained by the ability of AR filters to provide fun and engaging experiences. These positive experiences make users feel good about using the filters, encouraging them to return [74,78,79].

The study also finds that user loyalty plays an important role in predicting behavioral intention. Loyal users are more likely to stick with AR filters over time and show a stronger desire to use them in the future. To better understand these behaviors, the study combines two models: the TAM and the PVSL model. TAM focuses on the early stages of technology adoption, looking at factors like how useful and easy a technology is to use. On the other hand, the PVSL model looks at longer-term behaviors, such as how users find value in a product, how satisfied they are, and how loyal they become. While TAM is great for understanding why people adopt new technology, it does not fully explain long-term behaviors. That is where the PVSL model comes in, helping to capture the bigger picture of what keeps users engaged over time. In summary, the study highlights how important user satisfaction is for building loyalty and driving continued use of AR filters. Positive experiences with AR filters make users more likely to stay engaged and use them regularly. Additionally, user loyalty is a key factor in predicting future behavior, as it reflects users' ongoing commitment to the filters. These findings show that both short-term satisfaction and long-term loyalty are essential for encouraging sustained use of AR filters.

5.2. *Investigation Regarding the Data of Self-Designed AR Filter Usage in Spark AR*

Spark AR, a platform for managing AR filters on Facebook and Instagram, has revealed some fascinating insights. Developers and publishers on the platform use various metrics to track how their filters perform, and one standout observation is about AR Filter 2. Among the self-designed filters, AR Filter 2 has the highest posting rate, view rate, and photo-taking rate globally. This suggests that interactivity plays a big role in how people engage with these filters. Interestingly, AR Filter 2 is widely seen as the most interactive design out of the four, which likely explains its popularity.

The study also highlights how AR filters have become a key part of mobile social media platforms like Instagram, Facebook, and even YouTube. These filters are now woven into people's daily routines, showing their value and appeal. The research points to a strong connection between interactivity, enjoyment, and ease of use. In simple terms, the more interactive and fun the experience, the more users enjoy it. This finding is consistent with earlier studies that emphasize how interactivity can enhance AR experiences. Another important takeaway is the role of visual appeal and creativity in user satisfaction. Filters that look good and feel original tend to make users happier. The study found that enjoyment is the biggest factor driving satisfaction, followed by ease of use. This means that creating fun, engaging, and visually appealing AR filters is essential for keeping users satisfied. When users are happy, they are more likely to stay loyal and continue using the filters, which shows how positive experiences can lead to long-term engagement. To dig deeper into these behaviors, the study combined two models: the TAM and the PVSL model. TAM is great for understanding why people adopt new technology, focusing on things like usefulness and ease of use. However, it does not explain why people stick around. That is where the PVSL model comes in—it looks at long-term factors like satisfaction and loyalty. By combining these models, the research gives a more complete picture of what drives people to not only try but also keep using AR filters. These insights are useful for both researchers and professionals in industries like marketing and hospitality.

Although the present study achieves substantial statistical power, we acknowledge the merit in a more fine-grained analysis of the data about behavior-involved variables, such as AR filter use intensity. We find (with the support of previous research) that those who have used AR filters more often are more likely to perceive enjoyment and satisfaction, possibly because of increased familiarity and engagement. On the other hand, infrequent users are less interested in perceived usefulness and ease of use since they would be more task-based or utilitarian. These differences imply that the relationships between PERUSE and PU, PEU, JS, JL, and BI may not be the same for users with different degrees of intensity of use. It may be useful to investigate these behavioral segments in a more detailed way in downstream experiments for a better understanding of AR filter adoption and continuous engagement.

The results of the study also imply several modifications to the TAM model. For instance, perceived enjoyment should be regarded as an important antecedent as well. This would cover the emotional and fun aspects of using AR filters, which affect how people feel about them. Perceived Interactivity is another useful extension—it emphasizes how filters' interactive features are perceived by users and their effect on their acceptance. Consideration of aesthetics and originality, which were found to enhance satisfaction, is also warranted in the model. The TAM model, with these additions, might lead to a deeper understanding of what affects user acceptance and usage of AR filters. In summary, this study offers rich contributions to understanding how people employ and make sense of AR filters, in particular on social media platforms. It indicates that the motivation of enjoyment, interactivity, and creativity is important for driving user satisfaction and loyalty. These conclusions not only enrich current research but also provide practical guidance for the industry in order to help in the optimal use of AR filters to engage their audiences.

The inquiry was so persuasive that it could not be overlooked, as it demonstrated that colors, text, music, and animation can be integrated under "Aesthetic Quality" which is one concept. The results from CFA showed that these variables had a significant effect on the total concept. Moreover, the research confirmed that these elements are consistent and concordant, which signifies that overall they render a similar distortion to the aesthetic charm of AR filters.

Apart from providing evidence for the core constructs of perceived enjoyment, perceived usefulness, user satisfaction, and behavioral intention, this study poses interesting research questions concerning the heterogeneity of the relationships between perceived enjoyment, perceived usefulness, user satisfaction, and behavioral intention across diverse groups and contexts of users. Although the relative predictive power of perceived enjoyment emerges as the strongest predictor of user satisfaction and subsequent behavioral intention, the invariance of these relationships across demographic subgroups requires additional attention. For example, preliminary findings from our dataset, as well as the literature, reveal that gender may mediate the effects of a number of constructs. Such differences demonstrate the importance of taking a more granular view in academic analysis and managerial practice, as this paper recommends segmenting the AR filter user according to the above-mentioned demographic and psychographic characteristics in order to maximize the efficiency of both design and marketing strategies.

More broadly applicable, the findings have implications for other experiential consumption-hedonic environments, such as tourism, hospitality, and retail, even though this research study was conducted within the catering industry. The role of pleasure, interactivity, and novelty as antecedents of satisfaction and loyalty implies that the proposed extended TAM-SLM model in this study might gain considerable explanatory power beyond the context of AR filters in catering. Future research can fill this empirical void and test the generalizability of the relationships in different settings, as well as consider potential boundary conditions and mediating mechanisms. For instance, based on cultural differences, technological literacy, and the strength of social media usage, the adaptation and continued use of AR filters may be influenced.

From an applied perspective, these findings underscore the importance that practitioners should not take a one-size-fits-all strategy, and should rather focus on tailoring AR filter experiences to the diverse motivation and preference needs of different user segments. Investing in creative and interactive aspects of AR filters—like interactive visual features, customization by the user, and easy sharing on social media—can result in big engagement and loyalty wins. Meanwhile, the research suggests further refining technology acceptance models to include hedonic, aesthetic, and interactive constructs that have emerged in the digital consumer experience context.

6. Conclusions

This research aimed to further investigate the reasons behind AR filters' usage by applying a conceptual model that includes originality, interactivity, and aesthetics appeal. Integrating constructs of the established models such as the Technology Acceptance Model (TAM) and the Satisfaction–Loyalty Model, this study gives a comprehensive insight into user engagement in AR filters. The implications are profound for both developers and marketers, as well as for new avenues of research in the fast-changing technology game.

A major finding of this study is the centrality of interactivity when it comes to the development of users' attitudes toward AR filters. It shows that users are not just passive recipients of visual effects but actively look for interactive experiences, which stimulate their sensation of being involved, as well as their feeling of control. This increased involvement not only leads to better perceived enjoyment but also to perceived ease of use. In certain industries, such as catering, customer experiences without AR filters might otherwise be stationary experiences as opposed to memorable moments. These results illustrate the importance of creating AR filters that emphasize a balance between aesthetics and user interaction. Second, an important contribution of this study is the need for fun to encourage continued usage and positive WOM regarding online learning. AR filters not only work as utilitarian instruments but also entertain, and the fun greatly affects users' intentions to reuse and recommend AR filters. This realization is especially applicable with industries where customer engagement and the experiential value are crucial, including gaming, entertainment, and fashion.

Practitioners in the catering industry are advised to implement such AR filters that not only generate stunning visuals but also have the highest degree of interactivity. Elements like fabricators, feedback in real time, and gamified experiences are likely to significantly improve user engagement and create unforgettable client relations. Instead of offering customers ordinary dining experiences, restaurants can foster the interaction with their branded content and thus provide an avenue for oral marketing through social sharing. AR filter design can be related to the preferences and behavior of targeted audiences in order to enhance brand trust and, by that, set themselves apart in competitive market environments.

Furthermore, digital marketers should endorse AR filters in the entertaining and pleasure aspect rather than just pointing out practical advantages. The campaign that successfully depicts the fun part of the experience will be more likely to attract the audience and gain positive reviews. The constant refresh of AR content with seasonal themes, client feedback, or some recent trends can excite users and, in turn, make the brand relevant. Moreover, the right tactic, which mingles both satisfaction issues and fun, will lead to the intended result of AR filters heavily increasing customer engagement and, consequently, business profit.

The research also has wider implications, including the growing popularity of AR filters on social apps and ongoing advances in AR tech use overall. For companies, such developments offer great potential to carve their image by designing AR filters that correspond to targeted users' preferences and behaviors.

However, some limitations must be considered. First, the highly representative sample of the catering industry may limit the generalizability of the findings to other industries, as each of them might have different user expectations and usage patterns. Second, the use of self-reported data produced possible biases, such as social desirability and imprecision in the self-apperception of the behaviors and experiences on the participants' part [118–121]. These biases are indicative of issues of validity. Third, the sample is limited and might not be representative of all AR filter users, as other demographic factors, such as age, digital literacy, and cultural differences, may moderate user perceptions of and adoption of these designs in ways not discussed herein. In the end, the cross-sectional nature of the study provides only a snapshot of user attitudes and actions, without the benefit of being able to monitor for changes over time.

We suggest that future studies may overcome these limitations by utilizing longitudinal designs that track changes in user engagement with AR filters over time. Comparison across industries and cultural settings would also be useful in determining the generalizability of findings. In general, mixed-methods approaches, i.e., combining self-reported information with behavioral analytics or experimental approaches, may also serve to counteract biases and provide a deeper understanding of user motivations. Additionally, more research about the impact of digital literacy and cultural differences on AR filter adoption should be conducted. In future work, it will be interesting to perform related multi-group or moderation analysis that accounts for backwards differences from those reported in demographic and behavioral data, and therefore contribute a more granular insight into user-acceptable and practical insights for AR filter design and marketing. With the continuing evolution of AR technology, particularly with generative AI, the potential exists for truly personal and adaptive AR experiences. This offers fertile territory for future research examining the impact of these technical innovations on user engagement and marketing effectiveness. To conclude, this work reveals more about the determinants of AR filter adoption and use and suggests several specific avenues for future research. Future research can contribute to a richer and context-specific understanding of how AR technology might be a factor in shaping the experiences of users across a range of domains by attempting to tackle some of the limitations above and by following the research directions suggested.

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Conflicts of Interest: The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as potential conflicts of interest.

Appendix A. AR Filters

To make it easier for participants to understand the abstract concepts in this study, we created three AR filters using Spark AR Studio. These filters were designed to match the research goals and give participants visual and interactive cues while they answered questions on a 7-point scale. We set up a dedicated Instagram account so participants could easily access the filters, which were also available on Facebook. Each filter was designed to represent specific ideas from the study's model, helping participants connect with the concepts. To make things even clearer, we included images of the filters in the online questionnaire, so participants could refer to them while responding. This approach was meant to help participants provide more accurate and thoughtful answers. Since the focus of the study is on the catering industry, the filters were designed around restaurant-related themes, specifically the marketing mix elements: product, price, place, and promotion. Below is a breakdown of each AR filter:

AR Filter 1: Food Set

This filter was all about showing how interactive AR can be. Participants could play around with a virtual food set by resizing it, moving it, or changing its direction. The idea was to let them experience the interactivity construct firsthand. The filter also gave a 3D view of a catering service's food set, making it easier to visualize what is being offered. By engaging with this filter, participants obtained a clearer idea of how interactivity works in this context.

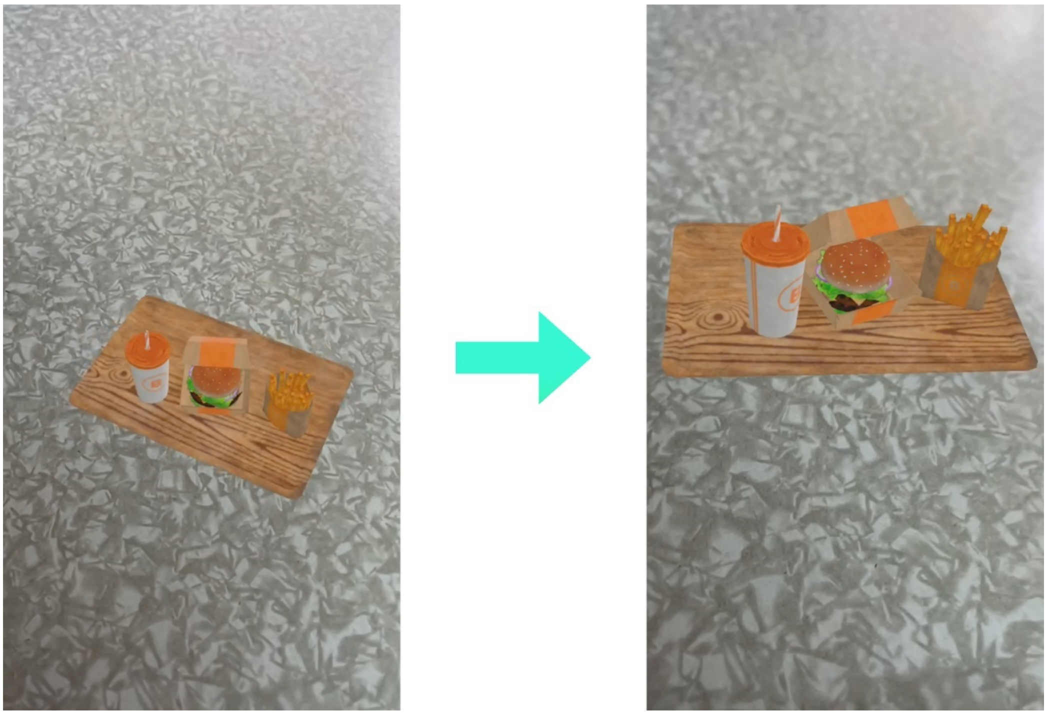

Figure A1. Detailed demonstration and interactivity of AR Filter 1.

AR Filter 2: Eating Food

The second filter, "Eating Food," was designed to highlight animation and interactivity. When participants opened their mouths, virtual food moved from the bottom of the screen to their mouths, and their faces would appear "fat" after eating. To make it even more engaging, the filter included background music, which tied into the music construct. This filter was meant to be fun and immersive, giving participants a better understanding of how animation, interactivity, and music can enhance the AR experience.

AR FilterA3

The "Photo Frame" filter lets participants explore color, text, animation, and price. They could choose different colored frames and font styles, which demonstrated the color and text constructs. There were also animated elements, like moving food and text, to show the animation construct. On top of that, the filter displayed restaurant pricing information, representing the price construct. Like the other filters, this one also included background music to make the experience more engaging. Overall, this filter gave participants a hands-on way to explore these concepts.

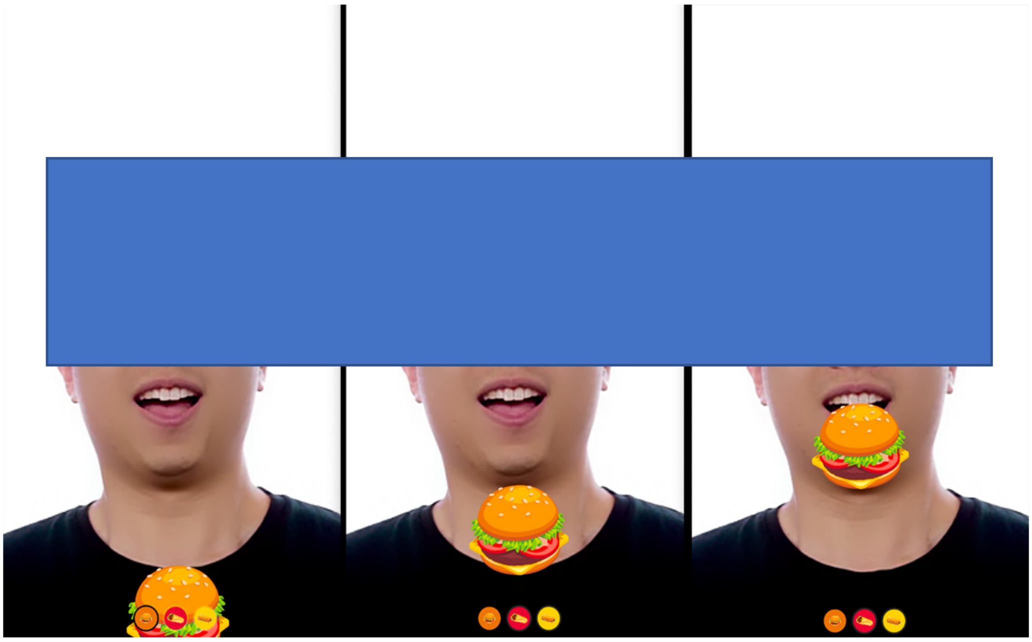

Figure A2. Detailed demonstration of AR Filter 2.

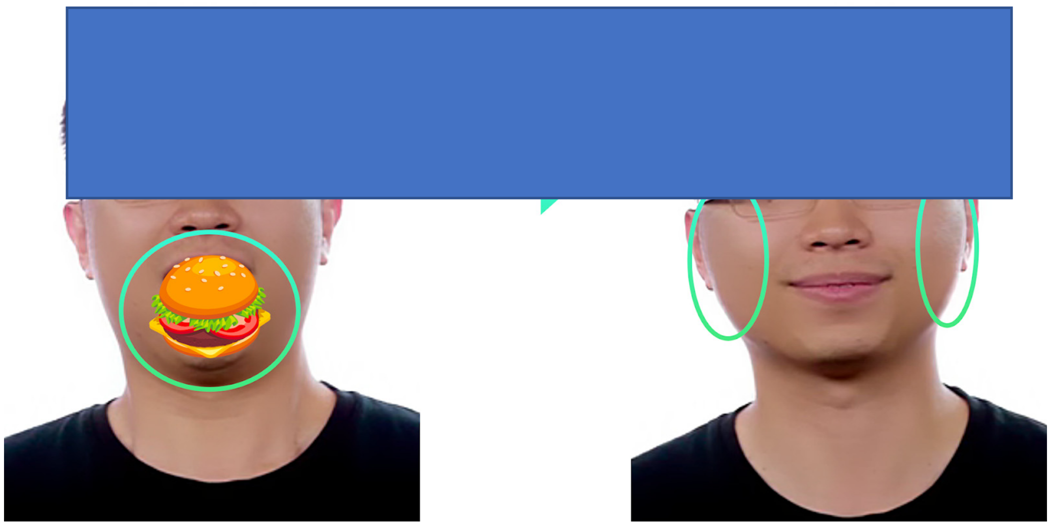

Figure A3. Interactivity of AR Filter 2.

Figure A4. Detailed demonstration and interactivity of AR Filter 3.

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