Mathematical Biosciences and Engineering

MBE, 18(6): 7218–7238.
DOI: 10.3934/mbe.2021357
Received: 31 May 2021
Accepted: 17 August 2021
Published: 26 August 2021

http://www.aimspress.com/journal/MBE

Research article

Toward a theory of smart media usage: The moderating role of smart media market development

Biao Gao[1,*] **and Lin Huang**[2]

[1] Jiangxi University of Finance and Economics, Nanchang 330013, China
[2] Graduate School of Business Administration, Kobe University, Kobe 6578501, Japan

* **Correspondence:** Email: biaogao.edu@outlook.com.

Abstract: Smart media usage is influenced by certain critical factors and can be further affected by the degree of diffusion in the market. However, existing research lacks sufficient understanding of the factors affecting smart media usage and their influential mechanisms. Taking AI-enabled smart TV in China as the research object, this study (1) develops a base model that includes users' three key gratifications (bi-directional communication, personalization, and co-creation); and (2) takes two sub-dimensions of market development (geographic segment and income segment) as moderators. Using data from 407 valid samples of current users, the partial least squares structural equation modeling analysis suggests that these three key smart gratifications can impact continuance intention with the moderating effect of market development. This study thus contributes to the literature by (1) clarifying the smart media gratification opportunities (smart media users' motivations or needs) for using smart media itself; (2) exploring the impact of the degree of market development on the uses and gratifications of the smart media itself; and (3) combining the uses and gratifications theory, and the diffusion of innovations theory, to complement each other in a model that provides a more complete picture of smart media usage.

Keywords: smart media; uses and gratifications; smart gratifications; diffusion of innovations; market development

1. Introduction

With the development of communication technology, profound changes are taking place in the media. The media industry is now entering the era of data-driven intelligence. Consequently, the so-called "smart media" has emerged. Smart media refers to media with unlimited information formed by integrating all previous media forms with artificial intelligence (AI) technology, assisted by the latest technical equipment and big data analysis. Smart media relies on different smart terminals, combined with cloud computing, cloud storage, AI, and other new technologies. Notably, smart media operate in such a manner that users become atomic nodes in the media chain.

With the continuous upgrading of Internet technology and the rapid penetration of pan-smart terminals, smart media based on smart terminals can provide not only high-speed bi-directional communication channels and personalized services for users, but also opportunities for users to participate in the production of media content [1]. Voice interaction is one of the focuses of the application of smart media at this stage. Through voice interaction, users and the media can naturally complete bi-directional communication. In addition, with the support of mobile Internet and big data technology, it is possible to offer services that meet the users' personalized needs. In addition, the new generation of Internet users is increasingly more adapted to information search, information sharing, and content creation. Smart media can meet these users' co-creation needs [1].

There are two primary perspectives on the understanding of smart media. First, from the perspective of technology, smart media is composed of media, AI, information technology, and big data. The second is the user perspective, which holds that smart media is the sum of information client and server that can perceive users and bring a better experience. Therefore, smart media is user-centric, can sense users' different life scenarios, and can provide them with real-time smart services. As a result, it is capable of meeting users' needs for bi-directional communication, personalization, and co-creation [2].

To explain smart media users' behavior, this study first presupposes that smart media is a user-centered medium to satisfy users' needs. To accomplish this, the media industry, through smart technology, gradually increases the media system's perception, memory, thinking, learning, adaptation, and decision-making abilities. Through this process, media intelligence forms new smart media that can meet user needs.

Uses and gratifications (U&G) theory is an approach to understanding why and how people actively seek out specific media to satisfy specific needs [3]. However, the existing research lacks an understanding of what gratifications for selecting smart media there are, and to what extent different gratifications influence users' continuance intention toward smart media. Another limitation of existing research is that the moderating effect of market development on gratifications regarding smart media usage has been neglected. These uncertainties suggest that more rigorous research needs to be conducted.

To fill these gaps, this study analyzes smart media users' continuance intention and focuses on user gratifications for the usage of smart media. This study also investigates the moderating effect of market development on the relationships between user gratifications and continuance intention. A quantitative research approach is applied using survey data from current smart media users.

Consequently, this study contributes to the literature by making the following contributions. First, this study will clarify smart media gratification opportunities (smart media users' motivations or needs). On this basis, this study will begin to answer Katz et al.'s (1973) early call to link the gratifications of specific human needs with particular media use [3]. Second, the moderating effect of market development on smart media users' gratifications on continuance intention will be clarified. Third, this study creates a model combining U&G theory and diffusion of innovations theory, to provide an overview of smart media usage.

The remainder of the paper is structured as follows. Section 2 outlines a literature review related to smart gratifications and market development, and then offers our hypotheses and theoretical framework. This is followed by descriptions of the research methods and data in Section 3. Next, in Section 4, we estimate the models and test the hypotheses. Finally, Section 5 concludes the study with discussions, theoretical contributions, practical implications, and directions for future research, etc.

2. Theory development and hypotheses

2.1. Uses and gratifications (U&G) theory

U&G theory explains the consequences of users' attitudes and behaviors, and the social or psychological desires that prompt them to choose a specific medium for the gratification of their intrinsic needs [4,5]. In U&G theory, needs that can motivate usage include psychological tendencies, environmental conditions, and social factors [3]. Gratification refers to the user's perceived fulfillment of her/his needs through usage activity pertaining to a medium [6]. Gratifications can impact a user's emotional state [7]. U&G theory has been applied to various Internet media, such as smartphones [8] and Weibo (Microblog) [7].

Gratifications sought vs. gratifications obtained is one of the essential issues in U&G theory. It is a contrast between "what users seek from an experience" and "what users get from an experience" [3,9–11].

In the context of Internet media, the audience's identity has changed from simple receivers to users, although they do not own the media. Accordingly, users no longer simply utilize media information but use the media itself [12]. Therefore, U&G theory generates the meaning of using the media itself (rather than media information). In the age of mass media, the media audience has come to include all people, because there are no isolated individuals who do not encounter media information in real life. However, as we gradually enter the age of Internet media, the audience is not satisfied with simply obtaining information, but begins to release information, publicize ideas, spread ideas, and plan activities in various ways. In other words, the audience is no longer a collection of "media information receivers" but has taken on a new identity as "media users." McLuhan (1964) suggested that the media itself is truly meaningful information [13]. That is to say, only when human beings have a specific medium can they engage in communication activities. Therefore, the essence of using media itself is the use of media information. Notably, "using the media itself" was originally included in U&G theory as an integral part of the theory [12].

Gratifications in U&G theory can be considered as critics of reinforcement learning in machine learning. Reinforcement learning is the process by which a computer agent learns how to act by observing the surrounding environment, which rewards its actions with either positive or negative results [14]. As a type of machine learning, reinforcement learning also shows the relationship between input and output. In the context of reinforcement learning, a computer agent's actions continually affect the environment, and feedback from the environment in the form of rewards is used as a guide. On the one hand, input for learning or feedback from the environment corresponds to the uses of U&G theory. On the other hand, gratifications of U&G theory incorporate the activeness of media users or autonomous choices (motivations and needs to be satisfied) into the model. In contrast to humans, the computer agent simply accepts and has no initiative. Therefore, the inclusion of antecedent factors, which are independent variables called gratifications, in the U&G framework can be considered an extension of the machine learning model.

The reason smart media is used must be linked to certain gratifications particular to smart media. This study calls these "smart gratifications."

2.2. Smart gratifications

Based on the user's need to use smart media and the characteristics of smart media itself, this study identifies three crucial smart gratifications: bi-directional communication, personalization, and co-creation.

2.2.1. Bi-directional communication

To begin with, the direction of communication needs to be viewed from the perspective of media evolution. Traditional mass media enables unidirectional communication, i.e., the media tends to provide information to the audience through a one-way channel. This is one-to-many communication. In contrast, bi-directional communication is interactive, in that users can respond to the information provided by the same channel in reverse [15]. Internet-based new media support one-to-one bi-directional communication between the media and users. It also supports many-to-many bi-directional communication among different users [16]. Smart media is the latest evolution of Internet-based new media, with AI functions such as natural language understanding and voice interaction, thereby realizing more natural bi-directional communication. Smart media users require bi-directional communication. Therefore, bi-directional communication is one of the critical motivations for smart media usage. The previous literature suggests that bi-directional communication positively influences a user's behavioral intention [17,18]. Thus, we propose the following hypothesis:

H1: Bi-directional communication directly positively impacts continuance intention.

2.2.2. Personalization

Personalization is a fundamental characteristic of smart media. Personalization refers to providing personalized information according to the unique preferences of different users. Media capable of sending individual-specific information to specific users can be said to have highly personalized characteristics [19]. Smart media has a smart recommendation function based on big data algorithms, thus realizing a high degree of personalization [20].

In basic personalization, the user's emotional information is powerful and valuable for providing relevant media services. Therefore, determining users' emotions for each given smart media service can be critical in business [20–23]. In the context of smart media, users' emotions, e.g., joy, trust, fear, surprise, sadness, disgust, or anger, can be extracted through machine learning. One of the methods used to accomplish this is sentiment analysis, which gleans emotions from textual content [20,21]. Another method is facial expression recognition (FER), which extracts a user's spatial and temporal features on the human face and converts them into physiological data [22,23].

Smart media users require personalization. Therefore, personalization is a critical motivation for smart media usage. Previous research suggests that personalization has a positive influence on user behavioral intention [24,25]. Thus, the following hypothesis is constructed:

H2: Personalization directly positively impacts continuance intention.

2.2.3. Co-creation

Traditional mass media leaves audiences with minimal co-creation spaces. With the development of communication technology represented by Internet media, the role of users in information creation, production, and distribution has been continuously strengthened [26]. The smart media platform provides users more opportunities for co-creation [1]. At this stage, users are both information receivers and co-creators on the smart media platform. Smart media users also need co-creation. Therefore, co-creation is a critical motivation for smart media usage. Previous research suggests that co-creation has a positive influence on a user's behavioral intention [27]. Thus, the following hypothesis is formed:

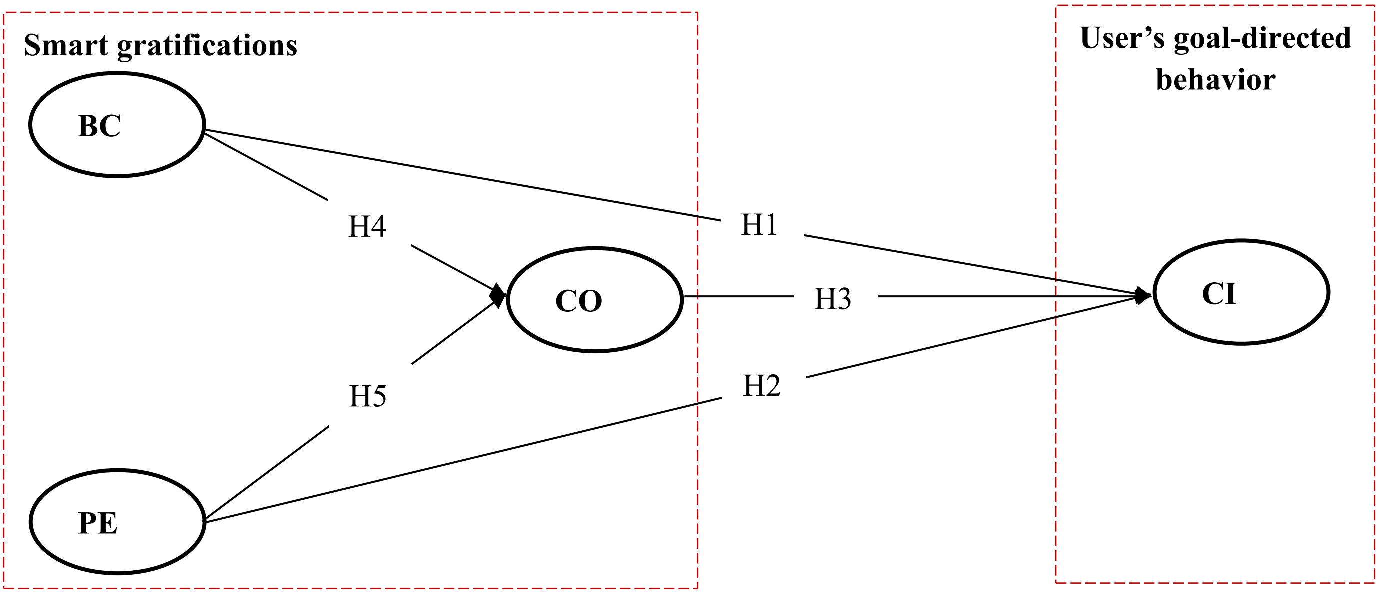
H3: Co-creation directly positively impacts continuance intention.

In addition, the function of smart media co-creation is realized based on the function of bi-directional communication and personalization. Therefore, the efficiency of smart media bi-directional communication and personalization could likely affect users' co-creation. In this study, bi-directional communication and personalization are two smart media attributes perceived separately by users. Therefore, both are independent attributes and do not affect each other. Based on this fact, we form the following hypotheses:

H4: Bi-directional communication directly positively impacts co-creation.

H5: Personalization directly positively impacts co-creation.

Figure 1 indicates the base model.



Note: BC=Bidirectional communication; PE=Personalization; CO=Co-creation; CI=Continuance intention.

Figure 1. Base model.

2.3. Smart media market development

Market development refers to the process of market entry and product dissemination. Market development is a growth strategy that identifies and develops new market segments for current products from a marketing segmentation strategy perspective. Market development involves expanding a firm's reach or tapping into different segments or unexplored markets. Accordingly, for technology providers, the process of new technology diffusion is a process of market development. As a growth strategy, it means expanding new technology products to new user groups in new market segments [28]. New market segments can be defined as new geographic segments, demographic segments, institutional segments, or psychographic segments [29].

Because of the research context of smart media, we focus on two sub-dimensions of market development: new geographic segments and new income segments. The geographic segment of market development refers to geographic expansion, which means that new users in geographic areas adopt new technology products. The income segment of market development means expanding to reach users of new income classes [28]. This study investigates how the two sub-dimensions of market development moderate the relationships between users' gratifications and continuance intention.

2.4. Diffusion of innovations theory

In the context of high-tech, such as smart media, discontinuous innovation is the norm, and market development strategies need to expand from the early user market to the mainstream user market. In this case, the diffusion of innovations theory can provide a theoretical basis for market development [29].

The diffusion of innovations theory can explain the method, reason, and speed of the spread of new technologies [30]. Rogers suggested that innovation must be widely adopted to be self-sustaining, and that there is a point of adoption rate that enables innovation to reach a critical mass. User motivation has a significant influence on the likelihood of potential users adopting innovations [31]. The categories of adopters include innovators, early adopters, early majority, late majority, and laggards [30].

Geographic and income segments have been applied as two sub-dimensions to reflect the differences in market development. Ryan and Gross (1943) posited that potential adopters have a close relationship with the community, represented by the city [32]. Different markets were found to have different degrees of acceptance of new technology products, and potential users in metropolitan areas were more likely to adopt innovation [33]. In addition, potential adopters with higher incomes were more likely to adopt an innovation. Innovators, early adopters, and the early majority generally have more personal wealth than the social average [30]. Accordingly, income level can be used to roughly represent the categories of adopters in the process of innovation diffusion. Thus, this study focuses on the moderating effect of the market's geographic and income segments.

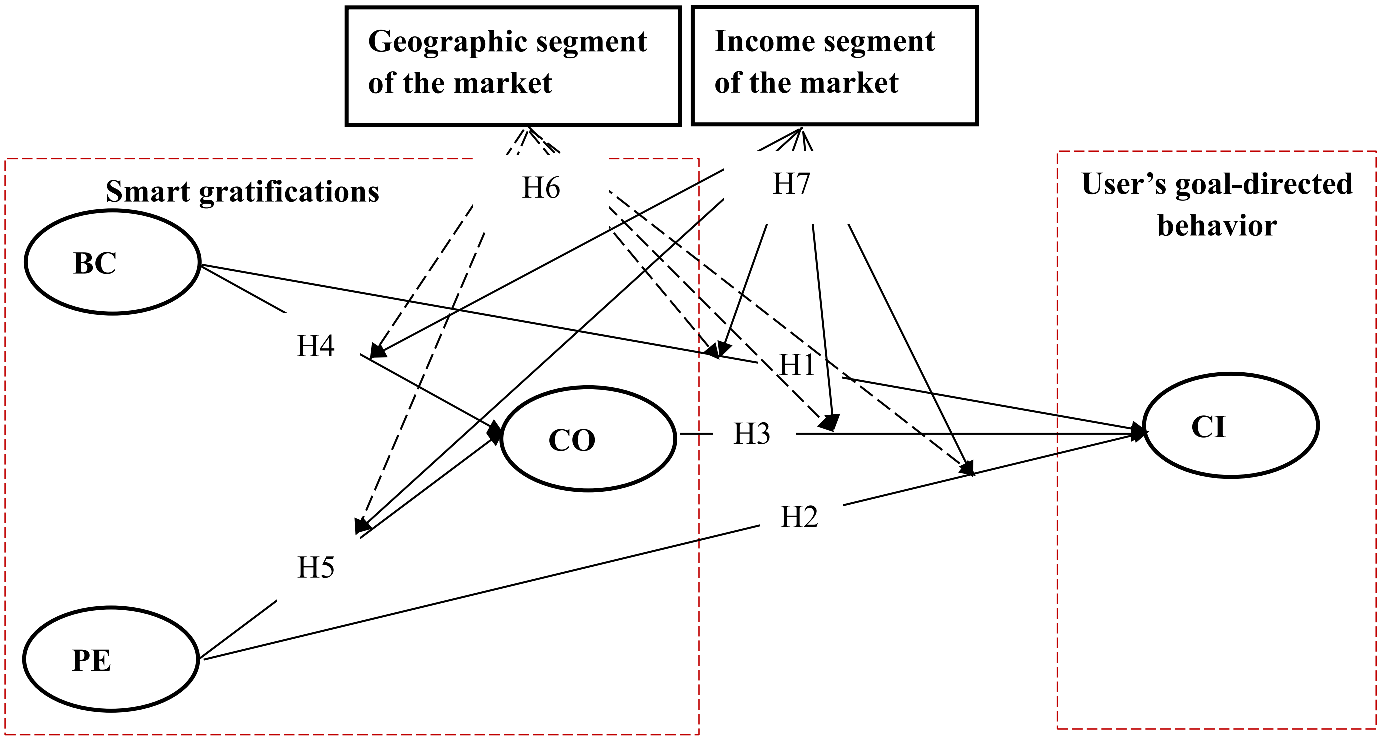
In this study, the moderating construct of the geographic segment is represented by two groups of cities in China: the first- and second-tier cities vs. the third- and fourth-tier cities (also known as the sinking market). By the end of 2019, activated smart TV terminals in three-or below-tier cities accounted for 63% of the total. In terms of scale, the second-tier cities have the largest smart TV activation scale, reaching 56.99 million units; the fourth-tier cities and the third-tier cities have 55.46 million units and 46.18 million units, respectively [34]. With regard to geographic segments, the diffusion process of smart media innovation is almost complete in China. China's smart media penetration rate in the third-and fourth-tier cities is close to that of the first-and second-tier cities. Based on this fact, we hypothesize the following:

*H6: Geographic segment **does not** have significant moderating effects on the relationships between the user's gratifications and continuance intention.*

In this study, the moderating construct of income segment is represented by users of two income groups in China: users with monthly income more than 5,000 CNY (high-income group) vs. users with monthly income less than 5,000 CNY (low-middle income group). Users with different income levels are likely to have different perceptions of the expected smart gratifications, which will affect their continuance intention. Thus, the following hypothesis is proposed:

H7: Income segment has significant moderating effects on the relationships between the user's gratifications and continuance intention.

Figure 2 indicates the proposed model with moderating constructs.



Note: BC=Bidirectional communication; PE=Personalization; CO=Co-creation; CI=Continuance intention.

Figure 2. Proposed model with moderating constructs.

3. Research method and data

3.1. Data measurement

A survey was conducted soliciting responses from current AI-enabled smart TV (AI TV) users, to analyze the proposed research model. The questionnaire has two versions: English and Chinese.

Researchers measure user attitudes with measurement scales. There are two types of scales that researchers most commonly use: The Likert scale and the semantic differential scale. The Likert scale asks respondents to score the degree of agreement or disagreement with a particular statement about expressions, concepts, or object attitudes [35]. The Likert scale is designed to measure attitude direction and intensity, and usually has a midpoint response option. The semantic differential scale is a technique for measuring the associated meanings of objects [36]. The semantic differential scale explores the connotative meaning or personal meaning of things, which differs from their actual physical characteristics. Users respond to stimulus words by assigning ratings on the bipolar scale of the semantic differential scale and using contrasting adjectives at each end. The questionnaire items in this study, like many similar studies [8,44], ask users to indicate their agreement or disagreement with the relevant statement and its degree, making the Likert scale more suitable as a measurement tool. The questionnaire items were adopted from previous studies using seven-point Likert scales [17,37–39], and then adjusted according to the current research context of smart media.

As a result, bi-directional communication was modified from McMillan and Hwang (2002) [17]; personalization was modified from Kim and Han (2014) [37]; co-creation was adapted from Mathis et al. (2016) [38], and continuance intention was revised from Bhattacherjee (2001) [39]. Geographic segment and income segment are both objective variables that can be directly accessed and grouped according to the user's IP address and income data.

3.2. Data collection and process

A pilot test was conducted prior to the main study, which provided preliminary evidence that the measurement scales were valid and reliable.

All surveys were conducted online using the Baidu sample service with simple random sampling in China. The Baidu sample service can provide accurate and valid third-party data [1]. Ethical approval was obtained from the Graduate School of Business Administration at Kobe University. Participants were informed of the aims of this study, and their participation was voluntary and anonymous. All personal information remained strictly confidential.

Surveys from 416 users who had prior experience with AI TV were collected. After the questionnaire data were received, it was processed with Microsoft Excel 2016. Nine participants who sent incomplete questionnaires were excluded. As a result, 407 participant responses were considered valid for further analysis. We then conducted a demographic analysis of the data. Subsequently, we performed a visual analysis of the measurement scales. Next, we applied ANOVA to conduct a test of homogeneity of variance against the demographic control variables using SPSS 25.0. After confirming the availability of data, the partial least squares structural equation modeling (PLS-SEM) approach with SmartPLS 3.0 was applied. We first tested the measurement model used in this study. Then we evaluated the relationships in the base model. Finally, we conducted a multi-group analysis to examine the moderating effect.

4. Data analysis and results

4.1. Descriptive statistics

Table 1 summarizes the demographics of the respondents.

Table 1. Demographic characteristics of the respondents.

Item	Type	Frequency	Percentage
Gender	Male	195	47.9%
	Female	212	52.1%
Age	18-25	123	30.2%
	26-35	216	53.1%
	36-45	54	13.3%
	Above 46	14	3.4%
Monthly income	Below 3,000 CNY	95	23.3%
	3,001-5,000 CNY	143	35.1%
	5,001-10,000 CNY	128	31.5%
	Above 10,000 CNY	41	10.1%
City	The first and second tier	271	66.6%
	The third and fourth tier	136	33.4%

Figure 3 shows the visualization of the results of Likert scale data.

Before formally conducting a PLS-SEM analysis, a test of homogeneity of variance with ANOVA is often performed, to determine whether the data can be mixed into a single data set [1,40]. In this study, we tested all scale items against the demographic control variables and confirmed that at the 95% confidence level, there was no difference in the average scores of the items.

4.2. Data analysis with PLS-SEM

We applied the partial least squares structural equation modeling (PLS-SEM) approach to test the base model of smart media usage, and the moderating effects of geographic and income segments in market development. PLS-SEM can be used to explain the relationships among independent variables, dependent variables, mediators, and moderators. Compared to covariance-based SEM, PLS-SEM has fewer identification issues and is more robust [41]. Since our study has a set of moderating variables, this increases the complexity. Under these circumstances, PLS-SEM is more suitable for this study [42]. Both the measurement model and the structural model were examined using SmartPLS 3.0 with partial least-squares estimation.

4.2.1. Measurement model

We first examined the measurement model fit to evaluate reliability and validity. Cronbach's alpha is a traditional criterion for internal consistency. The formula is as follows:

$$\text{Cronbach's } \alpha = \frac{K}{K-1}\left(1 - \frac{\sum_{i=1}^{K}\sigma_{Y_i}^2}{\sigma_X^2}\right)$$

Where K is the number of measurement scale items, σ_X^2 is the variance associated with the total scores observed, and $\sigma_{Y_i}^2$ is the variance associated with item i.

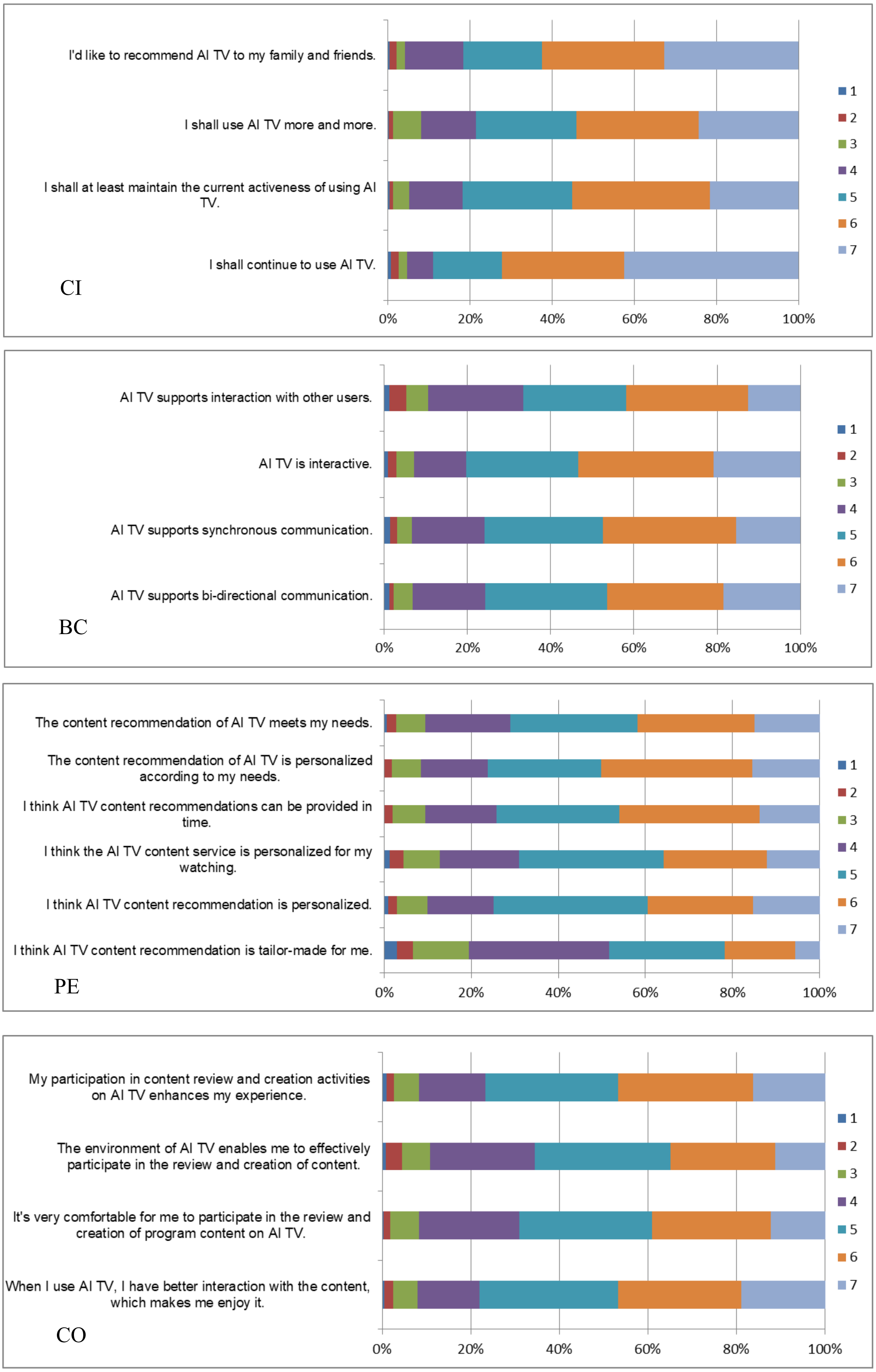


Figure 3. Visualization of the Likert scale data.

Cronbach's alpha has certain limitations. Thus, it is more appropriate to apply a different internal consistency reliability measure, called composite reliability (CR), which takes into account the different outer loadings of the indicator variables and can be calculated using the following formula:

$$\rho_c = \frac{\left(\sum_{i=1}^{p} \lambda_i\right)^2}{\left(\sum_{i=1}^{p} \lambda_i\right)^2 + \sum_{i}^{p} \mathrm{V}(\delta_i)}$$

Where λ_i is the completely standardized loading for the ith indicator, p refers to the number of indicators, and $\mathrm{V}(\delta_i)$ refers to the variance of the error term for the ith indicator.

A common measure to establish convergent validity at the construct level is the average variance extracted (AVE), whose formula is summarized as follows:

$$AVE = \frac{\sum \lambda_i^2 \mathrm{var}\ F}{\sum \lambda_i^2 \mathrm{var}\ F + \sum \Theta_{ii}}$$

Where λ_i, F, and Θ_{ii} are the factor loading, factor variance, and unique/error variance, respectively.

Table 2. Measurement items, validity, and reliability.

Constructs	**Adapted scales**	**Cronbach's alpha**	**CR**	**AVE**
Continuance intention [39]	1. I shall continue to use AI TV. 2. I shall at least maintain the current activeness of using AI TV. 3. I shall use AI TV more and more. 4. I'd like to recommend AI TV to my family and friends.	0.813	0.877	0.641
Bi-directional communication [17]	1. AI TV supports bi-directional communication. 2. AI TV supports synchronous communication. 3. AI TV is interactive. 4. AI TV supports interaction with other users.	0.829	0.886	0.663
Personalization [37]	1. I think AI TV content recommendation is tailor-made for me. 2. I think AI TV content recommendation is personalized. 3. I think the AI TV content service is personalized for my watching. 4. I think AI TV content recommendations can be provided in time. 5. The content recommendation of AI TV is personalized according to my needs. 6. The content recommendation of AI TV meets my needs.	0.866	0.900	0.599
Co-creation [38]	1. When I use AI TV, I have better interaction with the content, which makes me enjoy it. 2. It's very comfortable for me to participate in the review and creation of program content on AI TV. 3. The environment of AI TV enables me to effectively participate in the review and creation of content. 4. My participation in content review and creation activities on AI TV enhances my experience.	0.844	0.895	0.680

Tables 2–4 present the measurement model results, including information about reliability, validity, correlations, and factor loadings. As Table 2 indicates, the internal consistency reliabilities of multi-item scales, represented by Cronbach's alpha and CR, were above 0.80, suggesting that the scales were reliable. In addition, AVE was higher than the threshold value of 0.5 in all cases, thus establishing convergent validity.

Discriminant validity in this study was evaluated in two steps. First, the Fornell-Larcker criterion was applied, to test whether the square root of a construct's AVE was higher than the correlations between the construct and any other construct within the model [43]. As a result, the AVE was higher than the square of the correlations, thus suggesting discriminant validity. Second, the factor loading of an item on its associated construct should be higher than that of another non-construct item on that construct [44]. As a result, the data analysis showed that the results of loadings and cross-loadings supported internal consistency and discriminant validity. The discriminant validity of the base model is presented in Table 3. The PLS loadings and cross-loadings of the base model are shown in Table 4.

Table 3. Correlation matrices and discriminant validity of the base model.

	BC	CI	CO	PE
BC	**0.814**			
CI	0.550	**0.801**		
CO	0.548	0.484	**0.824**	
PE	0.578	0.535	0.693	**0.774**

Note: BC=Bidirectional communication; PE=Personalization; CO=Co-creation; CI=Continuance intention.

Table 4. PLS loadings and cross-loadings of the base model.

	BC	CI	CO	PE
BC1	0.865	0.495	0.442	0.490
BC2	0.842	0.504	0.440	0.464
BC3	0.832	0.449	0.502	0.502
BC4	0.706	0.320	0.397	0.423
CI1	0.434	0.822	0.376	0.418
CI2	0.425	0.776	0.366	0.384
CI3	0.464	0.792	0.401	0.430
CI4	0.436	0.812	0.404	0.476
CO1	0.550	0.536	0.823	0.596
CO2	0.419	0.381	0.840	0.566
CO3	0.416	0.305	0.831	0.548
CO4	0.395	0.336	0.803	0.569
PE1	0.485	0.373	0.572	0.798
PE2	0.498	0.463	0.541	0.789
PE3	0.475	0.384	0.523	0.770
PE4	0.456	0.460	0.558	0.785
PE5	0.369	0.401	0.506	0.761
PE6	0.393	0.395	0.515	0.740

Note: BC=Bidirectional communication; PE=Personalization; CO=Co-creation; CI=Continuance intention.

4.2.2. Structural model

Since the measurement model evaluation provided evidence of reliability and validity, the structural model was examined to evaluate the hypothesized relationships among the research model's constructs [45]. According to the recommendations from Hair et al. (2013) and Henseler et al. (2012), the structural model in this study was evaluated, and the bootstrapping technique was applied [45,46].

Test 1: testing the base model

Based on the data analysis, the base model explains 51% of the variance for co-creation and 37.6% of the variance for continuance intention. Cohen (1988) suggested that R^2 values for endogenous latent variables should be assessed as follows: 0.26 (substantial), 0.13 (moderate), 0.02 (weak) [47]. As a result, the R^2 values in the base model provided adequate explanatory power.

Tenenhaus et al. (2005) suggested a global fit measure for PLS-SEM modeling, which is the goodness of fit (GoF; 0 < GoF < 1) [48]; it can be calculated as the geometric mean of the average value of communality times the average value of R^2. The formula is summarized as follows:

$$\text{GoF} = \sqrt{\overline{com} * \overline{R^2}}$$

In the PLS modeling, the value of communality equals the value of AVE. Therefore, as Fornell and Larcker (1981) proposed, this study applies a threshold value of 0.50 for communality [49]. Furthermore, Cohen (1988) suggested small, medium, and large threshold values of the effect size for R^2 (small value=0.02; medium value= 0.13; large value=0.26) [47]. Therefore, by substituting the average AVE threshold value of 0.50 and the threshold value of the effect sizes for R^2 in the calculation formula of GoF, the threshold values of $\text{GoF}_{\text{small}} = 0.1$, $\text{GoF}_{\text{medium}} = 0.25$, and $\text{GoF}_{\text{large}} = 0.36$ can be calculated. These threshold values can serve as baseline values for validating the PLS-SEM model globally [50,51]. As a result, the GoF value of this study's base model is calculated to be 0.54, which exceeds the threshold value of 0.36, for a large value of GoF. As a result, the model in this study was found to provide a good fit for the data.

All path relationships in the base model were verified. First, as H1 predicts, we found direct positive impacts of bi-directional communication on continuance intention (β =0.334, $p < 0.001$). In addition, as H2 predicts, we found direct positive effects of personalization on continuance intention ($\beta = 0.257$, $p < 0.001$). Furthermore, as H3 predicts, we found direct positive impacts of co-creation on continuance intention ($\beta = 0.123$, $p < 0.05$). In addition, as H4 predicts, we found direct positive impacts of bi-directional communication on co-creation ($\beta = 0.221$, $p < 0.001$). Finally, as H5 predicts, we found direct positive effects of personalization on co-creation ($\beta = 0.565$, $p < 0.001$).

Mediation effects were observed in the base model. Specifically, co-creation mediates the influences of bi-directional communication and personalization on continuance intention.

The hypothesis testing results of the base model are presented in Table 5. The indirect effects are shown in Table 6.

Table 5. Hypothesis testing of the base model.

The hypothesis	Path coefficient	P-value	Result
H1: BC -> CI	0.334	***	Support
H2: PE -> CI	0.257	***	Support
H3: CO -> CI	0.123	*	Support
H4: BC -> CO	0.221	***	Support
H5: PE -> CO	0.565	***	Support

Note: BC=Bidirectional communication; PE=Personalization; CO=Co-creation; CI=Continuance intention. ***: $p < 0.001$, **: $p < 0.01$, *: $p < 0.05$, †: $p < 0.10$. 5,000 bootstrap samples were used.

Table 6. Indirect effects.

Specific path	Path coefficient	P-value
BC -> CO -> CI	0.027	†
PE -> CO -> CI	0.069	*

Note: BC=Bidirectional communication; PE=Personalization; CO=Co-creation; CI=Continuance intention. ***: $p < 0.001$, **: $p < 0.01$, *: $p < 0.05$, †: $p < 0.10$. 5,000 bootstrap samples were used.

Test 2: Testing for moderating effect of the degree of market development

This study applied the multi-group comparison approach (MGA) to test the moderating effect. Specifically, we examined whether there were significant differences in path coefficients between different market development groups, to determine whether there was a moderating effect [52]. This process includes calculating t-tests between two market development groups (samples), where m (n) represents the number of observations in sample 1 (2), which is summarized as follows:

$$t = \frac{\text{Path}_{\text{sample 1}} - \text{Path}_{\text{sample 2}}}{\left[\sqrt{\frac{(m-1)^2}{(m+n-2)} * S.E._{\text{sample1}}^2 + \frac{(n-1)^2}{(m+n-2)} * S.E._{\text{sample2}}^2}\right] * \left[\sqrt{\frac{1}{m} + \frac{1}{n}}\right]}$$

MGA has the following advantages: 1) It allows researchers to determine whether the parameters in the model are equal in two or more sub-groups [53]. 2) It can effectively verify the validity of the measurement model and the cross-setting reproducibility of the structural model. 3) It can be used to compare the differences between sub-groups or cross-groups of the same population [54]. This study divides the data into two sub-groups for geographic segment (the first-and second-tier cities vs. the third-and fourth-tier cities) and income segment (income level above 5,000 CNY vs. income level less than 5,000 CNY). Then, MGA is applied to estimate the path coefficient of each sub-group [55]. Finally, this study analyzes the differences between path coefficients, to determine whether there is a moderating effect.

In addition, to test the effectiveness of the geographic segment moderator for multi-group analysis, we conducted a t-test according to participant income in the two city groups. The P-value of this t-test was less than 0.05, indicating that the grouping moderator is valid. According to the results of the PLS-MGA analysis across geographic segments, H6 is supported. The data analysis results are listed in Table 7.

Table 7. Results of PLS-MGA analysis across geographic segments.

Path	Path coefficient	P-value	Hypothesis
BC -> CO	0.058	n.s.	Support
PE -> CO	0.016	n.s.	Support
BC -> CI	0.011	n.s.	Support
PE -> CI	0.077	n.s.	Support
CO -> CI	-0.033	n.s.	Support

Note: ***: $p < 0.001$, **: $p < 0.01$, *: $p < 0.05$, †: $p < 0.10$. BC=Bi-directional communication; PE=Personalization; CO=Co-creation; CI=Continuance intention. Path coefficient (A-B): A means first and second tier cities, B means third and fourth tier cities.

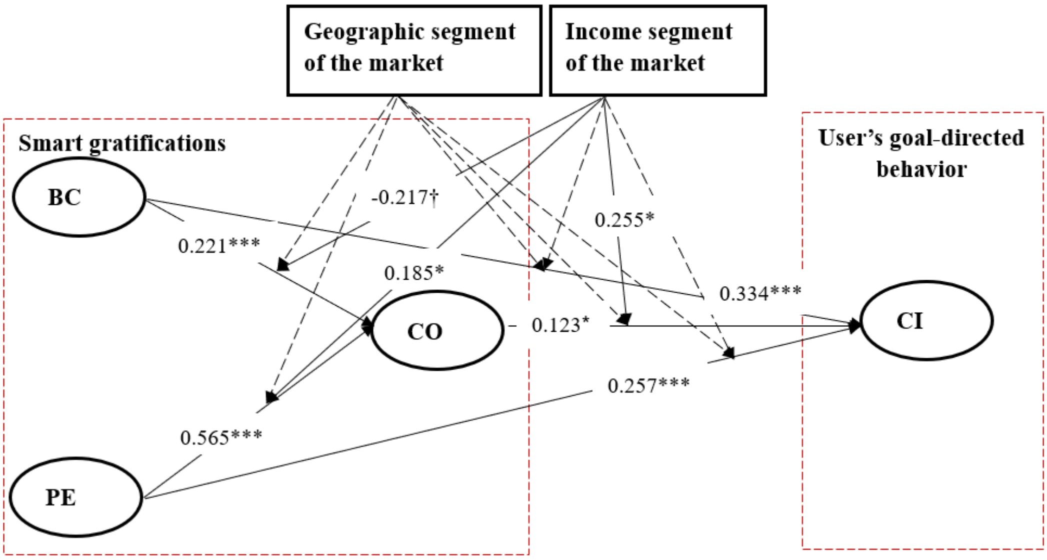
According to the results of the PLS-MGA analysis across income segments, H7 is partially supported. The data analysis results are listed in Table 8.

Table 8. Results of PLS-MGA analysis across income segments.

Path	Path coefficient	P-value	Hypothesis
BC -> CO	-0.217	†	Support
PE -> CO	0.185	*	Support
BC -> CI	-0.001	n.s.	Not support
PE -> CI	-0.147	n.s.	Not support
CO -> CI	0.255	*	Support

Note: ***: $p < 0.001$, **: $p < 0.01$, *: $p < 0.05$, †: $p < 0.10$. BC=Bi-directional communication; PE=Personalization; CO=Co-creation; CI=Continuance intention. Path Coefficient (A-B): A means monthly income level above 5,000 CNY, B means monthly income level less than 5,000 CNY.

Figure 4 indicates the results of the data analysis.



Note: BC=Bidirectional communication; PE=Personalization; CO=Co-creation; CI=Continuance intention. ***: $p < 0.001$, **: $p < 0.01$, *: $p < 0.05$, †: $p < 0.10$.

Figure 4. Results of the data analysis.

5. Conclusions and implications

5.1. Discussion

In this study, we developed a theoretical framework and used PLS-SEM to investigate how smart gratifications (bi-directional communication, personalization, and co-creation) influence smart media users' continuance intention in the smart media context, and understand the influence path mechanisms of these factors.

Bi-directional communication allows users to respond to information provided by the same channel [15] and is one of the critical motivations for smart media usage [16]. The data analysis results suggest that bi-directional communication positively influences smart media users' continuance intention, which is consistent with previous studies [17,18]. Next, personalization refers to providing personalized information according to the unique preferences of different users [19]. The extant literature shows that users' emotional information is powerful and valuable for providing personalized media services, as well as critical in business [20–23]. As predicted, consistent with previous research [24,25], personalization positively impacts smart media users' continuance intention. Smart media can also meet the co-creation needs of users [1]. As expected, consistent with previous studies [27], co-creation positively influences smart media users' continuance intention. In addition, based on logical reasoning and empirical analysis, the results indicate that bi-directional communication and personalization positively impact co-creation. To the best of our knowledge, these findings have not been previously explored.

The moderating effects of income level are effective for three of the five paths in the base model: bi-directional communication to co-creation, personalization to co-creation, and co-creation to continuance intention. The data analysis results show a significant difference between the users' two sub-groups of income level on the three paths relevant to co-creation. Users with a monthly income of less than 5,000 CNY are more concerned about the impact of bi-directional communication on co-creation. In comparison, users with a monthly income of more than 5,000 CNY are more concerned about the effect of personalization on co-creation, and their perception of co-creation can more effectively impact continuance intention.

There was no significant moderating effect of geographic segment. This result reflects that in terms of municipal administrative regions in China, the acceptance and perceptions of users in the administrative regions of third-and fourth-tier cities, are no longer significantly different from those of first-and second-tier cities.

5.2. Theoretical contributions

This study contributes to the literature by clarifying the smart media gratification opportunities (smart media users' motivations or needs) of smart media by providing a base model of smart gratifications. This study also discussed and confirmed that, through corresponding technical means, smart media could provide bi-directional communication [16], personalization [20-23], and co-creation [1] to meet smart media users' gratification opportunities and promote their continuance intention.

In addition, this study clarified the influential mechanisms of bi-directional communication, personalization, and co-creation on continuance intention. In addition to the direct impact on continuance intention, this study also clarified that bi-directional communication and personalization could affect continuance intention through the mediating mechanism of co-creation.

In the previous literature, U&G theory was mostly applied to explain the user motivation and gratification with media information. This study applies U&G theory to explain user motivation for the media itself and subsequent gratification. Based on U&G theory, prior studies suggest that users choose one type of media over the alternatives to gratify their needs [7]. By taking U&G theory to explain the usage of smart media itself (rather than media information), this study further explains the reasons for this and begins to answer Katz et al.'s (1973) early call to link the gratification of specific human needs with particular media use. This study demonstrates that people actively involved with smart media are doing so based on basic human needs [3], which they fulfil by using it.

In addition, taking the diffusion of innovations theory as theoretical support, this study further contributes to the literature by exploring the impact of the degree of market development on the uses and gratifications of smart media itself. Complementing the smart media usage model based on U&G theory, this study takes the degree of market development based on the diffusion of innovations framework as a moderating variable to understand different user segments' perceptions in greater detail. In this study, we use two sub-dimensions (income and geographic segments) to measure the degree of market development. The moderating effects of income segment of market development on smart media users' motivations for continuance intention reflect the diffusion of innovations degree in terms of income. The insignificant moderating effects of geographic segment indicate that the innovation of smart media has reached a critical mass in terms of China's geographic regions.

Finally, the combination of U&G theory and the diffusion of innovations theory in this study generate new theoretical contributions. When a new innovation is adopted in the diffusion of innovations model, it is the perceived attribute of the innovation that affects "adoption speed and scope." This study reveals the structure of smart gratifications of smart media perceived attributes that influence users' continuance intention, which is closely related to the adoption speed and scope in the diffusion of innovations theory.

5.3. Practical implications

Many of the findings of this study provide practical guidance for smart media practitioners. This study suggests that practitioners should focus on enhancing users' smart gratifications in their marketing strategies.

Smart media practitioners should focus on the three aspects of bi-directional communication, personalization, and co-creation, and improve these functions of smart media. This can better meet users' needs in these three aspects, to improve user awareness. User continuance intention will be enhanced accordingly.

For low- and middle-income groups, smart media practitioners should pay more attention to bi-directional communication to increase their continuance intention. This can promote the market development of smart media in low- and middle-income segments. For the high-income group, smart media practitioners should focus more on personalization and co-creation to increase their continuance intention. This can promote the market development of smart media in the high-income segment.

There is no noticeable difference in the critical demand points of smart media among users in various regional markets in China. Therefore, smart media practitioners can take uniform countermeasures for the entire user market and strengthen the three most critical aspects of smart media functions.

5.4. Conclusions

This study aimed to understand users' smart media usage and the similarities and differences in users' perceptions in different market development segments. This theoretical framework combines two streams in the literature; it integrates U&G theory and diffusion of innovations theory to understand smart media usage in the context of market development. Specifically, it investigated the effects of three critical smart gratifications (bi-directional communication, personalization, and co-creation) on continuance intention with the moderating effects of two sub-dimensions of market development (geographic and income segments). Finally, this study concludes that: (1) smart media users are involved in the process of smart media communication through the active usage of media; (2) the usage of smart media is based on smart media users' smart gratifications; and (3) smart gratifications vary based on the different segments of market development.

5.5. Limitations and future research directions

The limitations of this study are primarily reflected in two aspects. First, geographic segment grouping is based on the user's IP address. As a result, the data analysis results may not be sufficiently accurate. Future research can use more accurate methods to measure users' geographic locations. The second limitation is the influence of the time axis on the degree of market development. When we collected the data, China's smart media penetration rate in the third-and fourth-tier cities was close to that of the first-and second-tier cities.

To further enhance the model's applicability in this study and facilitate an in-depth understanding of smart media usage, it would be meaningful to study other latest representative smart media forms and compare them with this study. It would also be beneficial to use more accurate methods, e.g., big data generated by users using smart media, to measure users' geographic locations and obtain a more precise understanding of the geographic segment of market development. User gratifications, with the essential features of smart media, such as personalization, are worthy of more in-depth study. User gratifications with other features of smart media are also worth researching, to obtain a more comprehensive and in-depth understanding of smart media user behavior.

Acknowledgments

As a Ph.D. graduate and researcher, the first author wishes to thank the Graduate School of Business Administration, Kobe University, for its support.

Conflict of interest

All authors declare no conflicts of interest in this paper.

References

1. B. Gao, L. Huang, Understanding interactive user behavior in smart media content service: An

integration of TAM and smart service belief factors, *Heliyon*, **12** (2019), 1–13.
2. Z. R. Hu, The future development direction of media: Constructing an all-media ecosystem, *Chinese Broadcast. (In Chinese),* **11** (2016), 48–52.
3. E. Katz, M. Gurevitch, H. Haas, On the use of the mass media for important things, *Am. Sociol. Rev.,* **38** (1973)*,* 164–181.
4. A. M. Rubin, Media uses and effects: A uses and gratifications perspective, in *Media effects: Advances in theory and research* (eds. J. Bryant and D. Zillmann), Lawrence Erlbaum Associates, Inc., (1994), 417–436.
5. T. E. Ruggiero, Uses and Gratifications Theory in the 21st Century, *Mass Commun. Soc.,* **1** (2000), 3–37.
6. P. Palmgreen, Uses and gratifications: A theoretical perspective, in *communication Yearbook 8* (eds. R. Bostrom), Sage, (1984), 20–55.
7. I. C. W. Gogan, Z. Zhang, E. D. Matemba, Impacts of gratifications on consumers' emotions and continuance use intention: An empirical study of Weibo in China, *Sustainability,* **10** (2018), 3162.
8. J. Joo, Y. Sang, Exploring Koreans' smartphone usage: An integrated model of the technology acceptance model and uses and gratifications theory, *Comput. Hum. Behav.,* **6** (2013), 2512–2518.
9. J. G. Blumler, The role of theory in uses and gratifications studies, *Commun. Res.,* **1** (1979), 9–36.
10. P. Palmgreen, L. A. Wenner, J. D. Rayburn, Relations between gratifications sought and obtained a study of television news, *Commun. Res.,* **2** (1980), 161–192.
11. L. Leung, Generational differences in content generation in social media: The roles of the gratifications sought and of narcissism, *Comput. Hum. Behav.,* **3** (2013), 997–1006.
12. L. Hou, Supplement to the theory of "uses" in the theory of "uses and gratifications", *Shandong audiovisual (In Chinese),* **8** (2006).
13. M. Mcluhan, *Understanding media: the extensions of man,* MIT Press, (1964).
14. B. R. Kiran, I. Sobh, V. Talpaert, P. Mannion, A.A.A. Sallab, S. Yogamani, et al., Deep reinforcement learning for autonomous driving: A survey, *IEEE T. Intell. Transp.,* (2020), 1–18.
15. B. Hogan, A. Quan-Haase, Persistence and change in social media, *B. Sci. Technol. Soc.,* **5** (2010), 309–315.
16. S. Livingstone, The challenge of changing audiences or, what is the audience researcher to do in the age of the Internet?, *Eur. J. Commun.,* **1** (2004), 75–86.
17. S. J. McMillan, J. S. Hwang, Measures of perceived interactivity: An exploration of the role of direction of communication, user control, and time in shaping perceptions of interactivity, *J. Advert.,* **3** (2002), 29–42.
18. S. S. Sundar, S. Bellur, J. Oh, H. Jia, H.-S. Kim, Theoretical importance of contingency in human-computer interaction, *Commun. Res.,* **5** (2014), 595–625.
19. R. P. Hawkins, M. Kreuter, K. Resnicow, M. Fishbein, A. Dijkstra, Understanding tailoring in communicating about health, *Health Educ. Res.,* **3** (2008), 454–466.
20. L. Nahar, Z. Sultana, N. Iqbal, A. Chowdhury, Sentiment analysis and emotion extraction: A review of research paradigm, *1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT)*, (2019).
21. S. Kumar, M. Gahalawat, P. P. Roy, D. P. Dogra, B. G. Kim, Exploring impact of age and gender on sentiment analysis using machine learning, *Electronics,* **9** (2020), 374.
22. D. Jeong, B. G. Kim, S. Y. Dong, Deep Joint Spatiotemporal Network (DJSTN) for efficient facial expression recognition, *Sensors,* **20** (2020), 1936.

23. J. H. Kim, B. G. Kim, P. P. Roy, D. M. Jeong, Efficient facial expression recognition algorithm based on hierarchical deep neural network structure, *IEEE Access*, **7** (2019), 41273–41285.
24. S. Y. Ho, D. Bodoff, The effects of web personalization on user attitude and behavior: an integration of the elaboration likelihood model and consumer search theory, *MIS Quart.,* **2** (2014), 497–520.
25. J. Kim, A. Gambino, Do we trust the crowd or information system? Effects of personalization and bandwagon cues on users' attitudes and behavioral intentions toward a restaurant recommendation website, *Comput. Hum. Behav.,* **65** (2016), 369–379.
26. P. M. Napoli, *Audience Evolution: New Technologies and the Transformation of Media Audiences,* Columbia University Press, (2011).
27. X. Duan, L. Dai, Study on the relationship between experience quality, Co-created value and users' behavioral intention of making continuous contributions on internet UGC platforms, *J. Serv. Sci. Manage.,* **2** (2018), 267–277.
28. D. Smallbone, R. Leig, D. North, The characteristics and strategies of high growth SMEs, *Int. J. Entrep. Behav. Res.,* **3** (1995), 44–62.
29. S. F. Slater, J. C. Narver, Product-market strategy and performance: an analysis of the miles and snow strategy types, *Eur. J. Market.,* **10** (1993), 33–51.
30. E. M. Rogers, *Diffusion of innovations (1st ed.),* Free Press of Glencoe, (1962).
31. E. Ferlie, L. Gabbay, L. Fitzgerald, L. Locock, S. Dopson, Organisational Behaviour and Organisational Studies in Health Care: Reflections on the Future, in *Evidence-Based Medicine and Organisational Change: An Overview of Some Recent Qualitiative Research, 8* (eds. L. Ashburner), Palgrave, (2001).
32. B. Ryan, N. C. Gross, The diffusion of hybrid seed corn in two Iowa communities, *Rural Sociol.,* **8** (1943), 15–24.
33. J. Suriãnach, C. Autant-Bernard, F. Manca, N. Massard, R. Moreno, The diffusion/adoption of innovation in the internal market, *European Economy Economic Papers,* (2009).
34. Forward-looking Industry Research Institute, *China's smart home equipment industry market outlook and investment strategy planning report (In Chinese),* (2020).
35. R. Likert, A technique for the measurement of attitudes, *Arch. Psychol.,* **140** (1932), 44–53.
36. C. E. Osgood, G. J. Suci, P. Tannenbaum, *The measurement of meaning,* University of Illinois Press, (1957).
37. Y. J. Kim, J. Han, Why smartphone advertising attracts customers: A model of web advertising, flow, and personalization, *Comput. Hum. Behav.,* **2** (2014), 256–269.
38. E. F. Mathis, H. Kim, M. Uysal, J. M. Sirgy, N. K. Prebensen, The effect of co-creation experience on outcome variable, *Annu. Tour. Res.,* **57** (2016), 62–75.
39. A. Bhattacherjee, Understanding information system continuance: An expectation-confirmation model, *MIS Quart.,* **3** (2001), 351–370.
40. V. Cho, A study of the roles of trusts and risks in information-oriented online legal services using an integrated model, *Inform. Manag.,* **4** (2006), 502–520.
41. J. F. Hair, C. M. Ringle, M. Sarstedt, PLS-SEM: Indeed a silver bullet, *J. Market. Theory Prac.,* **2** (2011), 139–152.
42. W. W. Chin, B. Marcolin, P. R. Newsted, A partial least squares latent variable modelling approach for measuring interaction effects: Results from a Monte Carlo simulation study and an electronic-mail emotion/adoption study, *Inform. Syst. Res.,* **2** (2003), 189–217.
43. C. Fornell, D. F. Larcker, A Second Generation of Multivariate Analysis: Classification of Methods

and Implication for Marketing Research, in *Review of Marketing* (eds. M. J. Houston), American Marketing Association, (1987), 407–450.
44. V. Venkatesh, J. Y. L. Thong, X. Xu, Consumer acceptance and use of Information technology: Extending the unified theory of acceptance and use of technology, *MIS Quart.,* **1** (2012), 157-178.
45. J. F. Hair, C. M. Ringle, M. Sarstedt, Partial least squares structural equation modelling: Rigorous applications, better results and higher acceptance, *Long Range Plann.,* **46** (2013), 1-12.
46. J. Henseler, C. M. Ringle, M. Sarstedt, *Using partial least squares path modelling in advertising research: Basic concepts and recent issues*. *Handbook of Research on International Advertising,* Edward Elgar Publishing, (2012).
47. J. Cohen, *Statistical power analysis for the behavioural sciences (2nd ed.).* Lawrence Erlbaum, (1988).
48. M. Tenenhaus, V. E. Vinzi, Y. M. Chatelin, C. Lauro, PLS path modeling, *Comput. Stat. Data An.,* **1** (2005), 159–205.
49. C. Fornell, D. F. Larcker, Evaluating Structural Equation Models with unobservable variables and measurement error, *J. Market. Res.,* **1** (1981), 39–50.
50. D. Croasdell, A. Mcleod, M. G. Simkin, Why don't more women major in information systems?, *Inform. Technol. Peopl.,* **2** (2011), 158–183.
51. M. Wetzels, G. Odekerken-Schröder, C. Oppen, Using PLS path modelling for assessing hierarchical construct models: Guidelines and empirical illustration, *MIS Quart.,* **1** (2009), 177–195.
52. M. Keil, B. C. Y. Tan, K. K. Wei, T. Saarinen, A Cross-Cultural Study on Escalation of Commitment Behavior in Software Projects, *MIS Quart.,* **2** (2000), 299–325.
53. W. W. Chin, A. M. Mills, D. J. Steel, A. Schwarz, Multi-group invariance testing: An illustrative comparison of PLS permutation and covariance-based SEM invariance analysis, in *The Multiple Facets of Partial Least Squares and Related Methods* (eds. H. Abdi et al.), Springer International Publishing, (2016), 267–284.
54. S. E. Fawcett, C. Wallin, C. Allred, A. M. Fawcett, G. M. Magnan, Information technology as an enabler of supply chain collaboration: A dynamic-capabilities perspective, *J. Supply Chain Manag.,* **1** (2011), 38–59.
55. M. Sarstedt, J. Henseler, C. M. Ringle, Multigroup analysis in partial least squares (PLS) path modeling: Alternative methods and empirical results. *Adv. Int. Marketing,* **1** (2011), 195–218.