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Understanding interactive user behavior in smart media content service: An integration of TAM and smart service belief factors

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ABSTRACT

Smart media combines media and artificial intelligence (AI) and can also be a user-centered content service market. However, existing research lacks an understanding of user's perceptions concerning smart services generated by different user experience types across different payment groups. Taking AI-powered Smart TV (AI TV) as a typical research object, this study (1) develops a theoretical model by integrating the technology acceptance model with users' smart service belief factors and (2) employs the user experience type as an original moderator. Using data from 585 AI TV users, the structural equation modeling analysis suggests that perceived two-way communication, perceived personalization, and perceived co-creation as three belief factors, are important antecedent constructs in the extended technology acceptance model. The analysis also suggests that the user experience type exerts positive moderating effects on two-way communication and personalization to attitude toward behavior and purchase intention. This study thus contributes to the literature on smart service by identifying and studying smart service belief factors. The addition of smart service belief factors as antecedents, as well as user experience type as a moderator, are crucial to expand the generalizability of TAM to the smart media service context. From a customer experience management perspective, this study shows how to convert ad-supported users into new paid subscribers, while keeping existing subscribers by fulfilling their smart service requirements.

1. Introduction

The market share of smart TVs has steadily increased throughout the world, including the United States, Europe, China, and elsewhere (Mordor Intelligence, 2019). Smart TV is undergoing a gradual intellectualization process; it is becoming smarter with time. As a combination of artificial intelligence (AI) technology and original smart TV, AI-powered Smart TV[1] (AI TV, also known as Smart TV 2.0) meets the characteristics of the smart media.

AI technology is profoundly reshaping the media. Nowadays, AI technologies, such as speech recognition and natural language understanding, are making the two-way exchange of information between AI TV and users more natural (Fernandes et al., 2019). Besides, AI TV, which is currently based on data analysis of the user's media habits, is capable of accurately offering personalized service (Foss et al., 2019). Furthermore, in the context of smart service, AI TV with smart technologies allow for co-creation (Beverungen et al., 2017). AI TV is a platform for smart content services. For example, since 2017, many companies, including Netflix and Tencent, have started interactive programs where users participate in personalized TV programs through a variety of interactions with AI TVs. In order to explore smart media, this study takes AI TV as a representative research object.

Customer experience is constituted by every point of user interaction with the service; customer experience management (CEM) represents a business strategy designed to manage the user experience (Grewal et al., 2009; Homburg et al., 2017). Grönroos (2004) suggested that interaction can be regarded as a process and this interaction process, as a service flow, can be included in the marketing mix. In terms of the management of customer experience, the identification of the user's smart service belief factors is significant. Because in the case of smart media service consumption, smart service belief factors function as drivers of users' perceptions toward smart service elements; these user's belief factors concerning key elements of smart services play a critical role in the interaction process. However, there is a lack of research on the smart

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[1] AI TVs have added AI functions such as voice interaction and smart recommendation, as compared to Smart TVs. Representative brands of AI TVs include LG, Sony, Samsung, TCL, Skyworth, and others (Misal, 2018).

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service belief factors in the prior literature (Beverungen et al., 2017; Macinnis, 2013; Wünderlich et al., 2013; Wünderlich et al., 2015). Upon the identification of the user's smart service belief factors, customer experience can thus be effectively managed.

This study defines the smart media market as a two-sided market wherein smart content service is consumed by users. A smart media market can be considered as a "two-sided market;" the two separate outputs that smart media produces are: content service and ad-supported users (Doyle, 2013; Kim, 2016). Nowadays, the content service directly consumed by paid subscribers has become a more important source of profit (e.g., (Gaivoronski et al., 2017; Lambrecht and Misra, 2017)). In other instances, free content is provided as a marketing strategy or to generate revenues from advertising (Lambrecht and Misra, 2017; Pauwels and Weiss, 2008). However, content service providers, who intend to move online service offerings from free to fee, are faced with users' unwillingness to pay (Brax and Jonsson, 2009; Lambrecht and Misra, 2017; Pauwels and Weiss, 2008). When properly targeted, there are markets where users will be willing to pay for a variety of reasons. However, existing research lacks an understanding of differences in perceptions across different payment groups, based on the user experience type. (e.g., (Choi et al., 2010; Kim et al., 2018; Venkatesh et al., 2012)). Thus, research on converting free users to new paid subscribers while keeping existing subscribers by studying differences in smart service perceptions between paid subscriber group and ad-supported user group is theoretically and practically important.

Smart media, which combines media and AI, is an information system using up-to-date smart technology. This study thus employs the technology acceptance model (TAM) as a research framework. On this basis, a theoretical model that integrates a user's smart service belief factors toward AI TV into TAM and applies user experience type as a moderator from a CEM perspective is developed. The model is tested using structural equation modeling (SEM) of survey data.

This study is expected to make important theoretical and managerial contributions to smart media services. It applies TAM and an understanding of smart service belief factors from a CEM perspective. By extending prior research with this theoretical integration, this study expects to make three key contributions. First, by identifying smart service belief factors, studying the relationships between smart service belief factors and users' attitude toward behavior, and analyzing intention to purchase, the knowledge gained will facilitate a better understanding of interactive user behavior in smart media content service. Second, by incorporating three smart service belief factors into TAM, this study has expanded the overall theoretical network related to technology use and have furthered the generalizability of TAM to a smart media service context. Third, by taking user experience type as an original moderator, this study should demonstrate how to convert ad-supported users into new paid subscribers, while keeping existing subscribers, by fulfilling their smart service requirements, from a CEM perspective.

2. Theory development and hypotheses

2.1. Background

Storey et al. (2010) defined smart media object as a combination of data, representation, channel, and intelligence. Accordingly, smart media objects are capable of perceiving users' different needs in different life situations. By analyzing user's data, these objects can predict, adapt to, react to, participate in, evolve, and convert users' needs. A smart device can be defined as an information processing device that facilitates the interaction between user and service (Lim et al., 2012). Maybury (1998) concluded that smart refers to an improvement in the naturalness, effectiveness, and efficiency of human-machine interaction, based on advances in human-machine interfaces. Smart media channels link the users with the smart media devices. In this sense, smart media plays a mediation role when users interact with smart services (Storey et al., 2010).

The functional awareness and connectivity of services provided through smart products are known as smart services (Allmendinger and Lombreglia, 2005). Smart services are transmitted to or through smart devices that have a sensibility and are capable of real-time data collection and continuous communication (Wünderlich et al., 2015). Smart services are characterized by intelligence, connectivity and interaction (Allmendinger and Lombreglia, 2005; Rijsdijk et al., 2007; Rijsdijk and Hultink, 2010; Wünderlich et al., 2013). In this context, the interaction between the smart service and users in an internet environment plays an essential role. For example, Verhoef et al. (2017) analyzed the interaction among users, smart objects, and the physical environment. Volpentesta and Antonio (2015) focused on the user interaction with a smart service in a ubiquitous environment.

Smart media is a "user-centric" media that focuses on satisfying users' needs. Therefore, user's perceptions concerning key elements of smart services play a key role in the interaction process. Previous literature suggests there is a large gap in understanding how smart services impact the perceptions of end users in B2C environments (Beverungen et al., 2017; Macinnis, 2013; Wünderlich et al., 2013; Wünderlich et al., 2015). The existing literature has only captured a small number of relevant factors to understand users' attitude and adoption behavior. Smart service belief factors comprising a user's perceptions toward key elements of smart service need to be clearly identified. In the context of smart service, smart technologies facilitate higher levels of human-machine interaction (Gretzel et al., 2016). They bring about personalization and co-creation (Neuhofer et al., 2015). Based on a literature review, three key belief factors associated with the model have been identified in this study: perceived two-way communication, perceived personalization, and perceived co-creation.

Another limitation associated with the emerging smart media service and information system literature is that differences in perceptions across groups are only considered in terms of certain moderating effects, such as age (Venkatesh et al., 2012), gender (Kim et al., 2018; Venkatesh et al., 2012), or inexperienced and experienced groups (Castañeda et al., 2007; Choi et al., 2010; Kim et al., 2018). There is a lack of research on the differences in smart service perceptions generated by different user experience types across groups with different payment types. This study thus explores how users' perceptions concerning smart service change across different user experience groups in terms of payment type as users gain different types of experience. This is done by developing a theoretical model that accounts for smart technology and user interaction from a CEM perspective, determinants of user perceptions toward smart services are analyzed with user experience type as a moderator.

2.2. Smart service belief factors

2.2.1. Two-way communication

Smart communication between users and AI enabled devices is a type of human–machine communication, it theorizes the smart device as a communicator with which users communicate, not merely a channel (Guzman, 2018). The concept of two-way communication is closely related to the term interactivity. In the communication approach to define interactivity, Pavlik (1997) defined interactivity as a bi-directional communication between a source and a receiver. With respect to two-way communication, some researchers proposed that information sharing and exchange are key elements within the communication process (Bretz and Schmidbauer, 1983; Rafaeli, 1988; Williams et al., 1988). According to other researchers, two-way communication can be characterized by a mutual discourse (Burgoon et al., 1999; Hanssen et al., 1996; Williams et al., 1988). It can also be described as the ability to engage in mutual communication (Liu and Shrum, 2002; Liu, 2003) because user demand is no longer just "one-to-many" but may be "one-to-one" or even "many-to-many." Additionally, two-way communication can be described as the ability to give feedback (Duncan and Moriarty, 1998; Ha and James, 1998; Newhagen et al., 1996).

Two-way communication is one of the essential characteristics of smart services. Advanced smart service systems enhance two-way communication, such that all users are connected in real time so continuous communication and information sharing can be achieved (Lee et al., 2018; Li et al., 2018). Recurrent two-way communication increases the possibilities of an in-depth understanding of users, promotes relationships between users and smart service providers, and also allows for more targeted service designs for users (Valencia et al., 2015).

Previous literature has suggested that users' perceived two-way communication can exert a positive influence on users' attitudes and involvement toward new media (McMillan and Hwang, 2002; Sundar et al., 2014). Thus, in the context of the AI TV content service, users' perceived two-way communication can very likely affect users' attitude toward behavior and behavioral intention, whereby attitude toward behavior refers to the user's overall evaluation of performance behavior (Davis, 1986, 1989) and the key behavioral intention is the intention to purchase. In addition, based on the two-way communication system, AI TV's human-computer bi-directional information exchange process is very likely to impact users' perceived usefulness of the service. Abdullah, Jayaraman, Shariff, Bahari & Nor (2017) suggested a positive impact of the two-way communication on perceived usefulness. Thus, we hypothesize:

H1a. Perceived two-way communication of an AI TV service has a positive direct effect on intention to purchase.

H1b. Perceived two-way communication of an AI TV service has a positive direct effect on attitude toward behavior.

H1c. Perceived two-way communication of an AI TV service has a positive direct effect on perceived usefulness.

2.2.2. Personalization

Personalization enables service providers to differentiate a service on the basis of each user, which means that users are more likely to accept that their needs are met by the service's offerings (Anand and Shachar, 2009). Personalization also involves tailoring the marketing mix performed by the service provider (Arora et al., 2008; Rust and Huang, 2011), such that the service provider decides what marketing mix is suitable for each user on the basis of user data (Nunes and Kambil, 2001). All in all, personalization goes one step further than customization, because the service provider determines the proper degree of customization and thus, anticipates what the user needs (Montgomery and Smith, 2009).

With users' personal data, smart service systems can develop broader customer understanding (Demirkan et al., 2015; Peters et al., 2016) and thus, create a better user experience based on innovative value propositions, as well as deeper customer relationships, as a result of personalization (Ostrom et al., 2015; Thomas et al., 2017). In the context of a content service, smart media can offer personalized services (Kim, Kim and Kim, 2017a). AI functions, such as AI speaker recognition, make personalized service for each individual user feasible.

DeZoysa (2002) suggested that users are highly receptive to personalized services. In addition, personalized recommendations, according to each user's preferences, can generate better responses (Xu and Araki, 2006). Prior literature has suggested that users' attitudes and behaviors can be affected by personalization (Ho and Bodoff, 2014; Kim and Gambino, 2016). Thus, it is very probable that users' perceived personalization affects users' attitude toward behavior and behavioral intention. Additionally, personalization was found to be a significant factor influencing perceived usefulness in the online environment (Chau and Lai, 2003; Desai, 2018). AI TV's smart recommendation system, aided by machine learning based on a large amount of data, is capable of personalization by monitoring and identifying the habits and needs of users, and it is very likely to impact users' perceived usefulness. Thus, we hypothesize:

H2a. Perceived personalization of an AI TV service has a positive direct effect on intention to purchase.

H2b. Perceived personalization of an AI TV service has a positive direct effect on attitude toward behavior.

H2c. Perceived personalization of an AI TV service has a positive direct effect on perceived usefulness.

2.2.3. Co-creation

Co-creation is based on a wider trend whereby users, who are no longer satisfied with their traditional role as an end-user, tend to get involved in creating and developing services, as well as sharing their experiences with others (Ramaswamy and Guillart, 2010). Smart service systems serve users better, create more opportunities for win-win situations, and increase co-creation, which creates value for both service providers and end users (Beverungen et al., 2017). In the co-creation process, service providers make a value proposition and users play an active role in refining the value proposition, so the user obtains value by using the service (Barile and Polese, 2010). Users' co-creation activity is critical to encourage participation based on interactions with a co-creation system (Füller and Matzler, 2007; Nambisan and Nambisan, 2008).

The development of smart communication technologies fosters value co-creation with end users (Bassano et al., 2018). Smart service systems enable value creation between service providers and end users through their joint performance of service activities (Anke, 2018). Smart service systems digitally mediate the interaction between service providers and end users, thus achieving the personalized co-creation of value (Beverungen et al., 2017). Smart media makes users much more active and productive in terms of co-creation by offering a wide range of co-creative opportunities. Active users demand a smart media platform that can facilitate personalized participation without barriers. They demand an increase in the scope for co-creation and participation, and are more willing to pay for the content with which they engage.

Previous literature (e.g., (Duan and Dai, 2018)) has suggested that users' perceived degree of co-creation may very likely affect users' attitude toward behavior and behavioral intention. In addition, as users' perceived degree of co-creation is based on their interaction with the AI TV co-creation system, it is very likely to impact users' perceived usefulness. Thus, we hypothesize:

H3a. Perceived co-creation of an AI TV service has a positive direct effect on intention to purchase.

H3b. Perceived co-creation of an AI TV service has a positive direct effect on attitude toward behavior.

H3c. Perceived co-creation of an AI TV service has a positive direct effect on perceived usefulness.

2.3. Technology acceptance model (TAM)

TAM is one of the most widely used frameworks to explain the use of specific systems or services; it suggests that when a new technology is presented, there are certain factors influencing users' decisions with respect to usage (Davis, 1986). TAM has been validated as a reliable theoretical model to explore smart services, such as smart sharing services (Lai, 2015), smart watches (Kim and Shin, 2015), smart wearable devices (Gao et al., 2016), a smart car service (Yoon and Cho, 2016) and a smart home service (Kim, Park, Choi, 2017b; Park et al., 2017). Furthermore, TAM provides empirical support for many studies on internet-based TV (Jang and Noh, 2011; Jung et al., 2009; Wagner et al., 2017). In addition, TAM is well-verified by the fact that many scholars use it for research on the online service context to explore users' behavioral patterns and their willingness to pay (Chen et al., 2002; Gefen and Straub, 2000; Gefen et al., 2003; Lin and Lu, 2000). Therefore, TAM is considered to be a suitable framework for this study.

TAM suggests that the user's behavioral intention can be determined by three constructs: perceived usefulness, perceived ease of use, and attitude toward behavior (Davis, 1986). Perceived usefulness refers to the degree of users' belief that using the system can increase their efficacy (Davis, 1986, 1989). Perceived ease of use refers to the degree of users' belief that using the system would be effortless (Davis, 1986, 1989). Attitude toward behavior refers to users' overall evaluation of performance behavior (Davis, 1986, 1989).

There are three major types of TAM extensions. The first extension includes external variables that are attached to the two belief factors of perceived usefulness and perceived ease of use, such as demographic characteristics (Venkatesh and Davis, 1996; Venkatesh and Morris, 2000) and personality traits (Gefen and Straub, 1997). The second extension identifies additional belief factors, such as visibility (Karahanna et al., 1999) and content richness (Lee and Lehto, 2013). The third extension incorporates factors from other models of technology acceptance, for instance, perceived behavioral control (Liaw and Huang, 2003) and subjective norm (Barki and Hartwick, 1994).

In the TAM extension models, the effect of the extended factors on intentions can be mediated by perceived usefulness (Ooi and Tan, 2016; Venkatesh and Davis, 2000; Wu and Chen, 2016) and attitude (Davis et al., 1989). Thus, this extended TAM model positions perceived usefulness and attitude as mediating variables in the context of smart service consumption, to explain the influence mechanism of smart service belief factors on intention to purchase.

This research is one of the first studies to test a new extension of TAM in the context of smart media, represented by AI TV. This extended TAM model incorporates users' smart service belief factors (perceived two-way communication, perceived personalization, and perceived co-creation) as additional theoretical constructs and develops a theoretical basis for the causal relationships in the model. An original moderator of user experience type is introduced in this extended TAM framework to explore how users' belief factors may change with payment type as users gain different types of experience.

AI TV content service users need to believe that using AI TV content is a useful way to enjoy high quality content more conveniently. In addition, users must consider the service to be easy to use. Both perceived usefulness and perceived ease of use are belief variables affecting the attitude toward behavior. The perceived ease of use impacts the perceived usefulness (Davis, 1989). Furthermore, when individuals form positive attitudes toward an AI TV content service, they are likely to have stronger purchase intentions (Agag and El-Masry, 2016; Cronin et al., 2000; Jang and Noh, 2011; Wagner et al., 2017). Thus, we hypothesize:

H4a. Perceived ease of use of an AI TV service has a positive direct effect on perceived usefulness.

H4b. Perceived usefulness of an AI TV service has a positive direct effect on attitude toward behavior.

H4c. Perceived ease of use of an AI TV service has a positive direct effect on attitude toward behavior.

H4d. Attitude toward behavior of an AI TV service has a positive direct effect on intention to purchase.

2.4. Smart media user experience type

Researchers have defined the concept of experience in the marketing field, as well as in the information systems field. From the perspective of CEM in the marketing field, Hirschman and Holbrook (1982) explained customer experience as a personal event with significant emotional importance based on interactions with consumer products and services stimuli. Meyer and Schwager (2007) defined customer experience as customers' internal and subjective responses to direct or indirect contact with the service provider. Gentile, Spiller and Noci (2007) considered customer experience to be a psychological structure which encompasses a customer's holistic and subjective response to retailers. Novak, Hoffman and Yung (2000) concluded that online customer experience refers to the state of that experience during online navigation.

In the information systems field, Thompson et al. (1991) gave an example of experience using a particular software package and considered it as a direct experience with a particular system. Dishaw and Strong (1998) defined experience as a two-dimensional variable: previous and past experiences. However, they did not provide an explicit definition. Venkatesh (2000) defined experience as a direct and hands-on experience of using a system. Similarly, Choi et al. (2010) defined experience as the direct experience of using a target system.

Constantinides (2004) suggested that the set of service elements which comprises the online user experience includes usability and interactivity. The evaluation depends on a comparison between the stimulus from the customer's expectations and the interaction with the service provider (Gentile et al., 2007). The user experience of a smart service is the culmination of a series of interactions with smart service systems. This experience is a personalized occurrence based on instantaneous two-way communication and it involves service elements that can affect users' evaluations.

This study defines the user experience type as users who share the same type of experience while using smart service. In the context of smart media content service consumption, the two different payment types (paid subscriber and ad-supported user) essentially lead to the two most important user experience types in terms of understanding the content consumption. Furthermore, the consequence of the two payment types fundamentally creates two different qualities of customer service experience. Therefore, from a CEM perspective, the exploration of user experience type is both theoretically and practically important.

As a result, user experience type in this study is generated by users of two different payment types. It refers to paid subscriber users' experiences and ad-supported users' experiences. As they enjoy different qualities of customer service experience, they are very likely to perceive the smart service elements differently. Thus, the different user experience types are likely to have different behavioral attitudes, as well as intentions to purchase.

There is evidence that the direct impact of belief factors on attitude toward behavior and purchase intention may vary according to different types of user experiences. Studies comparing different user experience groups concerning IT system usage suggested the need to develop a TAM for each individual user experience group. For example, based on user experience groups, Castañeda et al. (2007) found a moderating effect on the importance of TAM belief factors as determinants of the future intention to use a website. Choi, Kim and Kim (2010) also evidenced a positive moderating effect on the relationship between belief factors and behavioral intention in the context of IPTV. In addition, Kim et al. (2018) showed that the user experience type had a moderating role on the association between belief factors and behavioral intention in the context of social media. In this study, user experience type is employed to compare effect sizes between constructs across the two payment type groups in order to determine whether user experience type moderates the impact of users' perceptions on the users' attitude toward behavior and purchase intention. Thus, we hypothesize:

H5a. The user experience type has moderating effects on smart service belief factors as determinants of intention to purchase.

H5b. The user experience type has moderating effects on smart service belief factors as determinants of attitude toward behavior.

H6a. The user experience type has a moderating effect on perceived usefulness as a determinant of attitude toward behavior.

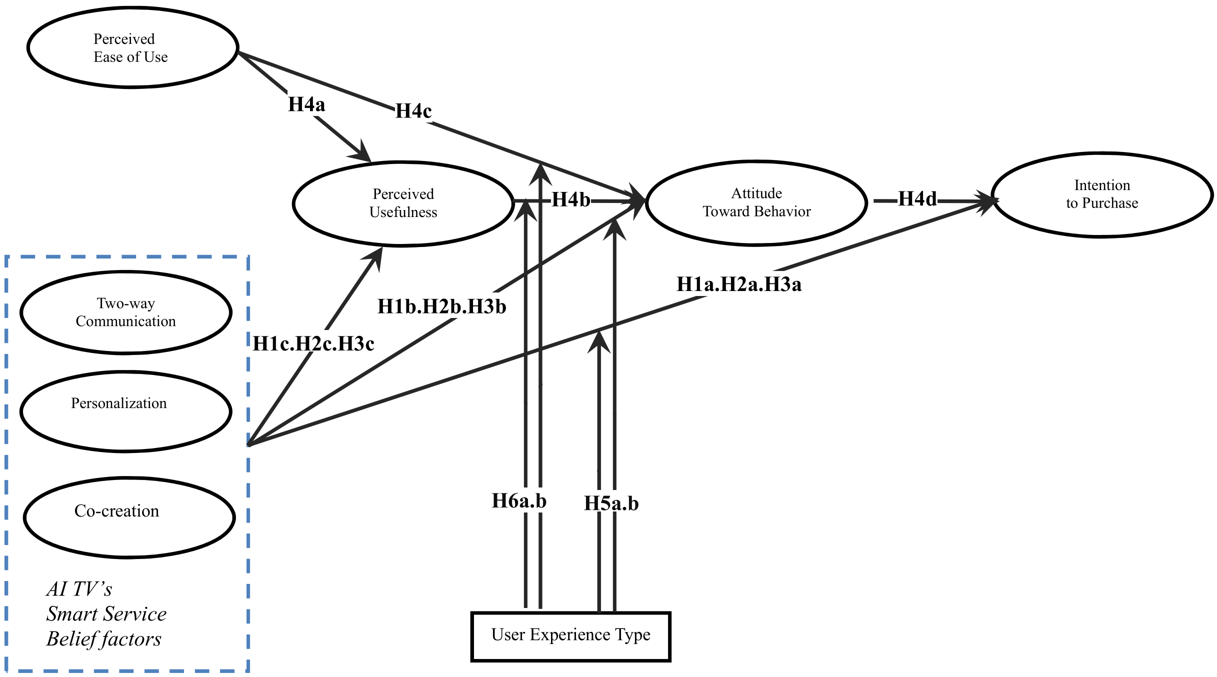

Figure 1. Proposed research model.

H6b. The user experience type has a moderating effect on perceived ease of use as a determinant of attitude toward behavior.

Figure 1 presents the proposed research model which summaries the hypothesized relationships.

3. Research method and data

3.1. Measurement development

Measurement scales in a questionnaire survey were adapted from relevant prior literature. 26 measurement items corresponding to the seven constructs were measured using a 7-point Likert scale. To measure two-way communication, a scale provided by McMillan and Hwang (2002) is adapted. Personalization is adapted from Kim and Han (2014), which is modified from Xu et al. (2008), and Ünal et al. (2011). Co-creation is revised from Mathis et al. (2016). The measurement scale for ease of use and usefulness are modified from Venkatesh and Davis (2000). Intention to purchase is revised from Pavlou (2003). Attitude toward behavior is adapted from Davis (1993). User experience type is a directly accessible objective variable. Thus, it was not explicitly measured and was simply coded based on the user payment type.

3.2. Data collection methods

Participants in this study are household users who owned an AI TV and used AI TV content service. Only respondents who answered "yes" to question one, "Have you used AI Powered smart TV?" were allowed to complete the rest of the questionnaire. On answering question two, participants were divided into two groups, according to their payment type (paid subscribers or ad-supported users).

The internet questionnaire survey was hosted by Baidu[2] company. The questionnaire sample service relied on the database of the Baidu Company, based on internet user demographic characteristic tags and the application of logical screening mechanisms to accurately locate target respondents. Through a series of anti-cheat mechanisms such as basic account information verification, the reliability of the questionnaire samples was ensured. In order to solicit a pool of respondents who would be as close to the target AI TV users as possible, a simple random sampling procedure was conducted. Ethical approval of this study was obtained, as a sub-study of the research project "Building a Research-Based International Collaboration Education System" by the Graduate School of Business Administration, Kobe University. All participants were informed of the aims of this study. Participants completed an online questionnaire voluntarily and anonymously. All data were analyzed statistically and all personal information remained strictly confidential. Since China is a major manufacturer of AI TVs, and the latest smart media services are offered in China, a Chinese sample is representative of a broad user based and thus, can adequately verify the validity of the theory.

The questionnaire collection was conducted for an approximate duration of two weeks. A total of 1801 questionnaires were distributed in China and 588 responses were received. Three respondents who were obviously uninterested in the survey were eliminated. The answering duration of two respondents was less than 150 s, and one respondent gave the same rating to all items. Hence, 585 responses were retained for analysis.

Table 1. Demographic characteristics of respondents.

Item	Type	Frequency	Percentage
Gender	Male	288	49.2%
	Female	297	50.8%
Age	18–25	156	26.7%
	26–35	332	56.8%
	36–45	75	12.8%
	46+	22	3.8%
Monthly Income (RMB:Yuan)	3000-	124	21.2%
	3001–5000	204	34.9%
	5001–10000	191	32.7%
	10001+	66	11.3%
Payment type	Paid subscribers	310	53.0%
	Ad-supported users	275	47.0%

[2] As a leading Chinese multinational internet company, Baidu specializes in internet-related services, products, and AI (Prince, 2019).

3.3. Pilot test

This study conducted a pilot test on 107 AI TV users, who were not included in the main survey. The results of the pilot test were evaluated using Cronbach's alpha reliability and factor analysis. The analysis results of the measurement scales were all within the satisfactory range, except for the original two-way communication scale and co-creation scale. After the analysis, the two items in the original seven items in the two-way communication scale which used reverse formulations showed inconsistency. Therefore, the two reverse items were deleted. In addition, the original co-creation scale with five items was adapted from previous literature on tourism services, which share common features with content services. After the analysis, two of the items did not significantly contribute to the reliability of the measures. They were also relatively unimportant to the AI TV co-creation system; therefore, they were eliminated. After re-testing all the measurement scales, this study found preliminary evidence that they were reliable and valid.

4. Data analysis and results

4.1. Descriptive statistics

Table 1 summarizes the demographics of the respondents.

A test of homogeneity was done. All scale items were tested against demographic controls (gender, age, monthly income, and payment type), by applying ANOVA, which was adopted from Cho (2006). At the 95% confidence level, no difference was found in the mean scores of the items. As a result, the survey responses could be mixed as a single dataset.

4.2. Data analysis

SEM was considered as the most appropriate method to answer the research questions here, since it can examine overall data fit indices and handle the existing multiple relationships among dependent, mediating, moderating, and independent variables (Zweig and Webster, 2003). As suggested by Arbuckle (2003), both the measurement model and the structural model were subsequently examined using Mplus Version 7 with maximum likelihood estimation.

4.2.1. Measurement model

Confirmatory factor analysis enables the convergent validity, discriminant validity, and reliability of each latent variable to be tested. In SEM analysis, before the examination of the structural model, the measurement model is usually first evaluated (Anderson and Gerbing, 1988). Hair, Anderson, Tatham and Black (1998) suggested that loading factors greater than 0.5 can be considered significant. In the initial test, each loading factor exceeded 0.6.

Subsequently, this study conducted validity evaluations, including content, discriminant, and convergent validity. Content validity was established based on a review of the past literature by adopting scales

Table 2. Measurement items, validity and reliability.

Construct	Adapted Scale	Standardized Loading	CR	AVE	Cronbach's alpha
Intention to Purchase Pavlou (2003)	IP1: It is likely that I will purchase the AI TV content services within the next 6 months.	0.764	0.752	0.503	0.750
	IP2: Given the chance, I intend to purchase the AI TV content service.	0.655			
	IP3: I recommend my family and friends to purchase the AI TV content service.	0.705			
Attitude Toward Behavior Davis (1993)	ATB1: Using the AI TV is a good idea.	0.813	0.876	0.588	0.876
	ATB2: Using the AI TV is a wise idea.	0.826			
	ATB3: I like the idea of using the AI TV.	0.766			
	ATB4: Using AI TV is pleasant.	0.735			
	ATB5: I have a positive perception toward using AI TV.	0.684			
Two-way Communication McMillan and Hwang (2002)	PTC1: AI TV enables two-way communication.	0.820	0.846	0.527	0.845
	PTC2: AI TV enables concurrent communication.	0.784			
	PTC3: AI TV is interactive.	0.745			
	PTC4: AI TV is interpersonal.	0.647			
	PTC5: AI TV enables conversation.	0.612			
Personalization Kim and Han (2014)	PP1: I feel that AI TV content service recommendations are tailored to my interests.	0.824	0.840	0.569	0.838
	PP2: I feel that AI TV content service recommendations are personalized.	0.761			
	PP3: I feel that AI TV content service is personalized for my use.	0.769			
	PP4: I feel that AI TV content service recommendations are delivered in a timely way.	0.653			
Co-creation Mathis et al. (2016)	PCC1: I feel comfortable co-creating content (including comments) on AI TV.	0.728	0.806	0.580	0.805
	PCC2: The setting of the AI TV allows me to effectively co-create content.	0.767			
	PCC3: My AI TV using experience was enhanced because of my content co-creation activity.	0.789			
Ease of Use Venkatesh and Davis (2000)	PEU1: I found that learning to operate AI TV is easy.	0.735	0.807	0.583	0.805
	PEU2: The operation of AI TV is clear and understandable.	0.820			
	PEU3: Operating AI TV does not require a lot of my mental effort.	0.733			
Usefulness Venkatesh and Davis (2000)	PU1: Using the AI TV makes “TV watching” more convenient.	0.761	0.786	0.553	0.780
	PU2: Using the AI TV can enhance the effectiveness of “TV watching.”	0.825			
	PU3: Using the AI TV can assist my life.	0.631			

Table 3. Correlation matrices and discriminant validity.

	1	2	3	4	5	6	7
1. Usefulness	**0.744**						
2. Ease of Use	0.645***	**0.764**					
3.Two-way Communication	0.593***	0.558***	**0.726**				
4. Personalization	0.575***	0.580***	0.650***	**0.754**			
5. Co-creation	0.607***	0.534***	0.561***	0.653***	**0.762**		
6. Attitude Toward Behavior	0.653***	0.621***	0.628***	0.631***	0.586***	**0.767**	
7. Intention to Purchase	0.402***	0.340***	0.490***	0.507***	0.452***	0.485***	**0.709**

Note: 1: Zero-order correlation (***:$p < 0.001$,**:$p < 0.01$,*:$p < 0.05$).
2: The bold number on the diagonal is the square root of AVE. Off-diagonal numbers are correlations among constructs.

validated by others. The discriminant validity was evaluated to test the correlations of measurements. Convergent validity was established by examining the average variance extracted (AVE), and the composite reliability (CR) of the measurements. In the test, AVE estimates were greater than 0.5 and CR estimates were greater than 0.7, which indicate a satisfactory range (Hair et al., 1998). The estimation of the model's statistical values was shown in Tables 2 and 3.

4.2.2. Structural model

4.2.2.1. Test 1: testing the base model. To test the base model, smart service belief factors, including perceived two-way communication (PTC), personalization (PP), co-creation (PCC), and ease of use (PEU), were set as independent variables, while perceived usefulness (PU) and attitude toward behavior (ATB) were set as mediating variables. The intention to purchase (IP) was adopted as a dependent variable.

The theory-trimming technique developed by James et al. (1982) and applied by both Chang and Chen (2008) and Mavondo and Rodrigo (2001), was applied in this study. The base model was thus re-examined by removing the following non-significant hypothesized relationships: PCC to ATB, PCC to IP, and PP to PU links.

As a result, the value of the chi-square distributed with degrees of freedom became 2.638, and the following values for the remaining indices were obtained: Goodness-of-fit index (GFI) = 0.903, Normed fit index (NFI) = 0.911, Comparative fit index (CFI) = 0.942, Tucker Lewis Index (TLI) = 0.934, Root mean square residual (RMSEA) = 0.053, and Standard root mean square residual (SRMR) = 0.039. Thus, as suggested by Hair et al. (1998), and Jöreskog and Sörbom (1994), all the goodness-of-fit estimates satisfied the recommended levels, indicating that the base model fits the data well. Table 4 shows the results.

4.2.2.2. Relationships between smart service belief factors and TAM. First, PTC significantly and directly affects IP, ATB and PU, which supports H1a ($\beta = 0.187$, $P < 0.05$), H1b ($\beta = 0.206$, $P < 0.001$) and H1c ($\beta = 0.191$, $P < 0.001$). In addition, PTC significantly indirectly affects IP via PU and ATB. Second, PP significantly and directly affects IP and ATB, which supports H2a ($\beta = 0.345$, $P < 0.001$) and H2b ($\beta = 0.216$, $P < 0.001$). However, PP does not impact PU significantly. Thus, H2c is not supported. Additionally, PP significantly indirectly affects IP via ATB. Third,

Table 4. Goodness of fit indices.

Model T Indices	Result	Recommended Value
Chi-square/degree of freedom	2.638	<3
Goodness-of-fit index (GFI)	0.903	>0.9
Normed fit index (NFI)	0.911	>0.9
Comparative fit index (CFI)	0.942	>0.9
Tucker Lewis Index (TLI)	0.934	>0.9
Root mean square residual (RMSEA)	0.053	<0.08
Standard root mean square residual (SRMR)	0.039	<0.05

Table 5. Hypothesis testing of test 1.

The Hypothesis	Path Coefficient	P-value	Result
H1a: Two-way Communication - Intention to Purchase	0.187	*	Yes
H1b: Two-way Communication – Attitude Toward Behavior	0.206	***	Yes
H1c: Two-way Communication – Usefulness	0.191	***	Yes
H2a: Personalization - Intention to Purchase	0.345	***	Yes
H2b: Personalization - Attitude Toward Behavior	0.216	***	Yes
H2c: Personalization - Usefulness	n.s	n.s	No
H3a: Co-creation - Intention to Purchase	n.s	n.s	No
H3b: Co-creation - Attitude Toward Behavior	n.s	n.s	No
H3c: Co-creation - Usefulness	0.287	***	Yes
H4a: Ease of Use - Usefulness	0.495	***	Yes
H4b: Usefulness - Attitude Toward Behavior	0.383	***	Yes
H4c: Ease of Use - Attitude Toward Behavior	0.127	†	Yes
H4d:Attitude Toward Behavior - Intention to Purchase	0.203	**	Yes

Note: ***: $p < 0.001$, **: $p < 0.01$,*: $p < 0.05$, †: $p < 0.10$.

PCC significantly and directly affects PU, which supports H3c ($\beta = 0.287$, $P < 0.001$). PCC does not directly impact IP and ATB significantly, which means that H3a and H3b are not supported. However, PCC significantly indirectly affects IP through PU and ATB.

4.2.2.3. Relationships in TAM. H4a ($\beta = 0.495$, $P < 0.001$) and H4b ($\beta = 0.383$, $P < 0.001$) are supported at the 99.9% confidence level, and H4d ($\beta = 0.203$, $P < 0.01$) is supported at the 99% confidence level. However, H4c ($\beta = 0.127$, $P < 0.10$) is only supported at the 90% confidence level. In addition, PEU significantly, indirectly affects IP through PU and ATB.

4.2.2.4. Indirect effects on intention to purchase. When testing the mediation, the indirect effect 95% bias corrected bootstrap confidence is significant. The indirect effects of PEU, PTC, PP and PCC on IP were 0.038, 0.015, and 0.044, and 0.022, respectively. The analytical results confirm that PEU, PTC and PCC indirectly increase IP through the serial mediators PU and ATB. PP indirectly increases IP through the mediator ATB.

The testing results of the hypothesized relationships within the base model are demonstrated in Table 5 and Figure 2. The indirect effects of PTC, PP, PCC and PEU on IP are demonstrated in Table 6.

4.2.2.5. Test 2: testing for moderating effect of the user experience type. To test the hypotheses with respect to the moderating effects of user experience type, this study applied multiple-group analysis, which is given by Jöreskog and Sörbom (1994), adopted by Chang and Chen (2008) and Kim et al. (2018). It is comprised of four steps:

The data was first divided into two groups based on the user experience type (a paid subscribers group and an ad-supported users group). Subsequently, a path model was estimated. All path values in the two

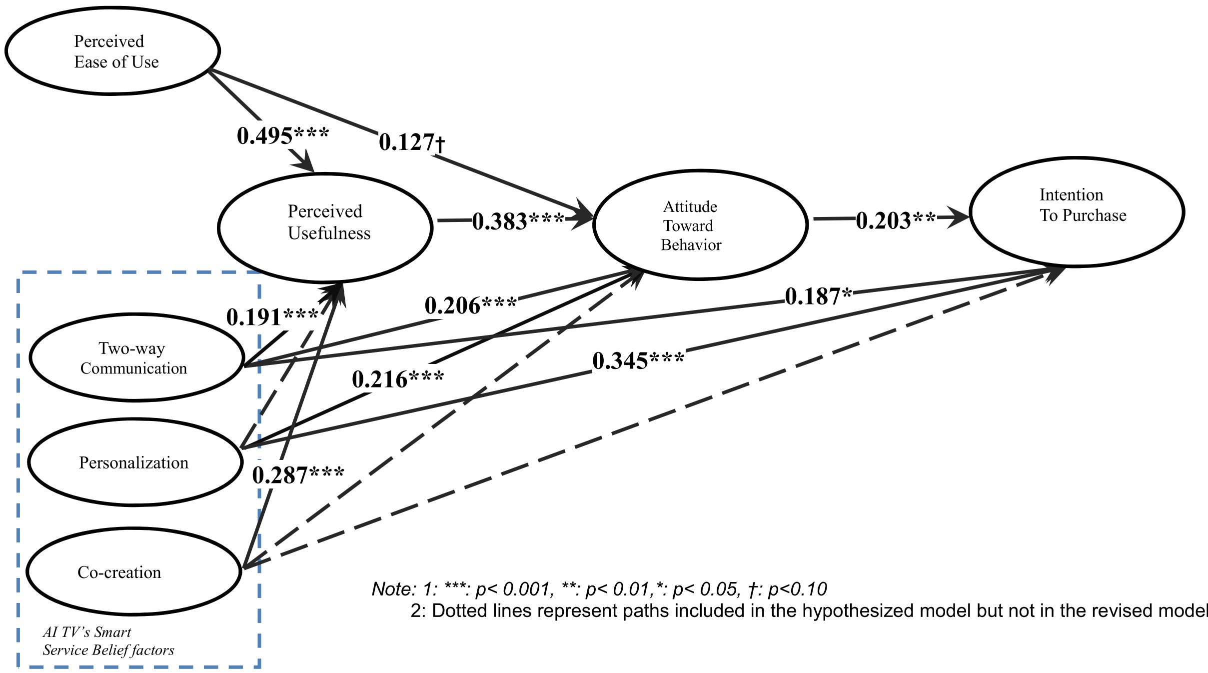

Figure 2. Path analysis.

Table 6. Indirect effects.

Pathway	Path Coefficient	LLCI	ULCI
Ease of Use→Usefulness→Attitude Toward Behavior→Intention to Purchase	0.038	0.006	0.171
Two-way Communication→Usefulness→Attitude Toward Behavior→Intention to Purchase	0.015	0.008	0.195
Personalization→Attitude Toward Behavior→Intention to Purchase	0.044	0.002	0.144
Co-creation→Usefulness→Attitude Toward Behavior→Intention to Purchase	0.022	0.002	0.078

Note: 2,000 bootstrap samples were used for the bias-corrected bootstrap 95% confidence intervals.

sub-models formed from the two sub-group samples were restricted to be equal, except the moderating path that was tested. After that, the moderating path values in the path models were estimated. The path from PTC and PP to ATB and IP, and from PU and PEU to ATB, were allowed to vary between the two sub-models. Finally, in order to determine the moderating effect, the Wald test[3] as proposed by Asparouhov (2007) and Satorra and Bentler (2010), was applied between the groups to identify whether the moderating paths of the two sub-models were significantly different.

Results show that the provided models all suggest a good fit (Hair et al., 1998; Jöreskog and Sörbom, 1994). When the two sub-groups are different in terms of variability, unstandardized estimates, rather than standardized, should be compared (Kline, 2005). Owing to the fact that the impact of PCC on the ATB link and the impact of PCC on the IP link are insignificant, this study does not test the moderating effects on those two links. Table 7 depicts all the details of results generated by Test 2.

Regarding the hypotheses testing results, first, H5a was supported. The Wald test result was 4.426 ($P < 0.05$) for the PTC – IP link, and 2.871 ($P < 0.10$) for the PP – IP link. The PTC – IP link shows a significant, positive moderating effect at the 95% confidence level. The PP – IP link shows a significant, positive moderating effect at the 90% confidence level. Thus, the user experience type moderates the effects of both PTC and PP on IP. In terms of the PTC – IP link, the paid subscriber group has more positive results than the ad-supported user group. In the ad-supported user group, the impact of PTC on IP is insignificant (ad-supported user group: 0.139; paid subscriber group: 0.338**). However, in both groups, PP positively impacts IP (ad-supported user group: 0.221* at the 95% confidence level; paid subscriber group: 0.432*** at the 99.9% confidence level). Second, H5b was partially supported. The Wald test result of 5.090 ($P < 0.05$) for the PP – ATB link shows a significant, positive moderating effect at the 95% confidence level. In both groups, PP impacts ATB positively (ad-supported user group: 0.247***; paid subscriber group: 0.144†), although in the ad-supported user group, PP impacts ATB more significantly. However, the Wald test result is 1.185 ($P > 0.10$) for the PTC – ATB link. Therefore, the user experience type only moderates the effect of PP on the ATB path. Finally, H6 was not supported. The Wald test result is 1.770 ($P > 0.10$) for the PU – ATB link (H6a) and 1.487 ($P > 0.10$) for the PEU – ATB link (H6b). However, PEU impacts ATB significantly at the 95% confidence level ($\beta = 0.165$, $P < 0.05$) in the ad-supported user group, whereas the impact of PEU on ATB is insignificant ($\beta = 0.097$, $P > 0.10$) in the paid subscriber group.

5. Discussions and conclusions

5.1. Discussions

The data analysis results show that smart service belief factors, including perceived two-way communication and personalization are found to be critical determinants of a user's attitude toward behavior and intention to purchase in the extended TAM. These findings are consistent with the prior literature (e.g., (Kim and Gambino, 2016; Sundar et al., 2014)). Besides, perceived two-way communication is found to be an important antecedent for perceived usefulness in this study, which is consistent with the finding from Abdullah et al. (2017). Through logical reasoning and empirical analysis, this study also found that perceived

[3] Based on the sample estimate, the Wald test can be applied to examine the true value of the parameter, no matter whether a relationship between or within data items can be expressed in a statistical model (Asparouhov, 2007; Satorra and Bentler, 2010).

Table 7. Chi-square difference test between paid subscribers and Ad-supported user groups.

Path	Base Model	H5a:Support (Model 1* (P<0.05), Model 2† (P<0.10))				H5b:Partially Support (Model 3 (P>0.10), Model 4* (P<0.05))				H6a:Not Support (Model 5 (P>0.10))		H6b:Not Support (Model 6 (P>0.10))	
		Model 1:Two-way Communication – Intention to Purchase		Model2: Personalization – Intention to Purchase		Model3: Two-way Communication- Attitude Toward Behavior		Model 4: Personalization – Attitude Toward Behavior		Model 5: Usefulness - Attitude Toward Behavior		Model 6: Ease of Use - Attitude Toward Behavior	
	Full sample	Ad-supported	Paid	Ad-supported	Paid	Ad-supported	Paid	Ad-supported	Paid	Ad-supported	Paid	Ad-supported	Paid
Unstandardized estimates													
Usefulness - Attitude Toward Behavior	0.390***	0.393***	0.393***	0.392***	0.392***	0.388***	0.388***	0.393***	0.393***	**0.419*****	**0.331*****	0.390***	0.390***
Ease of Use - Attitude Toward Behavior	0.129†	0.129†	0.129†	0.128†	0.128†	0.130†	0.130†	0.124†	0.124†	0.139†	0.139†	**0.169***	**0.090**
Two-way Communication – Attitude Toward Behavior	0.190***	0.183**	0.183**	0.184**	0.184**	**0.207*****	**0.141***	0.179**	0.179**	0.178**	0.178**	0.179**	0.179**
Personalization – Attitude Toward Behavior	0.193***	0.161**	0.161**	0.162**	0.162**	0.174**	0.174**	**0.241*****	**0.113†**	0.175**	0.175**	0.169**	0.169**
Attitude Toward Behavior – Intention to Purchase	0.238**	0.191*	0.191*	0.196*	0.196*	0.178*	0.178*	0.176*	0.176*	0.175*	0.175*	0.175*	0.175*
Two-way Communication – Intention to Purchase	0.202*	**0.133**	**0.322****	0.207*	0.207*	0.207*	0.207*	0.208*	0.208*	0.208*	0.208*	0.208*	0.208*
Personalization – Intention to Purchase	0.361***	0.281***	0.281***	**0.219***	**0.366*****	0.318***	0.318***	0.318***	0.318***	0.319***	0.319***	0.319***	0.319***
Ease of Use - Usefulness	0.493***	0.500***	0.500***	0.501***	0.501***	0.501***	0.501***	0.501***	0.501***	0.500***	0.500***	0.502***	0.502***
Two-way Communication - Usefulness	0.173**	0.174**	0.174**	0.172**	0.172**	0.173**	0.173**	0.173**	0.173**	0.172**	0.172**	0.172**	0.172**
Co-creation - Usefulness	0.289***	0.284***	0.284***	0.284**	0.284**	0.283***	0.283***	0.283***	0.283***	0.285***	0.285***	0.283***	0.283***
Standardized estimates													
Usefulness - Attitude Toward Behavior	0.383***	0.402***	0.394***	0.402***	0.394***	0.389***	0.398***	0.385***	0.415***	**0.416*****	**0.343*****	0.389***	0.402***
Ease of Use - Attitude Toward Behavior	0.127†	0.129†	0.134†	0.129†	0.134†	0.128†	0.139†	0.119†	0.136†	0.135†	0.149†	**0.165***	**0.097**
Two-way Communication – Attitude Toward Behavior	0.206***	0.204**	0.199**	0.204**	0.200**	**0.224*****	**0.157***	0.189**	0.205**	0.192**	0.200**	0.194**	0.200**
Personalization – Attitude Toward Behavior	0.216***	0.175**	0.196**	0.175**	0.196**	0.183**	0.217**	**0.247*****	**0.144†**	0.183**	0.219**	0.177**	0.211**
Attitude Toward Behavior – Intention to Purchase	0.203**	0.180*	0.184*	0.183*	0.190*	0.162*	0.178*	0.164*	0.173*	0.161*	0.174*	0.160*	0.174*
Two-way Communication – Intention to Purchase	0.187*	**0.139**	**0.338****	0.215*	0.219*	0.205*	0.232*	0.205*	0.233*	0.206*	0.232*	0.206*	0.232*
Personalization – Intention to Purchase	0.345***	0.287***	0.331***	**0.221***	**0.432*****	0.305***	0.397***	0.304***	0.401***	0.307***	0.399***	0.307***	0.399***
Ease of Use - Usefulness	0.495***	0.490***	0.520***	0.491***	0.521***	0.491***	0.521***	0.491***	0.521***	0.491***	0.519***	0.491***	0.522***
Two-way Communication - Usefulness	0.191**	0.188**	0.187**	0.187**	0.186**	0.188**	0.188**	0.187**	0.188**	0.187**	0.186***	0.187**	0.187**
Co-creation - Usefulness	0.287***	0.270***	0.292***	0.270***	0.292***	0.270***	0.291***	0.270***	0.290***	0.272***	0.292***	0.270***	0.290***
Attitude Toward Behavior - R^2	0.701***	0.658***	0.698***	0.658***	0.698***	0.676***	0.683***	0.697***	0.668***	0.683***	0.675***	0.679***	0.681***
Intention to Purchase - R^2	0.451***	0.297***	0.610***	0.307***	0.599***	0.368***	0.547***	0.371***	0.544***	0.368***	0.547***	0.368***	0.547***
Usefulness - R^2	0.751***	0.702***	0.798***	0.702***	0.798***	0.701***	0.799***	0.701***	0.800***	0.705***	0.795***	0.702***	0.798***
Wald Test		**4.426***		**2.871†**		**1.185**		**5.090***		**1.770**		**1.487**	
P-value		**0.035**		**0.090**		**0.276**		**0.024**		**0.183**		**0.223**	
Chi-square/Degree of Freedom	2.638	2.017		2.020		2.023		2.016		2.022		2.022	
Comparative fit index (CFI)	0.942	0.917		0.917		0.917		0.918		0.917		0.917	
Tucker Lewis Index (TLI)	0.934	0.912		0.912		0.912		0.913		0.912		0.912	
Root mean square residual (RMSEA)	0.053	0.059		0.059		0.059		0.059		0.059		0.059	

Note: ***: $p < 0.001$, **: $p < 0.01$, *: $p < 0.05$, †: $p < 0.10$.

co-creation is an important antecedent for perceived usefulness, which has not previously been explored to the best of our knowledge. It is worth noting that two-way communication is the most active variable, which positively impacts three constructs directly; namely perceived usefulness, attitude toward behavior, and intention to purchase. Perceived co-creation does not positively impact attitude toward behavior and purchase intention directly. This is inconsistent with the findings from Duan and Dai (2018). However, it can be explained both theoretically and practically. In practice, as users' perceived degree of co-creation is based on their interaction with the AI TV's co-creation system, it impacts users' perceived usefulness, as data analysis results suggest. However, at present, the co-creation functions are still technologically primitive. The lack of a direct relationship suggests that primitive co-creation features seem to increase customer apathy. Furthermore, in the sense of co-creation, content services such as interactive content enhance the users' sense of participation. However, using the co-creation content requires users to continually switch between active and passive modes. In addition, users' co-creation activities through AI TV functions on smart systems can often obscuring the screen and program content, and thus, influencing the user's basic viewing experience negatively. As a result, since a pleasant viewing experience is the main criteria (Coppens et al., 2004) for AI TV usage, co-creation functions do not directly enhance users' attitude toward behavior and intention. Additionally, an unexpected result of this study is the insignificance of perceived personalization on perceived usefulness. This is inconsistent with the findings from previous literature (e.g., (Desai, 2018)). In the context of AI TV content service, a plausible explanation is that, personalization is the service provider's decision of what is suitable for the individual consumer, based on an intelligent recommendation system and user data analysis. Thus, personalization is more of a marketing approach and therefore, it positively influences attitude toward behavior and intention to purchase, rather than perceived usefulness.

All the relationships in the basic TAM were empirically confirmed in the context of smart media service. These findings are consistent with the previous literature (e.g., (Davis, 1989; Gao et al., 2016)). However, the line between perceived ease of use and attitude toward behavior only supported at the 90% confidence level. This is consistent with the findings in recent studies in the context of Internet TV from Jang and Noh (2011); Jung et al. (2009); Wagner et al. (2017), in which this link was also found to be insignificant at the 95% confidence level. This is because the AI TV content service can be easily and effortlessly accessible for the average user. Thus, the user's attitude mainly depends on its functionality.

In light of the existing TAM literature, serial mediation effects are found in this study, such that perceived usefulness and attitude toward behavior mediates the relationships between smart service belief factors as well as perceived ease of use, and intention to purchase. The findings of perceived usefulness and attitude toward behavior as mediators are consistent with the prior literature (e.g., (Davis et al., 1989; Ooi and Tan, 2016; Wu and Chen, 2016)), in which perceived usefulness and attitude toward behavior also play mediating roles. The indirect effects of two-way communication, personalization, co-creation and perceived ease of use on intention to purchase were both found to be significant and positive. Therefore, in the context of smart media service consumption, this study confirmed that perceived usefulness and attitude toward behavior served as crucial mediating variables in the extended TAM model.

In this study, the user experience type in terms of ad-supported user groups and paid subscriber groups are found to exert a positive, moderating effect on the relationship between both personalization and two-way communication, and attitude toward behavior as well as intention to purchase. These findings are consistent with the previous literature (e.g., (Choi et al., 2010; Kim et al., 2018)), in which there is a moderating effect on the association between belief factors and behavioral intention, based on user experience groups. The smart service belief factors of perceived two-way communication and perceived personalization appear to more significantly influence intention to purchase in paid subscriber groups (Test 2, H5a). This is probably due to the fact that the paid subscriber group has already paid for the content service and hence, has had a better smart service experience and will have a stronger intention to keep purchasing in comparison with the ad-supported user group. In both the paid and ad-support groups, perceived personalization positively impacts purchase intention. However, in the ad-supported user group, perceived two-way communication has an insignificant impact on intention to purchase, which means that the paid experience is a requirement for the two-way communication to intention to purchase causal path to be established. Additionally, although perceived personalization appears to have a significant effect on attitude toward behavior in both user groups, the user experience type can exert a moderating effect on perceived personalization to attitude toward behavior. However, perceived personalization appears to more significantly influence attitude toward behavior in ad-supported user groups (Test 2, H5b). This means that perceived personalization generates better evaluations in ad-supported users' attitudes. Therefore, enhanced perceived personalization will more effectively influence ad-supported users' attitudes, and their purchase intentions will be influenced via their attitudes. Furthermore, results show that the user experience type does not exert a positive moderating effect on perceived ease of use to attitude toward behavior. However, perceived ease of use impacts attitude toward behavior significantly in the ad-supported user group, whereas perceived ease of use does not impact attitude toward behavior significantly in the paid subscriber group. Davis et al. (1989) concluded that the effect of perceived ease of use on attitude toward a technology dissolves with users' increased experience. This indicates that the paid subscriber's attitude toward behavior depends on perceived usefulness and other smart service belief factors, rather than perceived ease of use. Additionally, statistical analysis result shows that, although perceived two-way communication appears to more significantly influence attitude toward behavior in the ad-supported user group, there was an insignificant difference between both user experience type groups on perceived influence of two-way communication on attitude toward behavior. Similarly, although perceived usefulness appears to more significantly influence attitude toward behavior in ad-supported user groups, there was no significant difference between the two user experience type groups on the relationship between perceived usefulness and attitude toward behavior. In the context of AI TV, a possible explanation could be that users perceive the usefulness and two-way communication of AI TV as natural to its basic functions, these functions successfully satisfy both user groups' basic needs and thus, lead to similar evaluations in their attitudes.

5.2. Theoretical contributions

This study contributes to the literature on smart services from the perspective of user interaction by identifying the belief factors of users concerning smart services. By studying the relationships among smart service belief factors (perceived two-way communication, perceived personalization, and perceived co-creation), perceived ease of use, perceived usefulness, attitude toward behavior, as well as intention to purchase, the knowledge gained can facilitate a better understanding of interactive user behavior in the context of a smart media content service.

This knowledge leads to an additional theoretical contribution of this study; the extension of TAM by adding three smart service belief factors (perceived two-way communication, perceived personalization, and perceived co-creation) in the context of smart media service. The mediating effects of perceived usefulness and attitude toward behavior, which are consistent with the prior literature (e.g., (Davis et al., 1989; Ooi and Tan, 2016; Wu and Chen, 2016)), provide explanations of the influence mechanism of smart service belief factors on intention to purchase and thus clarify the predictive relationship among the constructs in the context of smart service consumption.

This study also found support for the original TAM with the remaining constructs in the model performing as expected in the smart media context. By doing so, this study has expanded the overall theoretical basis related to technology use, as well as expanding the scope and generalizability of TAM to be more applicable to the smart media service environment.

In addition, this study contributes to the literature by conceptualizing user experience type and investigating how user experience type moderates the effect of user perceptions concerning smart service on attitude toward behavior and intention to purchase. In the context of smart media service consumption, the two different payment types essentially lead to the two most important user experience types and fundamentally create two different qualities of customer service experience. Thus, the addition of user experience type as a moderator is crucial in expanding the generalizability of this extended TAM model to understand smart media content consumption.

As CEM represents a strategy for managing customer experience, and as customer experience comes from a series of interactions involving customer at various levels (Gentile et al., 2007; Homburg et al., 2017), this suggests that a comprehensive approach to managing customer experience must be taken. By developing an extended TAM model which incorporates smart service belief factors, as well as user experience type as a moderator, this study furthers the fundamental understanding of the nature of users' perceptions of smart services across two experience type groups. The understanding of the influence of users' perceptions on purchase intention is also furthered. Thus, this study is important if we are to better understand how to manage the customer experience within a smart media service environment.

5.3. Managerial implications

Many of our findings offer guidance to management and smart media practitioners. In a smart media context, enhancing intention to purchase is a difficult challenge that may require consideration by smart media practitioners wishing to differentiate themselves from competitors. This study suggests that smart media practitioners should consider focusing more on enhancing users' perceptions concerning smart media service, in their marketing strategies.

This study also confirmed that users' smart service belief factors are consistent with smart media interactive communication features in practice. The better the features are, the more positive the attitudes will be and the stronger the intention to purchase the smart media content service will be.

Two-way communication directly impacts purchase intention, attitude toward behavior and perceived usefulness. Personalization directly impacts purchase intention and attitude toward behavior. Thus, the enhancement of two-way communication and personalization can significantly improve the smart content service flow by making it more satisfactory to users. This will enhance both the user's attitude and intention to purchase.

When practitioners have limited resources for their marketing efforts, personalization and two-way communication could be two of the easier factors to target for enhancing users' evaluations of service performance and thus, enhancing purchase intentions. For example, smart media practitioners can focus on improving speech recognition capabilities by developing advanced implanted voice algorithms and thus, make two-way communication more effective. They can also invest substantially in self-learning technology and content aggregation search engine functionality to more accurately provide personalized content to each individual user.

Recognizing the differences between paid subscriber groups and ad-supported user groups' smart service perceptions, we can formulate proper CEM strategies for each group and effectively enhance intention to purchase. Increasing the level of a user's personalization and two-way communication awareness will more effectively increase the purchase intention levels of paid subscribers over ad-supported users. Hence, this strategy is more effective for retaining existing paid subscribers than acquiring new subscribers. However, increasing the level of a user's personalization awareness will effectively increase the behavioral attitude levels in ad-supported users, and will subsequently influence their purchase intention. Thus, it is an effective strategy for attracting new paid subscribers.

Consequently, from a CEM perspective, this research provides a further step toward better management of customer experience within the smart media content service market. It practically contributes to solving the problem of how to build a more scientific smart media service CEM system to attract new paid subscribers, while retaining existing subscribers.

5.4. Conclusions

Drawing broadly on TAM and the study of smart services, this study identified key smart service belief factors and conceptualized the user experience type, based on a review of the extant literature. This study developed and extended TAM by integrating smart service belief factors in the context of smart media and employed user experience type as a moderator. This theoretical framework reconciled three streams in the literature. First, TAM studies explain users' behavioral patterns and intention to purchase. Second, service studies explain users' key belief factors toward smart service elements. Third, this study attempts to explicate how the user experience type moderates the influence of smart service perceptions on attitude toward behavior and purchase intention from a CEM perspective.

An analysis of 585 AI TV user samples largely supported the hypothesized relationships in the model. These results contribute to the extant literature on smart services by providing a new way to analyze users' belief factors in the smart media service context. This study confirms the validity of TAM in a smart media context and identifies new belief factors that can be integrated into the extended TAM. It highlights the importance of the moderating role of the user experience type. Thus, it furthers the generalizability of TAM to the smart media service context. The findings of this research contribute in a practical way to solving problems associated with building a more scientific smart media content services CEM system.

5.5. Limitations and directions for future research

The findings of the study are subject to the following limitations. First, the generalizability would be enhanced if results could be compared with a sample from a developed country. Second, as a cross-sectional study, this research is difficult to explore the trends in the development of the research object. Finally, this study is a prospective study, which was conducted in the context of the developing smart media technology. AI TV technology is developing at such a rapid pace, richer and better application scenarios of AI TV content service will be presented in the future, however, the basic belief factors of smart service are very likely to remain the same.

Future studies can empirically examine other types of smart media. Theoretically, additional psychological and behavioral constructs can be explored by further extending TAM. Additionally, the effects of users' lifestyle, personality traits, and demographic factors can be explored by applying them as external variables in an extended TAM model for a more complete understanding of interactive user behavior in the context of smart services.

Declarations

Author contribution statement

B. Gao: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

L. Huang: Conceived and designed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data.

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The authors declare no conflict of interest.

Additional information

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