Kim, Jiwhan; Nam, Changi

Conference Paper

Analyzing continuance intention of recommendation algorithms

30th European Conference of the International Telecommunications Society (ITS): "Towards a Connected and Automated Society", Helsinki, Finland, 16th-19th June, 2019

Provided in Cooperation with:
International Telecommunications Society (ITS)

Analyzing continuance intention of recommendation algorithms

Jiwhan Kim[1], Changi Nam[1]

Abstract

As recommendation algorithms have been increasingly applied to content personalization services, scholars are voicing concern about the negative impacts of these algorithms, for instance filter bubbles and ideological polarization. This research attempts to analyze the various factors influencing users' continuance intention of recommendation algorithms through structural equation modeling. Based on the Expectation-Confirmation Model, this study proposes an extended framework to empirically examine the impact of confirmation, perceived usefulness, perceived enjoyment, perceived ease of use, perceived risk, and subjective norm on satisfaction and continuance intention. Results indicate that confirmation positively impacts satisfaction, perceived usefulness, and perceived enjoyment. Furthermore, all constructs had a significant effect on satisfaction as well as continuance intention. A group comparison analysis of consumers primarily using news recommendation algorithms and multimedia recommendation algorithms uncovered differences between the two groups. Managerial implications on how to retain recommendation algorithm users are suggested based on the results.

Keywords

Recommendation, algorithms, expectation-confirmation model, continuance intention

1. Introduction

Thanks to the availability of big data and analytic tools, nowadays recommendation algorithms are applied across a large range of ICT related services to provide personalized

---

[1] School of Business and Technology Management, College of Business, Korea Advanced Institute of Science and Technology, Korea, N22, 291 Daehak-ro, Yuseong-gu, Daejeon 305-701, Republic of Korea

services to each and every consumer. Content curation powered by artificial intelligence has already become an essential component of media streaming services, especially in the case of online content streaming sites including YouTube, Netflix, and Spotify. Recommendation algorithms are also heavily utilized in retrieving personalizing search results, improving various functions of social networking services, and curating news content. As such, recommendation algorithms are expected to be applied throughout multiple disciplines, improving the efficiency of existing services as well as enabling the emergence of new services.

However, the proliferation of recommendation algorithms is also raising many grave concerns. First, some scholars have voiced anxiety regarding the 'filter bubble', or intellectual isolation caused by personalized recommendations only feeding consumers information in accordance with their opinions. Second, others are arguing for the need of algorithmic accountability and algorithmic transparency due to the inability to fully understand how the 'black box' operates (Diakopoulos, 2015; Mittelstadt, 2016). Lastly, regulatory guidelines for the application of recommendation algorithms are either insufficient or absent.

While consumers are under the influence of recommendation algorithms every day, both knowingly and unknowingly, there is a lack of prior research on the subject of recommendation algorithms. Furthermore, consumers' awareness of their reliance on recommendation algorithms, as well as their motivations for using such services, have not been studied extensively. Consumers face a significant risk in the upcoming era of algorithms; since the nature of algorithms is not well known, this lack of algorithm transparency could disadvantage consumers. Furthermore, protecting the consumer must be an important component of future regulatory guidelines. Therefore, understanding consumers' intentions for using recommendation algorithms is crucial.

The purpose of this research is to employ structural equation modeling to analyze the motivations for using services and functions powered by recommendation algorithms, specifically focusing on what factors influence users' continuance intention of recommendation algorithms. It also aims to explore the extent to which recommendation algorithms are utilized throughout different content curation services, and how consumers' continuance intentions vary across different service types, namely news recommendation algorithms such as Google News, and multimedia recommendation algorithms employed by YouTube and Netflix. Examining factors leading to users' continuance intention as well as the difference between continuance intention of news and multimedia recommendation algorithms will provide meaningful strategic insights to businesses on how to formulate the most optimal business model and retain consumers over the long term. Furthermore, by understanding consumers' perceptions and motivations for using recommendation algorithms, it will be able to suggest regulatory guidelines on how to ensure the safe and responsible development of recommendation algorithms. Therefore, this study focuses on the following research questions.

1) What are the factors influencing consumers' continuance intention towards recommendation algorithms?

2) What meaningful differences exist between continuance intention of news recommendation algorithms and multimedia recommendation algorithms?

This paper proceeds as follows. Section 2 provides a brief overview of the issues surrounding recommendation algorithms and outlines the theoretical model as well as the constructs incorporated into the model. Section 3 introduces the methodology employed in this study. Section 4 presents the empirical results of the structural equation model. Section 5 discusses the results and provides implications. Finally, Section 6 presents conclusions and limitations of this study.

2. Literature Review and Theoretical Model

2.1. Recommendation algorithms and filter bubbles

Over the past years, algorithms have been increasingly applied to the field of recommendation. As such, scholars have contemplated the social and ethical issues that could arise from the implementation of personalized recommendation algorithms. One popular concept studied by scholars is the filter bubble, a term first coined by Pariser (2011). As a recommendation algorithm continues to provide ideal search results, users become gradually detached to opinions and ideologies opposing their own. As a result, users become trapped inside an echo chamber where their own opinions are repeatedly reinforced, which could ultimately incite dangerous circumstances, such as political fragmentation and polarization.

Indeed, scholars such as Adomavicious, Bockstedt, Curley, & Zhang (2013) found that biased outputs from recommendation systems could substantially influence consumers' preference. Bozdag (2013) argued that through the filtering of content, recommendation algorithms are decreasing information diversity and aggravating bias, becoming the new gatekeepers of information. Similarly, Sphor (2017) warned against the ideological polarization resulting from the filter bubble as well as selective exposure of content. Additionally, some scholars have also suggested that political fragmentation from the filter bubble is not the only significant shortcoming of recommendation algorithms. Rather, big data analysis and algorithms can cause a 'tyranny of the majority,' in which mass consumption becomes the single most important indicator of quality and public value (Harper, 2017).

As a response to this rising concern, scholars have proposed various methods to keep algorithms in check. Diakopoulos (2015) emphasized the concept of algorithmic accountability in the field of journalism, where the production of news is increasingly incorporating automation algorithms. He stated that it is essential to understand the intent and agency of algorithms in practice because a large part of algorithm use is determined by humans, for instance setting parameters, selecting databases, and interpreting results. Similarly, Ananny (2016) argued that since algorithms are employed as an amalgamation of digital codes, processes, and social norms, algorithmic transparency by itself is not enough to guarantee algorithmic accountability; we need to contemplate the ethical implications of how algorithms are actually being utilized in practice. Also, Diakopoulos and Koliska (2016) argued the need for achieving algorithmic transparency by incentivizing businesses to disclose information to users. Similarly, Mittelstadt (2016) proposed algorithm auditing as an approach to counter the innate opacity of recommendation algorithms. Bozdag and van den Haven (2015) asserted the importance of educating software designers on the different concepts of democracy in order to reduce the negative outcomes of filter bubbles.

Nonetheless, the filter bubble is often difficult to empirically detect. Some previous researchers have even found evidence that disproves the filter bubble. For instance, Borgesius, Trilling, Moller, Bodo, de Vreese, and Helberger (2016) concluded that, despite scholars' concerns, there is little empirical evidence that supports the existence of filter bubbles in media outlets. Haim, Arendt, and Scherr (2017) found that Google's search engine produces identical search results regardless of the personal characteristics of the user. Moreover, Moller, Trilling, Helberger, and van Es (2018) discovered that personalized recommendation by algorithms did not reduce the diversity of search results.

While recommendation algorithms have become a highly debatable subject, there is a lack of previous literature examining recommendation algorithms from a consumer perspective. Furthermore, the factors that influence users' continuance intention of recommendation algorithms have rarely been studied. Therefore, this paper aims to examine the various characteristics of recommendation algorithms through structural equation modeling in order to identify the constructs that affect users' continuance intention. Analyzing factors impacting the continuance intention of recommendation algorithm users would provide insights into formulating the most optimal recommendation service. Additionally, comparing the analysis results of news and multimedia recommendation algorithm users could uncover meaningful implications for businesses hoping to retain long term users.

2.2. Expectation-Confirmation Model (ECM)

The ECM has its roots in the Expectations-Confirmation Theory (ECT), which was originally coined by Oliver (1980). According to the ECT, users form an initial expectation of an IS prior to usage, and they compare this pre-consumption expectation with their perceptions (perceived performance) of the IS formed after consumption. Then, depending how the perceived performance confirms or disconfirms initial expectations (confirmation), users either form a satisfaction and continue to use the IS, or feel dissatisfied and discontinue to use the IS.

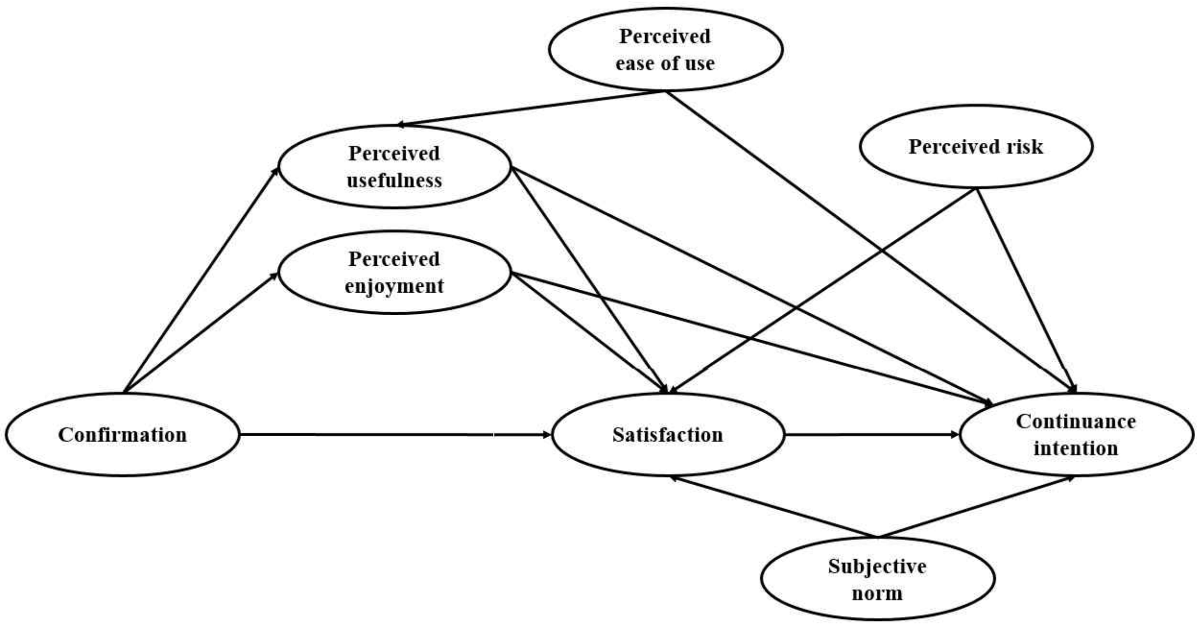
Later, Bhattacherjee (2001) extended the ECT to create the ECM and applied it to the IS context. The ECM posits that consumers' confirmation of initial expectations of products or services affect perceived usefulness and satisfaction, which leads to continuance intention. The ECT and ECM are different in that while the ECT examines both pre- and post- consumption variables, the ECM only focuses on post-consumption variables. Additionally, while the ECT focuses only on pre-consumption expectation, the ECM posits that post-consumption expectation has a more concrete effect on continuance intention, and thus includes perceived usefulness to capture this post-consumption expectation. Furthermore, the ECM does not incorporate the construct of perceived performance, as it assumes that effect is already captured by users' confirmation.

According to Bhattacherjee (2001), the ECM has five core hypotheses. First, users' level of satisfaction positively affects their continuance intention. Second, users' confirmation is positively associated with their satisfaction levels. Third, users' perceived usefulness of IS use positively influences their satisfaction. Fourth, users' perceived usefulness of IS use positively affects their continuance intention. Fifth, users' extent of confirmation is positively associated with their perceived usefulness of IS use.

Since its inception, the ECM has been appropriated by numerous scholars to examine continuance intention of several ISs, such as blog use (Tang & Chiang, 2010), social networking services (Chang & Zhu, 2012), e-learning (Lee, 2010), IPTV (Lin, Wu, Hsu, & Chou, 2012), and electronic textbooks (Stone & Baker-Eveleth, 2013). Recently, scholars have utilized the ECM to analyze continuance intention of various mobile ISs including mobile internet services (Thong, Hong, & Tam, 2006), mobile data service (Kim, 2010), mobile banking (Yuan, Liu, & Yao, 2016), mobile apps (Hsu & Lin, 2015), and mobile instant messaging (Oghuma, Libaque-Saenz, Wong, & Chang, 2016).

2.3. Expectation-Confirmation Model of recommendation algorithm use

Figure 1 Expectation-confirmation model of continuance intention towards recommendation algorithms



This paper employs the ECM as a theoretical foundation for developing an ECM of continuance intention towards recommendation algorithms. As in the ECM, we hypothesize that post-use confirmation will lead to perceived usefulness and satisfaction, which in turn will jointly influence continuance intention. In addition to these constructs, we propose that the inclusion of perceived enjoyment, perceived ease of use, perceived risk, and subjective norm into the model will provide further insights into the process by which users choose to or not to continuously use recommendation algorithms. The theoretical framework is presented in Figure 1.

2.3.1. Confirmation

Confirmation can be defined as the extent to which the actual use experience confirms users' prior expectation. While establishing the foundations for the ECM in the information systems context, Bhattacherjee (2001) referred to confirmation as "the realization of the expected benefits of IS use." Previous research has found that confirmation is positively related to satisfaction (Bhattacherjee, 2001; Thong et al., 2006; Chang & Zhu, 2012). If the actual use experience of recommendation algorithms either matches or surpasses the prior expectation, users will be satisfied with recommendation algorithms. Thus, we propose the following hypothesis:

H1. Confirmation has a positive effect on satisfaction.

Previous research on Cognitive Dissonance Theory (Festinger, 1957) suggests that users might experience cognitive dissonance if their initial expectation of the level of usefulness is disconfirmed during use. Then, users will attempt to adjust their usefulness perception in order to achieve consistency with the actual usefulness. This explanation, while applied to the ECM context by Bhattacherjee (2001) in explaining the role of confirmation and perceived usefulness, can also be extended to other use-related concepts, namely perceived enjoyment. Studies employing the ECM have shown that confirmation has a positive effect on both perceived usefulness as well as perceived enjoyment (Lin, Wu, & Tsai, 2005; Thong et al., 2006; Kim, 2010; Oghuma et al, 2016). Therefore,

H2. Confirmation has a positive effect on perceived usefulness

H3. Confirmation has a positive effect on perceived enjoyment

2.3.2. Satisfaction

Oliver (1981) defined satisfaction in the consumption context as “the summary psychological state resulting when the emotion surrounding disconfirmed expectations is coupled with the consumer’s prior feelings about the consumption experience.” The first main hypothesis in the ECM states that continuance intention of an IS is directly affected by users’ satisfaction. This relationship has been confirmed in a majority of studies employing the ECM (Bhattacherjee, 2001; Thong et al., 2006; Kim, 2010; Chang & Zhu, 2012; Oghuma et al, 2016). Thus, we can hypothesize that users’ continuance intention of recommendation algorithms will be influenced by their satisfaction levels.

H4. Satisfaction has a positive effect on continuance intention.

2.3.3. Perceived usefulness

Perceived usefulness is defined as “the degree to which the users believe that using an IS would increase their performance in accomplishing their goals (Davis, 1989).” Previous research regarding user intention has confirmed that perceived usefulness is one of the most crucial determinants of intention to adapt or continue behavior (Davis, Bagozzi, & Warshaw, 1989; Venkatesh & Davis, 2000). The ECM assumes that perceived usefulness has a positive effect on satisfaction as well as continuance intention of IS, and previous studies employing the ECM have confirmed this effect with various products and services (Bhattacherjee, 2001; Thong et al., 2006; Tang & Chiang, 2010; Yuan et al., 2016). Therefore, we propose the following:

H5. Perceived usefulness has a positive effect on satisfaction.

H6. Perceived usefulness has a positive effect on continuance intention.

2.3.4. Perceived enjoyment

Perceived enjoyment can be defined as “the extent to which the activity of using the computer (an IS) is perceived to be enjoyable in its own right, apart from any performance consequences that may be anticipated (Davis, Bagozzi, & Warshaw, 1992).” In this research, the authors described perceived enjoyment as intrinsic motivation, as opposed to perceived usefulness, which is extrinsic motivation. Intrinsically motivated users use an IS because of the positive affect and pleasure associated with it. This in turn positively influences user satisfaction and continuance intention of the IS. Indeed, scholars such as Lee, Cheung, & Chen (2005) and Lin et al. (2005) found that perceived enjoyment leads to increased usage intention of ISs. Moreover, Van der Heijden (2004) found that perceived enjoyment can have an even stronger effect on behavioral intention than perceived usefulness in the case of hedonic ISs. This could also be true with recommendation algorithms, especially since video and music streaming services actively employ recommendation algorithms to enhance user experience. Previous studies utilizing the ECM have found that perceived enjoyment positively influences both satisfaction and continuance intention of IS (Thong et al., 2006; Kim, 2010; Oghuma et al, 2016).Thus, we propose the following hypotheses:

H7. Perceived enjoyment has a positive effect on satisfaction.

H8. Perceived enjoyment has a positive effect on continuance intention.

2.3.5. Perceived ease of use

According to Davis (1989), perceived ease of use can be defined as “the degree to which a person believes that using a particular system would be free of effort.” In earlier studies on the TAM, perceived ease of use was assumed to affect intention through perceived usefulness. However, prior research employing the ECM has shown that there is also a direct influence on continuance as well as an indirect one via perceived usefulness (Thong et al, 2006; Yuan et al, 2016). Therefore, we propose:

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

H10. Perceived ease of use has a positive effect on continuance intention.

2.3.6. Perceived risk

Cox and Rich (1964) defined perceived risk as “the nature and amount of risk perceived by a consumer in contemplating a particular purchase decision.” In the online context, perceived risk tends to be higher since consumers face higher uncertainty in achieving their goals (Forsythe & Shi, 2003). Previous studies have found that perceived risk has a negative impact on behavioral intention, especially in the context of online and mobile services (McKnight, Choudhury, & Kacmar, 2002; Wu & Wang, 2005; Lin, Wang, Wang, & Lu, 2014; Yuan et al., 2016). As recommendation algorithms require sensitive information in order to provide personalized search results, if consumers believe they are at risk by providing such personal information, they might feel less satisfaction and even be reluctant to continuously use recommendation algorithms. Thus, we propose the following hypotheses:

H11. Perceived risk has a negative effect on satisfaction.

H12. Perceived risk has a negative effect on continuance intention.

2.3.7. Subjective norm

According to Ajzen (1991), subjective norm can be defined as “the perceived social pressure to perform or not to perform a behavior.” While subjective norm was initially coined as a concept referring to the social influence from peers, Bhattacherjee (2000) extended this concept to include external influences, such as mass media, in addition to interpersonal influences. Prior research in various contexts states that one can be motivated to comply with the views or behaviors of peers and/or superiors in order to gain approval or meet expectations (Ajzen & Fishbein, 1980; Bhattacherjee, 2000; Venkatesh, Morris, Davis, & Davis, 2003; Van Slyke, Ilie, Lou, & Staffor, 2007; Lee, 2010; Chen, Yen, & Hwang, 2012). Users of recommendation algorithms may choose to use them because their peers are also using recommendation algorithms. Moreover, social functions, such as sharing evaluations and sentiments towards content, are essential components that further the overall satisfaction coming from recommendation algorithm use. Thus, we propose the following hypotheses:

H13. Subjective norm has a positive effect on satisfaction.

H14. Subjective norm has a positive effect on continuance intention.

3. Methodology

3.1. Measurement items

Measurement items were drawn from past research regarding IS use. The items were then reworded to fit the context of recommendation algorithms. In order to refine the measurement items, a pilot test of the survey was conducted with graduate students who had experience in using recommendation algorithms. Each question was measured using a seven-point Likert scale, where items were scaled from 1 (strongly disagree) to 7 (strongly agree). The questionnaire items are presented in Appendix A.

3.2. Data collection

Table 1 Sample demographics

Demographics	Total sample (N = 654, %)	News recommendation algorithm users (N = 322, %)	Multimedia recommendation algorithm users (N = 332, %)
Gender			
Male	318 (48.6%)	159 (49.4%)	159 (47.9%)
Female	336 (51.4%)	163 (50.6%)	173 (52.1%)
Age			
< 19	126 (19.3%)	60 (18.6%)	66 (19.9%)
20-29	176 (26.9%)	84 (26.1%)	92 (27.7%)
30-39	172 (26.3%)	88 (27.3%)	84 (25.3%)
40-49	180 (27.5%)	90 (28%)	90 (27.1%)

Data was collected by online survey via Macromill Embrain, a professional consumer research firm. All subjects were current users of recommendation algorithms of age between 14 and 49. Respondents were asked to fill out the questionnaire based on their usage experience. Before starting the survey, respondents were asked to choose which type of recommendation algorithms they most regularly use; either news recommendation algorithms, such as those employed by Google News, or multimedia recommendation algorithms, such as those in YouTube and Netflix. A total of 676 responses were collected. 22 of the responses were eliminated due to invalid data. As a result, 654 valid responses were analyzed. 322 respondents more frequently used news recommendation algorithms, whereas 332 respondents more frequently used multimedia recommendation algorithms. Table 1 summarizes demographic characteristics of the respondents.

4. Results

4.1. Measurement model

The proposed model was tested using SmartPLS 2.0 software. The accuracy of the model was evaluated in terms of construct reliability, convergent validity, and discriminant validity. First, construct reliability of the model was evaluated by examining item loadings and internal consistency. Table 2 shows that all item loadings were higher than the recommended threshold of 0.7. Also, all Cronbach's Alpha values and composite reliability (CR) scores exceeded the minimum value of 0.7 (Fornell & Bookstein, 1982). Second, convergent validity was evaluated through average variance extracted (AVE). All AVE values exceeded the recommended threshold of 0.5 (Bagozzi & Yi, 1988). Thus, the results indicated the model's construct reliability and convergent validity are satisfactory.

Table 2 Reliability and convergent validity

Construct	Item	Loading	Cronbach's α	CR	AVE
Confirmation	CONF1	0.893	0.883	0.927	0.810
	CONF2	0.893			
	CONF3	0.914			
Perceived usefulness	PUSE1	0.860	0.892	0.925	0.754
	PUSE2	0.880			
	PUSE3	0.883			
	PUSE4	0.851			
Perceived enjoyment	PEN1	0.890	0.933	0.952	0.833
	PEN2	0.933			
	PEN3	0.926			
	PEN4	0.902			
Satisfaction	SAT1	0.892	0.929	0.950	0.825
	SAT2	0.933			
	SAT3	0.934			

	SAT4	0.872			
Perceived risk	PRISK1	0.820	0.854	0.898	0.689
	PRISK2	0.898			
	PRISK3	0.715			
	PRISK4	0.876			
Continuance intention	CONIN1	0.903	0.933	0.952	0.832
	CONIN2	0.913			
	CONIN3	0.923			
	CONIN4	0.910			
Perceived ease of use	PEOU1	0.862	0.902	0.931	0.771
	PEOU2	0.877			
	PEOU3	0.860			
	PEOU4	0.912			
Subjective norm	SN1	0.883	0.922	0.945	0.810
	SN2	0.907			
	SN3	0.913			
	SN4	0.896			

Table 3 Discriminant validity

Construct	CONF	PUSE	PEN	SAT	PRISK	CONIN	PEOU	SN
CONF	**0.900**							
PUSE	0.791	**0.869**						
PEN	0.720	0.772	**0.913**					
SAT	0.760	0.805	0.858	**0.908**				
PRISK	0.177	0.187	0.116	0.100	**0.830**			
CONIN	0.656	0.724	0.749	0.787	0.077	**0.912**		
PEOU	0.553	0.602	0.596	0.590	0.268	0.594	**0.878**	
SN	0.552	0.607	0.597	0.628	0.161	0.706	0.569	**0.900**

Third, discriminant validity of the model was assessed by comparing the square roots of the AVEs with the correlation coefficients between constructs. The square roots of the AVEs should be greater than the correlation coefficients, which should not exceed 0.9 (Fornell & Bookstein, 1982). Table 3 shows that the square roots of the AVEs, or the bolded diagonal values, exceed the correlation coefficients. Also, each correlation coefficient is lower than 0.9.

Furthermore, all variance inflation factor (VIF) values were found to be lower than five. These results indicate that the model does not face multicollinearity issues (Hair, Sarstedt, Pieper, & Ringle, 2012). Therefore, the evaluation of construct reliability, convergent validity, and discriminant validity ensured that the measurement model is satisfactory.

4.2. Structural model

Fit indices for the proposed model are summarized in Table 4. Model fit was evaluated in terms of the following eight indices; the ratio of χ^2/df, goodness-of-fit index (GFI), adjusted goodness-of-fit index (AGFI), normed fit index (NFI), comparative fit index (CFI), Tucker-Lewis index (TLI), standardized root mean square residual (SRMR), and root mean square error of approximation (RMSEA). The proposed model satisfied all recommended criteria, suggesting that the model has a reasonable fit.

Table 4 Model fit indices

Fit indices	Recommended values	Measurement model	References
χ^2/df	≤ 5	3.371	Wheaton, Muthen, Alwin, & Summers (1977)
GFI	≥ 0.8	0.863	Wang & Chiu (2011)
AGFI	≥ 0.8	0.836	Wang & Chiu (2011)
NFI	≥ 0.9	0.927	Bentler & Bonett (1980)
CFI	≥ 0.9	0.947	Gerbing & Anderson (1992)
TLI	≥ 0.9	0.941	Birch, Fisher, Grimm-Thomas, Markey, Sawyer, & Johnson (2001)
SRMR	≤ 0.08	0.045	Gerbing & Anderson (1992)
RMSEA	≤ 0.1	0.060	Gerbing & Anderson (1992)

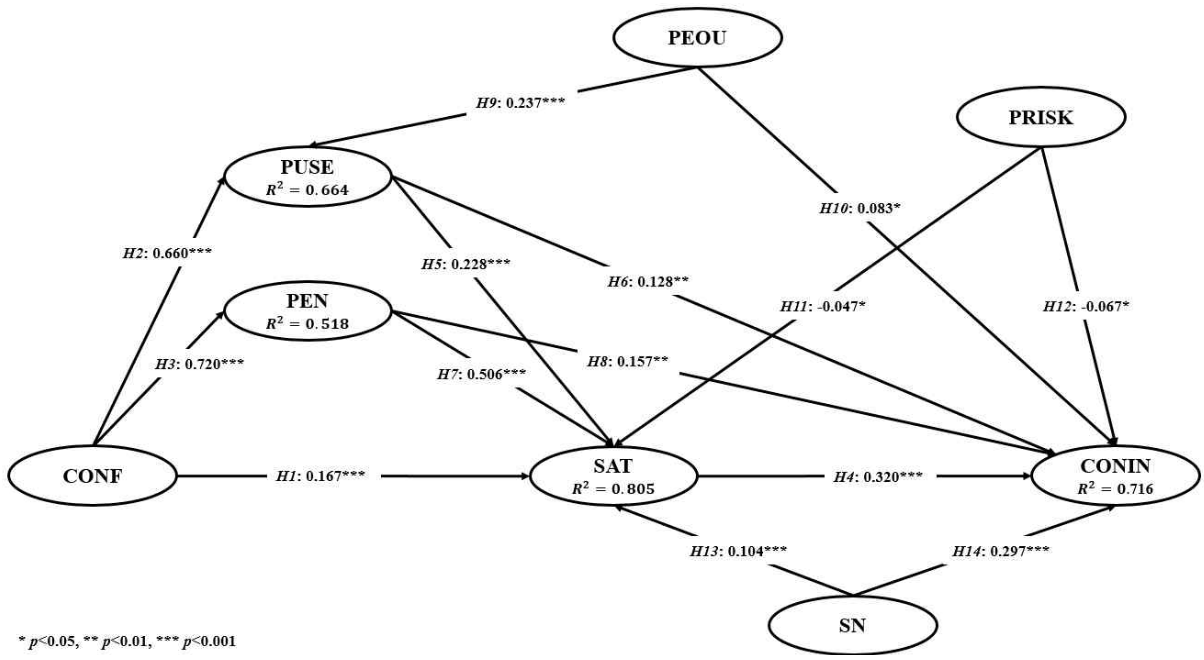
Path analysis results are summarized in Table 5 and depicted in Figure 2. Analysis of R^2 values indicates that the model accounts for 66.4%, 51.8%, 80.5%, and 71.6% of the variances in perceived usefulness, perceived enjoyment, satisfaction, and continuance intention, respectively. All of the proposed hypotheses were supported by the research model. As proposed, confirmation has a positive effect on satisfaction (H1), perceived usefulness (H2), and perceived enjoyment (H3). Satisfaction positively affects continuance intention (H4). Perceived usefulness, perceived enjoyment, and subjective norm each have a positive impact on satisfaction as well as continuance intention (H5, H6, H7, H8, H13, and H14). Moreover, perceived ease of use positively affects perceived usefulness (H9) and continuance intention (H10). Finally, perceived risk has a negative effect on satisfaction and continuance intention (H11, H12).

Table 5 Summary of hypotheses testing

Hypotheses	Path	Coefficient	*p*-value	Result
H1	CONF → SAT	0.167***	0.000	Supported
H2	CONF → PUSE	0.660***	0.000	Supported
H3	CONF → PEN	0.720***	0.000	Supported
H4	SAT → CONIN	0.320***	0.000	Supported
H5	PUSE → SAT	0.228***	0.000	Supported
H6	PUSE → CONIN	0.128**	0.005	Supported
H7	PEN → SAT	0.506***	0.000	Supported
H8	PEN → CONIN	0.157**	0.002	Supported
H9	PEOU → PUSE	0.237***	0.000	Supported
H10	PEOU → CONIN	0.083*	0.031	Supported
H11	PRISK → SAT	-0.047*	0.018	Supported
H12	PRISK → CONIN	-0.067*	0.019	Supported
H13	SN → SAT	0.104***	0.000	Supported
H14	SN → CONIN	0.297***	0.000	Supported

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 2 Results of path analysis



4.3. Analysis of group differences between recommendation algorithms

While the primary purpose of this research is to uncover antecedents of continuance intention towards recommendation algorithms, it is crucial to consider the differences that may arise from various recommendation algorithms. For instance, while perceived enjoyment could be an important factor when a user decides whether to continue or discontinue the use of a hedonic recommendation algorithm, such as Netflix, it might not be as important when the recommendation algorithm is of utilitarian nature, such as Google News. The same could be true for many of the factors that were previously examined. Therefore, it is essential to explore the difference between users who primarily use news recommendation algorithms and those who more often use multimedia recommendation algorithms. Users were sorted into each group depending on their response to the question regarding whether they more regularly use. This type of group comparison analysis is not uncommon when an IS has multiple facets. For example, Ha et al. (2015) conducted an exploratory analysis of group differences between two types of mobile SNS services, each with varied characteristics.

Analyses of model fit were performed to confirm the structural integrity of both models. Model fit of the multimedia group was satisfactory, while AGFI (0.770) and NFI (0.894) values were marginally unsatisfactory for the news group. However, since AGFI and NFI values statistics are sensitive to sample size, and the remaining six indices satisfied the recommended criteria, the overall model fit is acceptable. Results are summarized in Appendix B.

Table 6 outlines the results of path analysis by type of recommendation algorithm. R^2 analysis of the news group shows that the model accounts for 70.4%, 51.9%, 78.7%, 75.6% of the variances in perceived usefulness, perceived enjoyment, satisfaction, and continuance intention. Additionally, R^2 analysis of the multimedia group indicates that the model accounts for 61.9%, 50%, 82.2%, and 67.8% of the variances in perceived usefulness, perceived enjoyment, satisfaction, and continuance intention. While all hypotheses were supported in the overall sample, H10, H11, and H12 were rejected in both groups. Whereas H1 and H6 were also rejected in the news group, all other hypotheses were supported in the multimedia group.

Table 6 Summary of hypotheses testing (news recommendation algorithms vs. multimedia recommendation algorithms)

		News			Multimedia		
Hypotheses	Path	Coefficient	*p*-value	Result	Coefficient	*p*-value	Result
H1	CONF → SAT	0.094	0.077	Rejected	0.217***	0.000	Supported
H2	CONF → PUSE	0.664***	0.000	Supported	0.651***	0.000	Supported
H3	CONF → PEN	0.721***	0.000	Supported	0.707***	0.000	Supported
H4	SAT → CONIN	0.346***	0.000	Supported	0.274**	0.001	Supported
H5	PUSE → SAT	0.274***	0.000	Supported	0.198***	0.000	Supported
H6	PUSE → CONIN	0.052	0.414	Rejected	0.195**	0.003	Supported
H7	PEN → SAT	0.481***	0.000	Supported	0.520***	0.000	Supported
H8	PEN → CONIN	0.174**	0.009	Supported	0.156*	0.047	Supported
H9	PEOU → PUSE	0.245***	0.000	Supported	0.232***	0.000	Supported
H10	PEOU → CONIN	0.078	0.118	Rejected	0.074	0.189	Rejected
H11	PRISK → SAT	-0.030	0.341	Rejected	-0.060	0.069	Rejected
H12	PRISK → CONIN	-0.040	0.252	Rejected	-0.090	0.113	Rejected
H13	SN → SAT	0.141***	0.000	Supported	0.073*	0.030	Supported
H14	SN → CONIN	0.344***	0.000	Supported	0.256***	0.000	Supported

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5. Discussion and Implications

5.1. Overall model

The results show that all 14 proposed hypotheses were supported in the overall model. This confirms that the proposed model accurately outlines the antecedents of continuance intention of recommendation algorithms. The examination of factors affecting consumers' continuance intention toward recommendation algorithms provides managerial implications on how consumers perceive the utility of different recommendation services.

Results indicate that confirmation has a positive effect on perceived usefulness and satisfaction, which all have a positive effect on continuance intention. Since the inception of the ECM, this relationship has been confirmed by various studies employing the model (Bhattacherjee, 2001; Thong et al., 2006; Tang & Chiang, 2010; Yuan et al., 2016). These results entail meaningful managerial implications. First, managing users' expectations of recommendation algorithms can be a crucial task for service providers, since exceeding their expectations will lead to better perceptions of the usefulness of the system as well as higher satisfaction. Second, improving the overall usefulness of the algorithm will positively affect user satisfaction. Specifically, this includes optimizing the user experience (UX) of recommendation algorithms and ensuring that the recommendation algorithm provides more useful functions than users normally expect. Third, the results also demonstrate that the usefulness of the recommendation algorithm and user satisfaction are key factors to ensure continuous usage. Collectively, this suggests that perceived usefulness of the recommendation algorithm is an essential aspect that managers should strive to improve, since it affects continuance intention both directly and indirectly (via satisfaction).

Consistent with previous literature, confirmation was found to have a positive effect on perceived enjoyment, and perceived enjoyment was found to be an important factor influencing users' continuance intention. Previous studies on continuance intention of ISs have also confirmed this effect (Kim, 2011; Oghuma et al., 2016). Furthermore, researchers have often discovered the effect of hedonic motivations (Chang, Liu, & Chen, 2013; Lin & Lu, 2014; Ha, Kim, Libaque-Saenz, & Chang, 2015) on intention to use ISs, especially in the case of online/social ISs. These results suggest that assuring users' enjoyment of their recommendation algorithm usage experiences is vital for securing user satisfaction as well as user retention.

Overall, this demonstrates the substantial importance of satisfying users' expectations of recommendation algorithms, providing useful functions that could aid task completion, and offering a pleasurable experience.

Perceived ease of use was found to positively affect perceived usefulness and continuance intention, as observed in previous research (Venkatesh & Davis, 2000; Thong et al., 2006, Tan, Qin, Kim, & Hsu, 2011). This indicates that user interface (UI) is a significant issue for recommendation algorithm users, especially considering that the key concept of recommendation is to alleviate users' mental efforts by providing automated and personalized results. Previous research has suggested that being able to modify results produced by and algorithm can increase user satisfaction with the algorithm (Dievorst, Simmons, & Massey, 2018). Thus, it is essential for developers to ensure that the recommendation algorithm is easy to learn to use and it properly adjusts to users' demands.

Subjective norm was another factor found to positively influence satisfaction and continuance intention. As past research suggests, subjective norm (Bhattacherjee, 2000; Chen et al., 2012; Chang et al., 2013; Mouakket, 2015) or interpersonal influence (Kim, 2011) can be an important factor affecting consumers' intention to continue to use recommendation algorithms or not. Therefore, highlighting and incentivizing the social aspects of recommendation algorithms will aid in securing a long-term user base. Inducing users to invite their peers to use the recommendation algorithm by providing a (monetary) incentive could be an effective alternative.

Unlike the other constructs, perceived risk was found to have a negative impact on both satisfaction and continuance intention. These results demonstrate that users are well aware of the dangers, for instance privacy and security concerns, they could face from using recommendation algorithms. Since perceived risk could be a critical issue for recommendation algorithm users, managers ought to ease users' anxieties by taking the appropriate measures, for instance ensuring algorithmic transparency, to address their distress.

5.2. Group comparison analysis

Results of group comparison analysis show that most of the proposed hypotheses were supported, yet some were rejected. For instance, H1, H6, H10, H11, and H12 were rejected in the news recommendation algorithm group, while only H10, H11, and H12 were rejected in the multimedia group.

Analyses of the news and multimedia recommendation algorithm groups provide additional insights into the factors managers and developers ought to consider. First, in the news group, the proposed relationship between confirmation and satisfaction (H1) was rejected. This signals that users' post-experience evaluation of news recommendation algorithms did not exceed their initial expectations enough to lead to satisfaction with the algorithms. However, confirmation was found to have a significant indirect effect on satisfaction through perceived usefulness and perceived enjoyment, indicating that although news recommendation algorithms did not match their expectations, users still considered them useful and enjoyable, which caused them to be satisfied. Second, perceived usefulness was found to have no direct significant effect on continuance intention (H6 rejected) in the news group, although there was a significant indirect effect via satisfaction. This suggests that usefulness of a news recommendation algorithm does not lead to user retention by itself, but can contribute indirectly by increasing users' satisfaction with the algorithm. Overall, results regarding H1 and H6 demonstrate that retaining news recommendation algorithm users requires a different approach compared to multimedia recommendation algorithm users. This indicates that managers as well as developers should gain additional insights into users' perceptions and expectations with news recommendation algorithms, analyze the data, and take measures to meet the appropriate standards.

Third, perceived ease of use was found to have no significant effect on continuance intention in both the news and multimedia groups (H10 rejected). Nevertheless, in both groups, perceived ease of use had a significant indirect effect on continuance intention. In the news group, perceived ease of use had an indirect effect on continuance intention via perceived usefulness and satisfaction. This was also true for the multimedia group, except the indirect effect of perceived ease of use via perceived usefulness was also significant. Results imply that services employing recommendation algorithms, more so for multimedia than news algorithms, should devote more resources into making the interface easy to learn and use, since doing so would lead to user retention by increasing perceived usefulness and satisfaction towards the algorithm.

Finally, contrary to the results of the overall model, perceived risk did not have a significant effect on either satisfaction or continuance intention in both groups. This indicates that while users do commonly believe that recommendation algorithms could be dangerous to use, they do not perceive news or multimedia recommendation algorithms to be particularly vulnerable to security threats. Thus, their satisfaction with news and multimedia algorithms and their continuance intention is not affected by perceived risk. This may arise from the fact that news and multimedia recommendation algorithms do not explicitly require personal or preferential information from the user, but rather already have demographic data from the beginning or infer preferences from past usage patterns.

6. Conclusion

This paper examines consumers' continuance intention of recommendation algorithms by employing the expectation-confirmation model. In addition to the original constructs of confirmation, perceived usefulness, satisfaction, and continuance intention, this study incorporates perceived enjoyment, perceived ease of use, perceived risk, and subjective norm into the model to provide a more detailed account of why consumers choose to continuously use recommendation algorithms.

Results of the structural equation analysis indicate that all proposed hypotheses are supported, and thus all proposed relationships between constructs were confirmed. In particular, confirmation positively affects perceived usefulness, perceived enjoyment, and satisfaction, while satisfaction leads to continuance intention. Perceived usefulness, perceived enjoyment, and subjective norm have a significant positive impact on both satisfaction and continuance intention, while perceived risk has a significant negative impact on both constructs. Perceived ease of use positively affects perceived usefulness and continuance intention. Furthermore, a group comparison analysis was conducted to compare results of users mainly using news recommendation algorithms and multimedia recommendation algorithms. In both groups, perceived ease of use had no significant impact on continuance intention, and perceived risk had no significant impact on either satisfaction or continuance intention. Additionally, in the news group, the effect of confirmation on perceived usefulness and the effect of perceived usefulness on continuance intention was found to be insignificant.

The proposed ECM of continuance intention of recommendation algorithms has both managerial and academic contributions. In terms of managerial contributions, the results provide meaningful insights to recommendation services on formulating the most optimal business strategy to retain users. First, it is crucial to understand users' expectations of recommendation algorithms and enhancing the overall usefulness of the algorithm, since expectation leads to increased perceived usefulness and satisfaction, which jointly have a positive effect on continuance intention. This is especially true for news recommendation algorithms. Second, perceived enjoyment of the recommendation algorithm is also important, thus improving the user experience of the recommendation algorithm will aid user retention. Third, the significance of perceived ease of use indicates the significance of optimizing the user interface in order to make the algorithm easier to manipulate. Fourth, subjective norm had a positive impact on both satisfaction and continuance intention, suggesting that recommendation algorithms should focus on developing social functions. Finally, developers and managers should be aware of the users' concerns regarding the safety of the algorithm, as perceived risk could decrease satisfaction and continuance intention. Nevertheless, it is not solely firms' responsibility to create a business that better meets users' needs; rather, appropriate regulative guidelines and safety measures that could protect consumers are substantial in order to ensure further development of recommendation services.

This study also has several academic contributions. First, it extended the ECM to the context of recommendation algorithms. While the ECM has been utilized to investigate antecedents of continuance intentions towards various ISs, this study is the first to apply the framework to recommendation algorithms. Second, in addition to the basic constructs of the ECM, this study included various predictors, such as perceived enjoyment, perceived ease of use, perceived risk, and subjective norm into the model. As a result, the proposed model provides a more comprehensive understanding of users' continuance intention of recommendation algorithms. For instance, by including perceived risk into the model, this study considers not only the factors positively influencing continuance intention but also the factors negatively influencing continuance intention. Third, this study examined the effects of perceived usefulness and perceived enjoyment on continuance intention of recommendation algorithms. Previous studies have often distinguished between utilitarian and hedonic motivations for using ISs to produce insights into user behavior (Childers, Carr, Peck, & Carson, 2001; Chang et al., 2013). Moreover, scholars such as Kim (2010) have incorporated perceived usefulness and perceived enjoyment into the ECM. By assessing how both utility and entertainment affect continuance intention, this study is able to take a more detailed approach to motivations behind user behavior.

However, this study has a number of limitations. First, since the demographic for the survey was confined to Korean consumers, the findings of this research has limited generalizability. Second, even though this study incorporated perceived risk into the research model, it does not consider other factors, for instance technology resistance, that could negatively influence satisfaction or continuance intention. Future research ought to address these limitations to provide additional insights into continuance intention of recommendation algorithms.

Acknowledgement

This work was supported by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2016S1A3A2924760).

Appendix A

Measurement items.

Construct	Code	Measurement items
Confirmation	CONF1	My experience with using recommendation algorithms was better than what I expected
	CONF2	The accuracy of recommendations provided by recommendation algorithms was better than what I expected
	CONF3	Overall, most of my expectations from using recommendation algorithms were confirmed
Perceived usefulness	PUSE1	Using recommendation algorithms helps me accomplish this more efficiently
	PUSE2	Using recommendation algorithms helps me perform many thins more conveniently
	PUSE3	Recommendation algorithms can provide me with useful information about my life and work
	PUSE4	I find recommendation algorithms useful in my daily life
Perceived enjoyment	PEN1	Using recommendation algorithms is enjoyable
	PEN2	Using recommendation algorithms is pleasurable
	PEN3	I have fun using recommendation algorithms
	PEN4	I find using recommendation algorithms to be interesting
Satisfaction		How do you feel about your overall experience with/of recommendation algorithm use?
	SAT1	Very dissatisfied / very satisfied
	SAT2	Very displeased / very pleased
	SAT3	Very frustrated / very contented
	SAT4	Absolutely terrible / absolutely delighted
Perceived risk	PRISK1	Recommendation algorithms are dangerous for me to use
	PRISK2	Entering personal information to use recommendation algorithms is unsafe
	PRISK3	I would hesitate to enter personal information when using recommendation algorithms
	PRISK4	There is a considerable risk involved in participating in recommendation algorithms rather than other modes of recommendation
Continuance intention	CONIN1	I intend to continue my use of recommendation algorithms in the future
	CONIN2	I intend to increase my use of recommendation algorithms in the future
	CONIN3	My intention is to continue using recommendation algorithms than use any alternative means
	CONIN4	If I could, I would like to continue my use of recommendation algorithms
Perceived ease of use	PEOU1	Learning how to use recommendation algorithms is easy
	PEOU2	Interacting with recommendation algorithms does not require a lot of my mental effort
	PEOU3	I find it easy to get recommendation algorithms to do what I want them to do
	PEOU4	Overall, recommendation algorithms are easy to use
Subjective norm	SN1	People important to me support my use of recommendation algorithms
	SN2	People who influence me think that I should continue to use recommendation algorithms

	SN3	People who influence my behavior want me to continue to use recommendation algorithms instead of any alternative means
	SN4	People whose opinions I value prefer that I should use recommendation algorithms

Appendix B

Model fit indices for News and Multimedia groups.

Fit indices	Recommended values	News group	Multimedia group
χ^2/df	≤ 5	2.446	2.356
GFI	≥ 0.8	0.808	0.836
AGFI	≥ 0.8	0.770	0.804
NFI	≥ 0.9	0.894	0.903
CFI	≥ 0.9	0.934	0.941
TLI	≥ 0.9	0.926	0.934
SRMR	≤ 0.08	0.0463	0.0572
RMSEA	≤ 0.1	0.067	0.064

References

Ajzen, I., Fishbein, M. 1980. Understanding attitudes and predicting social behavior. Englewood Cliffs, New Jersey: Prentice-Hall.

Ajzen, I. 1991. The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179-211.

Ananny, M. 2016. Towards an ethics of algorithms: Convening, observation, probabililty, and timeliness. Science, Technology, & Human Values, 41(1), 93-117.

Adomavicious, G., Bockstedt, J. C., Curley, S. P., Zhang, J. 2013. Do recommender systems manipulate consumer preferences? A study of anchoring effects. Information Systems Research, 24(4), 956-975.

Bagozzi, R. P., Yi, Y. 1988. On the evaluation of structural equation models. Journal of the Academy of Marketing Science, 16(1), 74-94.

Bentler, P. M., Bonett, D. G. 1980. Significance tests and goodness of fit in the analysis of covariance structures. Psychological Bulletin, 88(3), 588-606.

Bhattacherjee, A. 2000. Acceptance of e-commerce services: The case of electronic brokerages. IEEE Transactions on Systems, Man, and Cybernetics – Part A: Systems and Humans, 30(4), 411-420.

Bhattacherjee, A. 2001. Understanding information systems continuance: An expectation-confirmation model. MIS Quarterly, 25, 351-370.

Birch, L. L., Fisher, J. O., Grimm-Thomas, K., Markey, C. N., Sawyer, R., Johnson, S. L. 2001. Confirmatory factor analysis of the Child Feeding Questionnaire: A measure of parental attitudes, beliefs and practices about child feeding and obesity proneness. Appetite, 36(3), 201-210.

Borgesius, F. J. Z., Trilling, D., Moller, J., Bodo, B., de Vreese, C. H., Helberger, N. 2016. Should we worry about filter bubbles? Internet Policy Review, 5(1), 1-16.

Bozdag, E. 2013. Bias in algorithmic filtering and personalization. Ethics and Information Technology, 15, 209-227.

Bozdag, E., van den Hoven, J. 2015. Breaking the filter bubble: Democracy and design. Ethics and Information Technology, 17, 249-265.

Chang, I., Liu, C., Chen, K. 2013. The effects of hedonic/utilitarian expectations and social influence on continuance intention to play online games. Internet Research, 24(1), 21-45.

Chang, Y. P., Zhu, D. H. 2012. The role of perceived social capital and flow experience in building users' continuance intention to social networking sites in China. Computers in Human Behavior, 28, 995-1001.

Chen, S., Yen, D. C., Hwang, M. I. 2012. Factors influencing the continuance intention to the usage of Web 2.0: An empirical study. Computers in Human Behavior, 28, 933-941.

Childers, T. L., Carr, C. L., Peck, J., Carson, S. 2001. Hedonic and utilitarian motivations for online retail shopping behavior. Journal of Retailing, 77, 511-535.

Cox, D. F, Rich, S. U. 1964. Perceived risk in consumer decision making – The case of telephone shopping. Journal of Marketing Research, 1(4), 32-39.

Davis, F. D. 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319-340.

Davis, F. D., Bagozzi, R. P., Warshaw, P. R. 1989. User acceptance of computer technology: A comparison of two theoretical models. Management Science, 35(8), 982-1003.

Davis, F. D., Bagozzi, R. P., Warshaw, P. R. 1992. Extrinsic and intrinsic motivation to use computers in the workplace. Journal of Applied Social Psychology, 22, 1111-1132.

Diakopoulos, N. 2015. Algorithmic accountability: Journalistic investigation of computational power structures. Digital Journalism, 3, 398-415.

Diakopoulos, N, Koliska, M. Algorithmic transparency in the news media. Digital Journalism, 5(7), 809-828.

Dievorst, B. J., Simmons, J. P., Massey, C. 2018. Overcoming algorithm aversion: People will use imperfect algorithms if they can (even slightly) modify them. Management Science, 64(3), 1155-1170.

Festinger, L. A. 1957. A theory of cognitive dissonance. Evanston, IL: Row and Peterson.

Fornell, C., Bookstein, F. L. 1982. Two structural equation models: LISREL and PLS applied to consumer exit-voice theory. Journal of Marketing Research, 19(4), 440-452.

Forsythe, S. M., Shi, B. 2003. Consumer patronage and risk perceptions in internet shopping. Journal of Business Research, 56, 867-875.

Gerbing, D. W., Anderson, J. C. 1992. Monte Carlo evaluations of goodness of fit indices for structural equation models. Sociological Methods & Research, 21, 132-160.

Ha, Y. W., Kim, J., Libaque-Saenz, C. F., Chang, Y. 2015. Use and gratifications of mobile SNSs: Facebook and KakaoTalk in Korea. Telematics and Informatics, 32, 425-438.

Haim, M., Arendt, F., Scherr, S. 2017. Abyss or shelter? On the relevance of web search engines' search results when people Google for suicide. Health Communication, 32(2), 253-258.

Hair, J. F., Sarstedt, M., Pieper, T. M., Ringle, C. M. 2012. The user of partial least squares structural equation modeling in strategic management research: A review of past practices and recommendations for future applications. Long Range Planning, 45(5), 320-340.

Harper, T. 2017. The big data public and its problems: Big data and the structural transformation of the public sphere. New Media & Society, 19(9), 1424-1439.

Hsu, C., Lin, J. C. 2015. What drives purchase intention for paid mobile apps? – An expectation confirmation model with perceived value. Electronic Commerce Research and Applications, 14, 46-57.

Kim, B. 2010. An empirical investigation of mobile data service continuance: Incorporating the theory of planned behavior into the expectation-confirmation model. Expert Systems with Applications, 37, 7033-7039.

Kim, B. 2011. Understanding antecedents of contiuance intention in social-networking services. Cyberpsychology, Behavior, and Social Networking, 14(4), 199-205.

Lee, M. K. O., Cheung, C. M. K, Chen, Z. 2005. Acceptance of internet-based learning medium: the role of extrinsic and intrinsic motivation. Information & Management, 42(8), 1095-1104.

Lee, M. 2010. Explaining and predicting users' continuance intention toward e-learning: An extension of the expectation-confirmation model. Computers & Education, 54, 506-516.

Lin, C. S., Wu, S., Tsai, R. J. 2005. Integrating perceived playfulness into expectation-confirmation model for web portal context. Information & Management, 42, 683-693.

Lin, J., Wang, B., Wang, N., Lu, Y. 2014. Understanding the evolution of consumer trust in mobile commerce: A logitudinal study. Information Technology and Management, 15(1), 37-49.

Lin, K., Lu, S. 2014. Predicting mobile social network acceptance based on mobile value and social influence. Internet Research, 25(1), 107-130.

Lin, T., Wu, S., Hsu, J. S., Chou, Y. 2012. The integration of value-based adoption and expectation-confirmation models: An example of IPTV continuance intention. Decision Support Systems, 54, 63-75.

McKnight, D. H., Choudhury, V., Kacmar, C. 2002. The impact of initial consumer trust on intentions to transact with a web site: A trust building model. Journal of Strategic Information Systems, 11, 297-323.

Mittelstadt, B. 2016. Auditing for transparency in content personalization systems. International Journal of Communication, 10, 4991-5002.

Moller, J., Trilling, D., Helberger, N., van Es, B. 2018. Do not blame it on the algorithm: An empirical assessment of multiple recommender systems and their impact on content diversity. Information, Communication & Society, 21(7), 959-977.

Mouakket, S. 2015. Factors influencing continuance intention to use social network sites: The Facebook case. Computers in Human Behavior, 53, 102-110.

Oghuma, A. P., Libaque-Saenz, C. F., Wong, S. F., Chang, Y. 2016. An expectation-confirmatino model of continuance intention to use mobile instant messaging. Telematics and Informatics, 33, 34-47.

Oliver, R. L. 1980. A cognitive model of the antecedents and consequences of satisfaction decisions. Journal of Marketing Research, 17(4), 460-469.

Oliver, R. L. 1981. Measurement and evaluation of satisfaction processes in retail settings. Journal of Retailing, 57(3), 25-48.

Pariser, E. 2011. The filter bubble: What the internet is hiding from you. London, England: Penguin Books.

Spohr, D. 2017. Fake news and ideological polarization: Filter bubbles and selective exposure on social media. Business Information Review, 34(3), 150-160.

Stone, R. W., Baker-Eveleth, L. B. Students' expectation, confirmation, and continuance intention to use electronic textbooks. Computers in Human Behavior, 29, 984-990.

Tan, X., Qin, L., Kim, Y., Hsu, J. 2011. Impact of privacy concern in social networking web sites. Internet Research, 22(2), 211-233.

Tang, J. E., Chiang, C. 2010. Integrating experiential value of blog use into the expectation-confirmation theory model. Social Behavior and Personality, 38(10), 1377-1390.

Thong, J. Y. L., Hong, S., Tam, K. Y. 2006. The effects of post-adoption beliefs on the expectation-confirmation model for information technology continuance. International Journal of Human-Computer Studies, 64, 799-810.

Wheaton, B., Muthen, B., Alwin, D. F., Summers, G. F. 1977. Assessing reliability and stability in panel models. Sociological Methodology, 8, 84-136.

Van der Heijden, H. 2004. User acceptance of hedonic information systems. MIS Quarterly, 28(4), 695-704.

Van Slyke, C., Ilie, V., Lou, H., Staffor, T. 2007. Perceived critical mass and the adoption of a communication technology. European Journal of Information Systems, 16(3), 270-283.

Venkatesh, V, Davis, F. D. 2000. A theoretical extension of the technology acceptance model: Four longitudinal field studies. Management Science, 46(2), 186-204.

Venkatesh, V., Morris, M G., Davis, G. B., Davis, F. D. 2003. User acceptance of information technology: toward a unified fiew. MIS Quarterly, 27(3), 425-478.

Wang, H. C., Chiu, Y. F. 2011. Assessing e-learning 2.0 systems success. Computers & Education, 57(2), 1790-1800.

Yuan, S., Liu, Y., Yao, R. 2016. An investigation of users' continuance intention towards mobile banking in China. Information Development, 32(1), 20-34.