Do Nudges Matter? Consumer Perception and Acceptance of Recommender Systems with Different Types of Nudges

Irina Dolgopolova
Chair of Marketing and Consumer Research
TUM School of Management
Technical University of Munich
Freising, Bavaria, Germany
irina.dolgopolova@tum.de

Bingqing Li
Chair of Marketing and Consumer Research
TUM School of Management
Technical University of Munich
Freising, Bavaria, Germany
isami.b.li@tum.de

Jutta Roosen
Chair of Marketing and Consumer Research
TUM School of Management
Technical University of Munich
Freising, Bavaria, Germany
jroosen@tum.de

ABSTRACT

Recommender systems are designed to ease and enhance consumer's decision making in complex online environments. Albeit devised to be convenient and ancillary, recommender systems may in turn influence and even dominate consumer's choices with available means of choice architecture. This raises concerns regarding consumer freedom of choice, which can be hindered by a recommender system without consumers being aware of being manipulated. We developed a survey that uses an example of an online food ordering screen and an information treatment to determine factors influencing consumer acceptance of a recommender system which employs nudging as a method to steer consumer choice in the desired direction. Using the Technology Acceptance Model as a framework, we demonstrated that perceived manipulation by a recommender system is one of the most important factors decreasing the perceived effectiveness of a recommendation and perceived ease of choice. At the same time, consumers were rather indifferent with regard to a recommender system that employs nudging to influence their choices. Consumer concerns appeared to be centered around the algorithms and the use of private information by a recommender system, but not around the possible modification of choice environment.

KEYWORDS

Recommender systems, Nudge, Technology Acceptance Model, Consumer choice, Privacy

1 Introduction

Modern consumers navigate information-rich environments facing an ever-increasing amount of choices. Recommender systems (RS) are software tools and techniques aimed at aiding consumers in making choices in online environments. Recommendations generated by these systems can be based on previous choices made by consumers, consumer product ratings, or other consumer characteristics and actions that can be interpreted as indicators of consumer preference [1].

In online choice environments, retailers and marketers have endless possibilities to influence consumer choice by means of choice architecture. One of the methods to influence consumer choice is nudging. A nudge is defined as "any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives" [2]. A classic example is the rearrangement of food in school cafeterias, placing certain food items at eye level or in a separate line. This type of reorganization can be used to promote healthier nutrition as school children would tend to choose foods that are easily accessible [2]. In online environments, nudging can function by modifying the content of a choice (e.g. which options and how many of them are presented) or the visualization of a choice (e.g. in user interface design) [3]. The effect of digital nudges was previously studied in the context of reward-based crowdfunding [3] and healthier recipe recommendations [4]. Nudging often pertains to heuristics or simplified decision-making processes that consumers use when making choices. For example, when a given product on the screen is highlighted with a popular choice sign, it appeals to consumers who simplify their choice strategy by choosing the option most popular among other consumers. Behavioral science suggests that consumers are susceptible to different types of heuristics and simplifying strategies, which make their decision making styles easily discernible [5, 6], thus allowing the recommender system to exploit these repetitive choice strategies to steer consumer choices into the desired direction without consumer knowledge [7]. Although embedding a smart nudging mechanism that offers personalized situation- and target-specific digital stimuli into an RS was proposed for different products and services [8], we use an example of a fast food ordering screen with nudges toward healthier food options.

The ability of an RS to alter choice environments based on consumer preferences and decision-making styles raises several concerns related to the autonomy of consumer choice and their ability to control their choices. André et al. [9] suggest that AI-enabled choice environments have the potential to both increase or decrease consumers' well-being, and that consumers might react negatively to the use of technology that undermines their autonomy. Thus, AI-enabled choice environments have the potential to make consumers worse off compared to environments of unaided choice.

Moreover, if not implemented appropriately, the perceived manipulation by RS can be aggravated when the choice environment is augmented with nudges, which are often accused of being subtle and covert. Among three types of nudges – heuristic-triggering, heuristic-blocking and informing nudges, heuristic nudges that rely on automatic process have repeatedly demonstrated to be effective across many applications but often considered ethically problematic [10]. On the contrary, informing nudges influences people’s decision by provision of information, based on which people are more conscious about choices and their environment, and are less subject to ethical debates and the criticism of libertarian paternalism. However, informing nudges, also referred as cognitively oriented nudges, such as descriptive and evaluative labeling, are least effective in influencing people’s decisions [11]. The tradeoff between the transparency of the systems (simultaneously the autonomy of people’s decision-making process) and the effectiveness of nudges needs to be deliberately evaluated when influencing user’s behavior in favorable direction while minimizing the risk of unethically obscuring information and maintaining user’s rights of autonomous decision making. From this perspective, it is important to know how consumers perceive AI-enabled choice environments and if consumer perception can create barriers in the use of technology.

An augmented Technology Acceptance Model (TAM) [12] is used as a conceptual framework for analyzing consumer perception of an AI-enabled recommender system. The technology acceptance model (TAM), as a powerful extension derived from the Theory of Reasoned Action (TRA), was developed by [12], to analyze and predict people's adoption and use of novel technology, especially in the IT field. It suggests that an individual's decision on whether or not to utilize a new technology depends on two immediate factors -- perceived usefulness and perceived ease of choice, which are influenced by a set of external variables. While TAM and its various extensions have been widely used to analyze and understand the acceptance of new technologies as tools and platforms, such as fitness apps [13], e-commerce [14], health informatics [15] and digital pedagogical tools [16], a number of papers using TAM to study user’s evaluation of more intelligent systems have especially focused on RS for facilitating decision making [17, 18], which include behavioral consumer patterns. Hu and Pu [19] evaluated user’s acceptance of personality-based RS compared to rating-based RS using TAM and revealed that even though rating-based RS is industry norm, personality-based RS is perceived more accurate and favorable. Lee et al. [20] applied TAM to test the usefulness of a virtual community recommender, which uses TAM variables and consumer needs as filtering function. They conclude that the use of behavioral consumer data does improve not only the effectiveness of a recommender system but also consumer satisfaction. In this study, we employed the TAM framework to explain consumer's acceptance of RS for facilitating decision making.

In this study, we aim to determine (i) which factors influence consumer perception of a recommender system, (ii) whether this perception differs when nudging is included in the system, and (iii) how the perceived manipulation and privacy concerns impair the acceptance of a recommender system for facilitating decision making.

2 Methodology

2.1 Survey Description

A survey was constructed to determine consumer perception of and ethical concern about a recommender system. The survey consisted of several steps (Figure 1). At first, screening questionnaire was used to ensure that survey participants do not follow any particular diet (are omnivores), have experience with ordering food online, do not have any food intolerances, and are familiar with RS. The first part of the questionnaire followed with questions regarding participants' level of hunger and the time since the last meal. The German adaptation [21] of the short version (13 questions) of the self-control scale was employed. Respondents assessed the items on a five-point scale ranging from 1 (completely disagree) to 5 (completely agree).

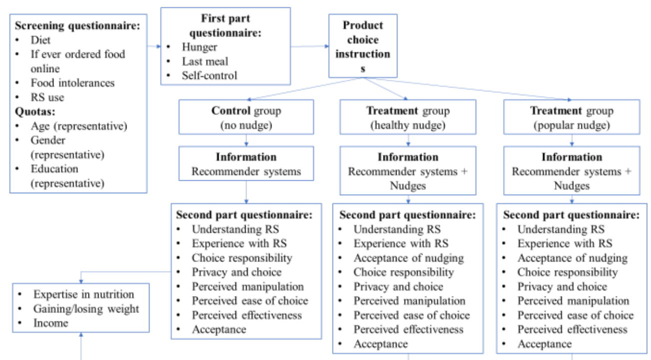

Figure 1: The organization of the experiment.

After that, participants were randomly assigned to one of three groups: a control group and two treatment groups. The setup of different nudge treatment groups allows us to test the variance of RS acceptance with the existence of nudging. Participants in all the groups were instructed to make a hypothetical product choice on a screen imitation of an online ordering platform from a restaurant. We used cheap talk to ensure that participants make realistic choices. Examples of the ordering screens are presented in Table 1. Respondents in the control group did not have any interventions on the screen; in both treatment groups, healthier food options were highlighted with an informational nudge “Healthy choice” for treatment group 1 and a social norm nudge “Popular choice” for treatment group 2. The order of the products on the screens was randomized.

After making product choice, participants proceeded to the information treatment, with the description of a recommender system with examples from Netflix and Amazon recommendations. Treatment groups also received additional information explaining what a nudge is and how it works, and were reminded that they had an example of a nudge on the screen. Participants' understanding of a recommender system was checked with two knowledge questions. They also had to indicate how often they come in contact with a recommender system. Subsequently, participants answered questions about the acceptance of nudging, choice responsibility, privacy and choice, perceived manipulation, perceived ease of choice, perceived effectiveness, and acceptance of a recommender system. The final questions in the survey concerned participants' expertise in nutrition, their diet, and the level of income.

Table 1: Ordering screen options for different experimental groups.

Experimental group	Ordering screen versions
Control	
Treatment 1 Healthy nudge	
Treatment 2 Popular nudge	

2.2 Sample Description

We used a sample of 3000 participants provided by a marketing company. The sample was randomly distributed into three groups: control group (N=1000), a healthy nudge group (N=1000), and a popular nudge group (N=1000). The socio-demographic characteristics of the whole sample, divided by groups, are presented in Table 2. The average age of the sample is 39.88 years for the whole sample, with the minimum age of 16 years and maximum of 74 years old. Most of the participants graduated at least from secondary school and have a middle monthly income level between €1.301 and €5.000 per month.

Table 2: Socio-demographic characteristics of the sample.

Variable	Description	Total sample (N=3000)	Control group (N=1000)	Healthy nudge group (N=1000)	Popular nudge group (N=1000)
Age	Age in years	39.88 (14.03)	39.78 (13.97)	39.85 (14.00)	40.02 (14.12)
Gender	1 – female, 2 - male	1.55 (0.50)	1.55 (0.51)	1.55 (0.50)	1.55 (0.50)
Education	1 – no school; 2 – elementary school; 3 – polytechnic secondary school; 4 – secondary school; 5 – vocational school; 6 – university degree	4.61 (1.23)	4.58 (1.23)	4.61 (1.23)	4.63 (1.24)
Income	1 – under 800 EURO; 2 – 801 to 1.300 EURO; 3 – 1.301 to 2.000 EURO; 4 – 2.001 to 3.000 EURO; 5 – 3.001 to 5.000 EURO; 6 – above 5.000 EURO	3.96 (1.31)	3.92 (1.35)	4.01 (1.25)	3.95 (1.33)

2.3 Theoretical Framework and Measures

We hypothesized that the acceptance of recommender system is determined by the perceived effectiveness and ease of choice, both of which depend on demographic factors, experience with RS, (locus of) choice responsibility, perceived manipulation, privacy and choice, and, additionally, nudge acceptance for the two treatment groups, as shown in Figure 2.

The dependent variable, "RS acceptance", was measured with a self-developed scale consisting of 3 items that assess how comfortable, safe, and free they feel using a recommender system. As for independent variables, "perceived effectiveness" and "perceived ease of choice", were measured with 11 and 2 items, which were tailored based on the scale originally developed by Davis et al. [12], respectively. "Experience with RS" was directly measured on a scale from 1 (every day) to 6 (less than once per month), which was reversed in the subsequent analysis. "Choice responsibility" was formulated into a trinary scale (0 completely others, 1 others and self, and 2 completely self), based on a multiple-choice question that "Which of the following interest group is responsible for whether people choose healthy or unhealthy food". Possible choices included the government, food manufacturer, supermarket, online food suppliers, consumers themselves, etc. "Perceived manipulation" was measured with a scale developed by Campbell [22], containing 6 items. All foregoing items were measured on a Likert scale from 1 (completely disagree) to 5 (completely disagree) and were used to extract latent factors for further analysis. "Privacy and choice" was measured with 3 items based on the previous research of Malhotra et al. [23] on Internet users' information privacy concerns. The questions asked participants the importance of making decisions without pressure from others, accessing all their own information, and preventing others from accessing their information. The last independent factor, "Nudge acceptance", was constructed from 7 items, which were inspired by the study of Sunstein et al. [24]. Table 3 details the items used for each construct.

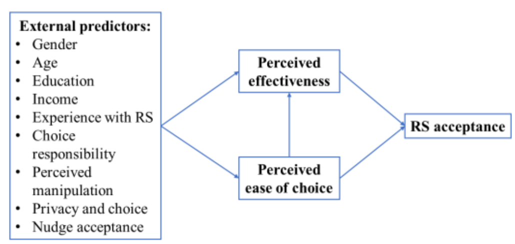

Figure 2: Conceptual framework based on the Technology Acceptance Model (Nudge acceptance predictor only for treatment groups).

3 Data Analysis

3.1 Confirmatory Factor analysis

Six constructs used in the proposed model, including RS acceptance, perceived effectiveness, perceived ease of choice, privacy and choice, perceived manipulation, and nudge acceptance, were calculated with a total of 32 items using principal component factor analysis, as shown in Table 3. Both Kaiser's cumulative eigenvalue and scree plot criteria were used to determine the number of extracted factors. Internal reliability of the underlying constructs was confirmed with Cronbach's alpha test to establish the soundness of the measurement incorporated in the final structural model.

3.2 Structural Equation Modeling

Table 3: Factor loadings and internal reliability for 6 constructs.

Constructs	Items	Factor loading	Cronbach's alpha
RS acceptance	I would feel comfortable using recommendation systems to facilitate my decisions.	0.91	0.81
	I would feel safe using recommender systems to facilitate my decisions.	0.89	
	I would feel free to choose whatever I want when using recommender systems to support my decisions.	0.76	
Perceived ease of choice	The way products in recommendation systems are presented on the screen is clear and understandable.	0.88	0.71
	The way information about products in recommendation systems is presented on the screen allows me to choose the product that is most appropriate.	0.88	
Perceived effectiveness	RS gives me valuable suggestions.	0.84	0.92
	Generally, I would recommend RS to other people.	0.79	
	I can find better products through RS.	0.82	
	I make better decisions with RS.	0.79	
	RS is useless.*	0.72	
	RS make me more aware of my options.	0.76	
	I do not need a RS to find suitable products.*	0.65	
	RS does not benefit me.*	0.78	
	RS is useful.	0.85	
	I can save time with RS.	0.78	
	I can find more suitable products without using RS.*	0.46	
Perceived manipulation	The way RS tries to convince people is acceptable to me.*	0.79	0.87
	RS manipulates users in ways I do not like.	0.80	
	RS bothers me because they seem to try to control consumers in an inappropriate way.	0.81	
	I don't mind RS - it tries to convince without being inappropriately manipulative.*	0.80	
	RS seems fair in what they say and display.*	0.73	
	I believe RS is unfair.	0.75	
Privacy and choice	Being able to make decisions online without the pressure of others.	0.84	0.74
	Having controlled access to all my information online.	0.78	
	To prevent others from accessing my information online.	0.81	
Nudge acceptance	The visibility of healthy products in supermarkets and cafeterias should be increased.	0.79	0.82
	Fruit and vegetables should be placed in the most visible areas of cafeterias.	0.73	
	Sweets should be placed in concealed compartments (like tobacco products).	0.51	
	The visibility of unhealthy food in supermarkets and cafeterias should be reduced.	0.58	
	A high content of salt, sugar and saturated fatty acids should be made mandatory.	0.76	
	Fast food restaurants (e.g. McDonalds, Burger King) should be obliged to display calories on their products.	0.72	
	Depending on the quality of the nutritional value of a product, coloured symbols should be printed in green, yellow and red.	0.74	

* Reverse coded items.

The final structural model consisted of 3 latent endogenous variables, acceptance of RS, 6 manifest and 3 latent exogenous variables, whose relationships were then computed. For the parsimony of computation, factors extracted in the previous CFA were used for the latent variables [25]. All constructs exhibited high reliability with Cronbach alpha coefficients ranging from 0.71 to 0.92. The structural equation modeling was conducted on 3 groups of data (1000 control group, 1000 healthy nudge group, and 1000 popular nudge group) with maximum likelihood model using STATA (Version 15.1). Figure 3 shows the standardized path coefficients and error terms in the final theoretical model for the healthy nudge treatment group. Whereas the popular nudge group fitted the same model with slightly different loadings, the control group was modeled without "Nudge acceptance".

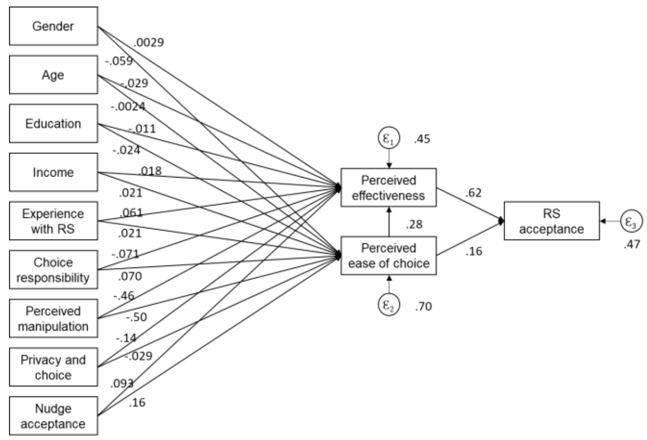

Figure 3: Finalized research model for the healthy nudge treatment group with standardized path loadings for interrelations among latent constructs and observed measures.

Table 4: Standardized path coefficients and levels of significance for 3 groups by structural equation modeling[1].

Variables		Beta		
		Control Group	Healthy Nudge Group	Popular Nudge Group
Perceived effectiveness		0.62***	0.62***	0.60***
	Perceived ease of choice	0.30***	0.28***	0.30***
	Gender	0.0045	0.0029	0.026
	Age	-0.016	-0.029	-0.051*
	Education	-0.0060	-0.011	0.015
	Income	0.021	0.018	0.015
	Experience with RS	0.064**	0.061**	0.038
	Choice responsibility	-0.080***	-0.071***	-0.068***
	Perceived manipulation	-0.45***	-0.46***	-0.50***
	Privacy and choice	-0.13***	-0.14***	-0.15***
	Nudge acceptance	-	0.093***	0.11***
Perceived ease of choice		0.16***	0.16***	0.17***
	Gender	-0.074**	-0.059*	-0.031
	Age	0.021	-0.0024	-0.017
	Education	-0.015	-0.024	-0.066*
	Income	0.028	0.021	-0.0085
	Experience with RS	0.027	0.021	0.027
	Choice responsibility	0.057*	0.070*	0.0098
	Perceived manipulation	-0.51***	-0.50***	-0.51***
	Privacy and choice	-0.011	-0.029	0.023
	Nudge acceptance	-	0.16***	0.045

* $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$

[1] Estimated parameters do not differ among the groups regarding perceived effectiveness ($chi^2(2) = 0.59$; $p = 0.74$), perceived ease of choice ($chi^2(2) = 0.73$; $p = 0.70$), and RS_acceptance ($chi^2(2) = 0.93$; $p = 0.64$).

3.3 Results

As hypothesized in the conceptual model, both perceived effectiveness and ease of choice showed statistically significant effects on the acceptance of RS across all three groups, with more substantial influence from perceived effectiveness. Further, perceived ease of choice was a statistically significant positive predictor for the perceived effectiveness. Among external predictors, perceived manipulation significantly predicted the perceived effectiveness and ease of choice in all conditions.

Consistent with existing literature, the result indicated that the perceived effectiveness of a recommender system decreases with the increased perceived manipulation by the system. More specifically, if a user perceived the system to be unfair, manipulative, trying to convince in inappropriate ways, the perceived effectiveness, ease of choice and hence the acceptance of the system would be weakened. Whereas choice responsibility influenced the perceived effectiveness of RS with statistical significance, no such correlation was found for perceived ease of choice. Nevertheless, it is sensible that a user with responsibility for choices allocating more to the user (2 on the 0~2 trinary scale) possesses the predilection to have autonomous control over decision making and consequently finds RS less useful. Noticeably, different from previous research [26, 27], the effect of prior experience with RS, which commonly demonstrated a positive correlation with technology acceptance, was either comparatively minute or statistically insignificant across all groups. Other socio-demographic characteristics of participants, including age and gender, also did not demonstrate a systematic effect on the perceived effectiveness or perceived ease of choice. This result contradicted previous findings in the literature as Knijnenburg et al. [28] suggested that age, gender, and domain expertise influence the perception of a recommender system and Venkatesh et al. [26] found the moderating effect of gender and age on behavioral intention in their modified version of TAM.

The result revealed that nudge acceptance positively influences perceived effectiveness and perceived ease of choice in the healthy nudge group. However, the variance of the perceived effectiveness and ease of use, as well as the overall RS acceptance with treatment groups of different nudges, did not shown statistical significance, as indicated by ANOVA results in Table 5. Although previous research demonstrated that modifications of choice environments by RS can significantly influence consumer preferences [29], consumers do not see nudges as a barrier for RS acceptance. Nudges are viewed as aiding consumers to achieve desirable choice outcomes and also ease the process of choice in the healthy nudge group.

Table 5: One-way ANOVA on the differences in means of perceived effectiveness, perceived ease of choice, and RS acceptance across all treatment groups.

Constructs	F-value	df	p-value
Perceived effectiveness	1.48	2	0.23
Perceived ease of choice	0.02	2	0.98
RS acceptance	0.77	2	0.46

4 Conclusion

This paper integrated the concept of nudging, which stems from the field of behavioral economics, into the TAM to study consumer acceptance of a recommender system. We found that consumer acceptance is substantially determined by perceived system effectiveness and, to a lesser degree, by perceived ease of choice. Also, while consumers explicitly demonstrated a decrease in acceptance of RS with the perception of being manipulated by the system, they showed an indifferent attitude toward the existence of nudging mechanism in the system. In other words, negative consumer concerns appeared to revolve around the information and algorithms used by an RS but not the methods of choice architecture used to modify choice environments. This finding created potential ethical concerns as consumers either disregard or diminish the influence of choice environments on the choice outcomes.

ACKNOWLEDGMENTS

The authors gratefully acknowledge the financial support from the Technical University of Munich - Institute for Ethics in Artificial Intelligence (IEAI).

REFERENCES

[1] Dan Cosley et al., 2003. Is Seeing Believing? How Recommender Interfaces Affect Users' Opinions. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, no. 5, 585–592.

[2] Richard H. Thaler and Cass R. Sunstein. 2008. *Nudge: Improving Decisions About Health, Wealth, and Happiness*. Yale University Press.

[3] Markus Weinmann et al. 2016. Digital Nudging. *Business and Information Systems Engineering*, vol. 58, no. 6, 433–436, doi:10.1007/s12599-016-0453-1.

[4] David Elsweiler et al., 2017. Exploiting Food Choice Biases for Healthier Recipe Recommendation. SIGIR 2017 - *Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval*, no. August, 575–84, doi:10.1145/3077136.3080826.

[5] Gerd Gigerenzer and Daniel G. Goldstein, 2011. The recognition heuristic: A decade of research. *Judgment and Decision Making*, vol. 6, no. 1, 100–121.

[6] Cristina del Campo et al., 2016. Decision making styles and the use of heuristics in decision making. *Journal of Business Economics*, vol. 86, 389–412. DOI 10.1007/s11573-016-0811-y

[7] Mariarosaria Taddeo and Luciano Floridi, 2018. How AI Can Be a Force for Good. *Science*, vol. 361, no. 6404, 751–753, http://arxiv.org/abs/1606.05718.

[8] Randi Karlsen and Anders Andersen, 2019. Recommendations with a Nudge. *Technologies*, vol. 7, no. 2, 45, doi:10.3390/technologies7020045.

[9] Quentin André et al., 2018. Consumer Choice and Autonomy in the Age of Artificial Intelligence and Big Data. *Customer Needs and Solutions*, vol. 5, no. 1–2, 28–37, doi:10.1007/s40547-017-0085-8.

[10] Adrien Barton and Till Grüne-Yanoff, 2015. From libertarian paternalism to nudging—and beyond. *Review of Philosophy and Psychology*, vol. 6, 341–359, doi.org/10.1007/s13164-015-0268-x.

[11] Romain Cadario and Pierre Chandon, 2019. Which healthy eating nudges work best? a meta-analysis of field experiments. *Marketing Science*, vol. 39, no.3, 1–22. doi.org/10.1287/mksc.2018.1128.

[12] Fred D. Davis et al., 1989. User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. *Manage Sci*, vol. 35, no. 8, 982–1003, doi:10.1287/mnsc.35.8.982.

[13] Ardion D. Beldad and Sabrina M. Hegner, 2018. Expanding the Technology Acceptance Model with the Inclusion of Trust, Social Influence, and Health Valuation to Determine the Predictors of German Users' Willingness to Continue Using a Fitness App: A Structural Equation Modeling Approach. *Int J of Hum-Comput Int*, vol. 34, no. 9, 882–893, doi:10.1080/10447318.2017.1403220.

[14] Paul A. Pavlou, 2003. Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *International Journal of Electronic Commerce,* vol. 7, no. 3, 101–134.

[15] Bahlol Rahimi et al., 2018. A systematic review of the technology acceptance model in health informatics. *Applied Clinical Informatics*, vol. 9, no. 3, 604–634.

[16] Ronny Scherer et al., 2019. The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. *Computers and Education*, vol. 128, 13-35.

[17] Marcelo G. Armentano et al., 2015. Applying the technology acceptance model to evaluation of recommender systems. *Polibits*, vol. 51, 73–79. doi.org/10.17562/PB-51-10.

[18] Marcelo G. Armentano et al., 2014. User acceptance of recommender systems: influence of the preference elicitation algorithm. *2014 9th International Workshop on Semantic and Social Media Adaptation and Personalization*, 72–76, doi: 10.1109/SMAP.2014.18.

[19] Rong Hu and Pearl Pu, 2009. Acceptance issues of personality-based recommender systems. *RecSys '09: Proceedings of the third ACM conference on Recommender systems*, no. October, 221–224, doi.org/10.1145/1639714.1639753.

[20] Hyoung Yong Lee et al., 2007. VCR: Virtual Community Recommender Using the Technology Acceptance Model and the User's Needs Type. *Expert Systems with Applications*, vol. 33, no. 4, 984–995, doi:10.1016/j.eswa..07.012.

[21] Alex Bertrams and Oliver Dickhäuser. 2009. Messung Dispositioneller Selbstkontroll-Kapazität: Eine Deutsche Adaptation Der Kurzform Der Self-Control Scale (SCS-K-D). *Diagnostica*, vol. 55, no. 1, 2–10, doi:10.1026/0012-1924.55.1.2.

[22] Margaret C. Campbell, 1995. When Attention-Getting Advertising Tactics Elicit Consumer Inferences of Manipulative Intent: The Importance of Balancing Benefits and Investments. *J Consum Psychol*, 4(3), 225–254

[23] Naresh Malhotra et al., 2004. Internet Users' Information Privacy Concerns (IUIPC): The Construct, the Scale, and a Causal Model. *Inform Syst Res*, 15(4), 336-355.

[24] Cass R. Sunstein et al., 2017. Behavioral Insights All over the World? Public Attitudes toward Nudging in a Multi-Country Study. *SSRN Electronic Journal*.

[25] James C. Anderson, and David W. Gerbing, 1988. Structural Equation Modeling in Practice: A Review and Recommended Two-Step Approach. *Psychol Bull*, vol. 103, no. 3, 411–423, doi:10.1037/0033-2909.103.3.411.

[26] Viswanath Venkatesh et al. 2003. Human Acceptance of Information Technology. *MIS Quaterly*, vol. 27, no. 3, 425–478, doi:10.1201/9780849375477.ch230.

[27] Daniel J. McFarland and Diane Hamilton, 2006. Adding Contextual Specificity to the Technology Acceptance Model. *Comput Hum Behav*, vol. 22, no. 3, 427–447, doi:10.1016/j.chb.2004.09.009.

[28] Bart P. Knijnenburg et al., 2012. Explaining the User Experience of Recommender Systems. *User Modeling and User-Adapted Interaction*, vol. 22, no. 4–5, 441–504, doi:10.1007/s11257-011-9118-4.

[29] Gediminas Adomavicius et al., 2013. Do Recommender Systems Manipulate Consumer Preferences? A Study of Anchoring Effects. *Inform Syst Res*, vol. 24, no. 4, 956–975, doi:10.1287/isre.2013.0497. [1] Gediminas Adomavicius et al., 2013. Do Recommender Systems Manipulate Consumer Preferences? A Study of Anchoring Effects. *Inform Syst Res*, vol. 24, no. 4, 956–975, doi:10.1287/isre.2013.0497.