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DO USERS ALWAYS WANT TO KNOW MORE? INVESTIGATING THE RELATIONSHIP BETWEEN SYSTEM TRANSPARENCY AND USERS' TRUST IN ADVICE-GIVING SYSTEMS

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DO USERS ALWAYS WANT TO KNOW MORE? INVESTIGATING THE RELATIONSHIP BETWEEN SYSTEM TRANSPARENCY AND USERS' TRUST IN ADVICE-GIVING SYSTEMS

Research in Progress

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Abstract

Users' adoptions of online-shopping advice-giving systems (AGSs) are crucial for e-commerce websites to attract users and increase profits. Users' trust in AGSs influences them to adopt AGSs. While previous studies have demonstrated that AGS transparency increases users' trust through enhancing users' understanding of AGSs' reasoning, hardly any attention has been paid to the possible inconsistency between the level of AGS transparency and the extent to which users feel they understand the logic of AGSs' inner working. We argue that the relationship between them may not always be positive. Specifically, we posit that providing information regarding how AGSs work can enhance users' trust only when users have enough time and ability to process and understand the information. Moreover, providing excessively detailed information may even reduce users' perceived understanding of AGSs, and thus hurt users' trust. In this research, we will use a lab experiment to explore how providing information with different levels of detail will influence users' perceived understanding of and trust in AGSs. Our study would contribute to the literature by exploring the potential inverted U-shape relationship among AGS transparency, users' perceived understanding of and trust in AGSs, and contribute to the practice by offering suggestions for designing trustworthy AGSs.

Keywords: Advice-giving system, Trust, Transparency, Perceived understanding.

1 Introduction

Advice-giving systems (AGSs) are software systems that offer users with personalized recommendations or decision aids based on users' unique preferences or needs (Xiao and Benbasat 2007; 2014). Due to their effectiveness in reducing users' information overload (Komiak and Benbasat, 2008) and facilitating users' decision-making process (Wang and Benbasat, 2008), maximizing users' adoptions of AGSs is an effective way for e-commerce websites to attract users and increase profits (Komiak and Benbasat 2006). Users' trust in AGSs enhances users' adoptions of AGSs (Wang and Benbasat, 2005), and can be influenced by many factors, such as cost-benefit calculations (Gefen et al., 2003; Wang and Benbasat, 2008), users' interactive experience with AGSs (Gefen 2000; Gefen et al., 2003; Wang and Benbasat, 2008), and users' knowledge of how AGSs work (Hengstler et al., 2016; Lakkaraju et al., 2016; Lehikoinen and Koistinen, 2014; Lim et al., 2009; Pieters, 2011; Pu et al., 2012; Wang and

Benbasat, 2007, 2008; Zliobaite et al., 2012). Among those factors, *system transparency*, defined as the extent to which information of a system's reasoning is provided and made available to users (Amalia, 2017; Cho et al., 2017; Hosseini et al., 2018; Leape et al. 2009; Yamazaki and Yoon, 2016; Zhu, 2002), is considered as a key influential factor of users' trust in AGSs (Diakopoulos and Koliska, 2017; Swearingen and Sinha, 2002; Tintarev and Masthoff, 2007). Previous studies have identified providing explanations as an effective way of enhancing AGS transparency and users' trust (Arnold et al. 2006; Bilgic and Mooney 2005; Gedikli et al. 2014; Gregor and Benbasat 1999; Herlocker 2000; Hernando et al. 2013; Mao and Benbasat 2000; Pu and Chen, 2007; Wang and Benbast 2007; Ye and Johnson 1995). Despite the fruitful research findings, there is still a lack of a clear and precise definition of AGS transparency in the IS literature. While AGS transparency is always defined as users' understanding of systems' inner logic (Pu et al., 2011), in other domains it is also defined as systems' voluntary release of information (Amalia, 2017; Hosseini et al., 2018; Leape et al. 2009) or the visibility and accessibility of such information (Cho et al., 2017; Zhu, 2002). This suggests two alternative ways of measuring system transparency, from users' perspective and systems' perspective respectively. In this paper, we define *objective transparency* as the extent to which systems release information about how they work, and *subjective transparency* as the extent to which users perceive such information is available. In addition, we also argue a necessity of differentiating subjective transparency from users' perceived understanding of AGSs. While subjective transparency refers to users' perceptions of the availability of the information provided by AGSs, users' perceived transparency of AGSs refers to the extent to which users feel that they know the meaning of the provided information. It is commonly believed that AGS transparency can positively influence users' trust in that it can enhance users' perceived understanding of AGSs (McSherry, 2005; Vig et al., 2009). While this may be seemingly true, we argue that such a claim fails to consider users' ability of processing and comprehending the information provided by AGSs. While revealing AGSs' inner logic at an abstract level (e.g. "users who are similar to you also bought…") may give users a general idea about why the advice is recommended, revealing too many details about how the advice is generated (e.g. the formula of calculating the similarity between users) may result in information overload and even bring more confusions to users because as laypeople, users may not be able to understand the complex steps of generating advice. Such a low level of perceived understanding may in turn reduce users' trust in AGSs. Therefore, we assume that there should be an optimal level of transparency which will generate the highest level of users' perceived understanding of and trust in AGSs. Any level of transparency below or over this threshold will lead to a lower perceived understanding of and trust in AGSs. In order to verify our assumptions, we would like to address the following research questions:

(1) How will AGS transparency, including both objective transparency and subjective transparency, influence users' perceived understanding of AGSs, trust in AGSs, and acceptance of AGS advice?

(2) What factors will moderate the relationships in the above question? How will they work?

We will use a lab experiment to test the research questions. Our study would contribute to the existing knowledge by exploring the potential inverted U-shape relationship among AGS transparency, users' perceived understanding of, and their trust in AGSs, and contribute to the practice by offering design suggestions on AGS explanation interfaces. The remainder is organized as follows: Section 2 provides a literature review and defines the concepts. Section 3 develops a research model and hypotheses. Section 4 describes the experimental design. Section 5 presents conclusions and potential contributions.

2 Literature Review and Conceptual Foundations

AGSs transparency is defined as users' understanding of systems' inner logic, i.e. why a particular recommendation is recommended (Pu et al., 2011; Swearingen and Sinha, 2002; Tintarev and Masthoff, 2007). Highly transparent systems articulate the goals of systems (Zouave and Marquenie, 2017), the purposes of collecting data from users (Hedbom et al., 2011), and the rationale for system outputs (Cramer et al., 2008; Diakopoulos and Koliska, 2017; Hedbom et al., 2011; Pu et al., 2011; Zouave and Marquenie, 2017). In this way, such systems could increase the accountability of system algorithms (Ananny and Crawford, 2018; Diakopoulos and Koliska, 2017; Spagnuelo and Lenzini, 2016), facilitate the elicitations of users' personal information (Hosseini et al., 2018), and enhance users' trust in systems (Diakopoulos and Koliska, 2017; Tintarev and Masthoff, 2007) and adoptions of systems outcomes (Cramer et al., 2008; Pu et al., 2011). However, if not provided in a proper way, transparency may be misused. Excessively detailed information might reduce the efficiency of systems in that it required too much time to be processed by users (Tintarev and Masthoff, 2007) and might make users become distracted from the central, more important information (Ananny and Crawford, 2018). Hosseini et al. (2018) and Xu et al. (2018) also warned that users' trust might be reduced if the information provided by systems was not understandable/interpretable/actionable.

In this paper, we define users' trust in AGSs as a trusting belief (Komiak and Benbasat, 2006; McKnight et al., 2002; Wang and Benbasat, 2007). Wang and Benbasat (2008) identified six categories of reasons users trust/distrust of a technology (for names and definitions of each category, see Wang and Benbasat, 2008). Our interest falls into the category of knowledge-based reasons, which refers to users' understanding of how systems work and why systems perform certain behaviors. Knowledge-based reasons are considered to be effective in enhancing users' trust in AGSs (Lakkaraju et al., 2016; Ribeiro et al., 2016; Wang and Benbasat, 2007; 2008), and users' trust can in turn increase users' acceptance of AGS outcomes (Cramer et al., 2008; Pu et al., 2011). Furthermore, providing explanations is identified to be effective in increasing users' trust in AGSs through positively influence knowledge-based reasons (Hengstler et al. 2016; Lakkaraju et al. 2016; Lehikoinen and Koistinen 2014; Lim et al. 2009; Pieters, 2011; Wang and Benbasat 2007; Zliobaite et al. 2012).

In addition, we define ***objective AGS transparency*** as the extent to which AGSs release information regarding what they do and why they behave in a certain way. According to Xiao and Benbasat (2007; 2014), the utilization of AGSs can be divided into input, process, and output stage. Input stage is where users' preferences or needs are elicited. Process stage is where advice is generated based on users' preferences or needs. Output stage is where systems present the generated advice to users. Table 1 shows the definitions of objective transparency in each stage and examples from Facebook.

Stage	Objective Transparency	Transparency Provision for Facebook Ads
Input Stage	What data is collected How is the data collected Why is the data needed	You may have shared your information with businesses by: Signing up for an email newsletter Making purchases at retail stores Signing up for a coupon or discount
Process Stage	How does the algorithm work Why is the algorithm selected by AGSs	When you share information like your phone number or email address with a business, they might add it to a customer list that can be matched to your Facebook profile. We can then try to match the ad to the most relevant audience.
Output Stage	Why is the advice suitable for users Why is the advice better than other alternatives	One reason you're seeing this ad is that Adidas wants to reach people who have visited their website or used one of their apps.

Table 1. Objective AGS Transparency in Different Stages

Lastly, ***subjective AGS transparency*** is defined as the extent to which users perceive that the information regarding what systems do and why they behave in a certain way is provided by AGSs and is visible/available/accessible to them (Cho et al., 2017; Zhu, 2002), and ***users' perceived understanding of AGSs*** is defined as the extent to which users perceive that they understand the meaning of the information provided by AGSs regarding what AGSs do and why they behave in a certain way.

3 Research Model and Hypotheses

The research model of this study is shown in Figure 1.

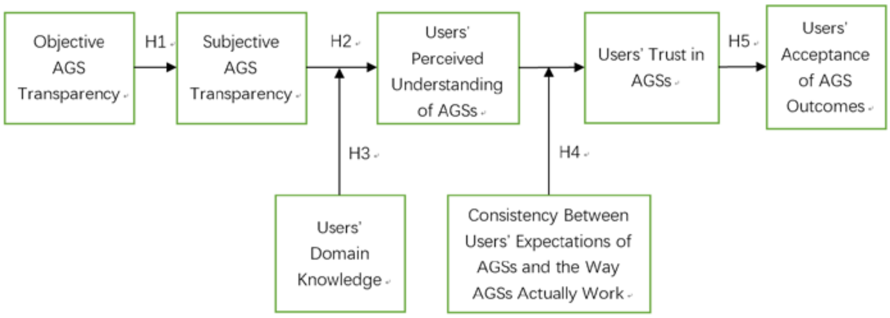

Figure 1. Research Model

A great many studies have shown that providing objective transparency can enhance users' trust in AGSs through enabling them to have a better understanding of AGSs (Dhaliwal and Benbasat 1996; Gregor and Benbasat 1999; Wang and Benbasat 2008). While this may be true in some cases, we indicate two flaws of this claim. First, we argue that instead of directly influencing users' perceived understanding of AGSs, objective transparency should first influence subjective transparency. This is because before perceiving whether they can understand the provided information, users need to first make sure that the information is available and can be accessed. It is such an availability of information, rather than users' perceptions of their understanding, that can be directly and positively influenced by AGSs' provision of information. Users' perceived understanding of AGSs should be in turn directly influenced by the availability of information, i.e. subjective transparency.

Hypothesis 1*: Objective AGS transparency positively influences subjective AGS transparency.*

Second, we propose that the relationship between subjective transparency and users' perceived understanding of AGSs may not always be positive. Although most existing studies suggest that more available information regarding how systems work will be helpful for users to understand systems better (Kim and Benbasat, 2006; 2009), we argue that this would be true only when users have enough time to process the information and enough ability to figure out the meaning of the information content. Once the available information reveals too many details and is beyond a user's comprehension, it may make the user feel more confused because she may become aware that her original ideas of how AGSs work are not accurate, and realize she actually knows very little about the real way AGSs work. In this case, although users may still perceive AGSs to be highly transparent due to the great amount of available information, they may perceive that their understanding of AGSs is at a relatively low level.

Hypothesis 2*: The relationship between subjective transparency and users' perceived understanding of AGSs will be an inverted U-shape. Specifically, while users' perceived understanding will at first increase as the level of subjective transparency increases, it will start to decrease after subjective transparency reaches a particular high threshold value.*

We also assume that the inverted U-shape relationship in Hypothesis 2 will be moderated by users' domain knowledge of AGSs, i.e. the vertex of the inverted U-shape will shift with the level of users' domain knowledge. This is because users with higher levels of domain knowledge will have a better capability to process and comprehend the available information of AGSs' inner logic, and can thus "endure" information with greater level of detail. In this way, their perceived understanding of AGSs will not start to decrease until the available information becomes extremely detailed and difficult to understand. Therefore, they will have higher threshold values of subjective transparency, within which their perceived understanding of AGSs will keep increasing with subjective transparency.

Hypothesis 3*: Users' domain knowledge of AGSs will moderate the inverted U-shape relationship between subjective transparency and users' perceived understanding of AGSs. Compared to users with lowers level of domain knowledge, those who have higher levels of domain knowledge will have a higher threshold value of subjective transparency, beyond which their levels of perceived understanding of AGSs will start to decrease.*

The existing literature suggests that higher levels of perceived understanding of AGSs will lead to higher levels of trust in AGSs (Diakopoulos and Koliska, 2017; Tintarev and Masthoff, 2007). We propose that the consistency between the way in which users expect AGSs to behave and the way in which AGSs actually behave will moderate the effect of users' perceived understanding of AGSs on their trust. Al-Natour et al. (2008) proposed that the similarity between users and AGSs, i.e. whether the advice-generating process and the outcomes met users' expectations, could positively influence users' trust. A higher-level perceived understanding of AGSs can help users know better about the way AGSs actually work, and can thus confirm users' perceptions of consistency/inconsistency between their expectations and the way AGSs work. Therefore, we assume that when there is a consistency, users' perceived understanding of AGSs can increase their trust because they are clearer that their expectations are met by AGSs. However, when there is an inconsistency, a higher-level perceived understanding of AGSs will lead to a lower-level user trust in that users become more aware that the way AGSs work are different from their original expectations. Finally, the existing research argues that users' trust in AGSs can effectively enhance users' acceptance of the advice generated by AGSs (Cramer et al., 2008; Pu et al., 2011).

Hypothesis 4*: The effect of users' perceived understanding of AGSs on users' trust in AGSs will be moderated by the consistency between users' expectations of AGSs and the way AGSs actually work. Specifically, if there is a consistency, users' perceived understanding of AGSs will positively influence users' trust in AGSs. On the contrary, if there is an inconsistency, users' perceived understanding of AGSs will negatively influence users' trust in AGSs.*

Hypothesis 5*: Users' trust in AGSs will positively influence their acceptance of AGS advice.*

4 Research Method

We will use a between-subject design in our experiment. Objective transparency will be manipulated in input, process, and output stage respectively with three levels in each stage (Level 1 to Level 3, with a gradually increased level of detail; see below). The 10 experimental groups are shown in Table 2.

Level	Input Transparency	Process Transparency	Output Transparency
Level 1	Group 1	Group 4	Group 7
Level 2	Group 2	Group 5	Group 8
Level 3	Group 3	Group 6	Group 9
Level 0	Group 10 (control group with no provisions of transparency in any stages)		

Table 2. Experimental Groups

Our experimental AGS will recommend restaurants for users in a particular city, simulating popular restaurant recommendation websites such as Yelp. The detailed information of restaurants will be assigned based on the real restaurant information. Our experimental AGS will adopt collaborative filtering (CF) algorithm. CF will first locate users who share similar interest with a target user (i.e. her neighbours) based on her ratings of restaurants, and then predict her rating of an unexplored restaurant based on the ratings of this restaurant given by her neighbours. The restaurants with high predicted ratings will be recommended to her. The manipulations of objective transparency (Table 3, 4, and 5) are based on the definitions of objective transparency proposed in Section 3.1.

Level	What data is collected	How is the data collected	Why is the data needed	Manipulation
Level 1	Inform that users' personal data is collected.	Explain from where and when the data will be collected.	Indicate that the data collected will be helpful for generating advice with specific features.	In order to recommend you the restaurants that are liked by people who share the same interest with you, we will collect some of your personal data. The data will be collected each time you browse the page of a specific restaurant.
Level 2	Inform what	Explain what	Explain briefly	In order to recommend you the restaurants that

	types of users' personal data is collected.	technique is used to collect data.	why the collected data can be related to specific advice using text.	are liked by people who share the same interest with you, we will use cookies to record your ratings of restaurants every time you use our website. The reason we collect your ratings data is that they can reveal your preferences of restaurants. Your preferences will be compared with other users' preferences and help us locate users who share similar interest with you.
Level 3	Inform what types of users' personal data is collected. Show the values of the data that is collected.	Explain how the technique works.	Explain in detail why the collected data can be related to specific advice using both text and formulas.	In order to recommend you the restaurants that are liked by people who share the same interest with you, we will use cookies to record your ratings of restaurants every time you use our website. The cookies will store your ratings and then return them to us each time you send a request. We have already recorded that you have given a rating of 5 to restaurant C and a rating of 4 to restaurant D. The reason we collect your ratings is that they can reveal your preferences of restaurants. Your preferences will be compared with other users' preferences using the formula of Pearson correlation similarity: $\mathrm{simil}(u,v) = \frac{\sum_{i\in I_{uv}}(r_{u,i}-\overline{r_u})(r_{v,i}-\overline{r_v})}{\sqrt{\sum_{i\in I_{uv}}(r_{u,i}-\overline{r_u})^2}\sqrt{\sum_{i\in I_{uv}}(r_{v,i}-\overline{r_v})^2}}$ (where u and v are users, i is item, r is rating given by users, and I_{uv} is the set of items rated by both user u and user v). The results of the comparisons will help us locate users who share similar interest with you.

Table 3. Manipulation of objective transparency in input stage.

Level	How does the algorithm work	Why is the algorithm selected by AGSs	Manipulation
Level 1	Explain that the advice is generated based on what types of input data. List key steps of the advice-generating process.	List the alternative algorithms. Indicate that the selected algorithm is better than other alternatives.	Your recommendations are based on the interest of other users who are similar to you. We first located other users who were similar to you, and then predict your interest based on what they liked. We use collaborative filtering to generate advice for you, which is a more effective way of generating high-quality advice compared to other techniques like content-based filtering.
Level 2	Explain that the advice is generated based on what types of input data. List key steps of the advice-generating process. Explain briefly how each key step works using text.	List the alternative algorithms. Justify briefly that the selected algorithm is better than other alternatives by showing its advantages.	Your recommendations are based on the interest of other users who are similar to you. We first locate users who were similar to you by comparing your ratings of restaurants with other users' ratings. We then predict your ratings of restaurants based on the ratings of these restaurants given by users who were similar to you. We use collaborative filtering to generate advice for you, which is a more effective way of generating high-quality advice compared to other techniques like content-based filtering in that collaborative filtering can always explore restaurants based on other users' interest, which are not extremely similar with what you are already interested in, and can thus create more serendipity in our recommendations.
Level 3	Explaining the advice is generated based on what	List the alternative algorithms.	Your recommendations are based on the interest of other users who were similar to you. We first built a user-item matrix, which records a user's ratings of restaurants, for you and other

	types of input data. List key steps of the advice-generating process. Explain in detail how each key step works using both text and formulas.	Justify in detail that the selected algorithm is better than other alternatives by comparing its characteristics with others'.	users. We then used the formula to calculate the similarity degree between your matrix and other users' matrices: $\text{simil}(u,v) = \frac{\sum_{i\in I_{uv}}(r_{u,i}-\overline{r_u})(r_{v,i}-\overline{r_v})}{\sqrt{\sum_{i\in I_{uv}}(r_{u,i}-\overline{r_u})^2}\sqrt{\sum_{i\in I_{uv}}(r_{v,i}-\overline{r_v})^2}}$ (where u and v are users, i is item, r is rating given by users, and I_{uv} is the set of items rated by both user u and user v). The users whose matrices had higher similarity scores with your matrix were identified as your "neighbours". We then predicted your ratings of unexplored restaurants based on the ratings of these restaurants given by your neighbours using the formula: $\hat{r}_{ui} = \mu_u + \frac{\sum_{v\in U_k(u;i)}(r_{vi}-\mu_v)sim(u,v)}{\sum_{v\in U_k(u;i)}\lvert sim(u,v)\rvert}$ ($U_k(u;i)$ is a sent of user u's neighbours, sim(u, i) is the similarity weight between user u and i, μ_u is the mean rating of user u). We will recommend you a restaurant if the value of it is high. We use collaborative filtering to generate advice for you, which is a more effective way of generating high-quality advice compared to other techniques like content-based filtering. This is because collaborative filtering explores restaurants based on other users' interest, which are not extremely similar with what you are already interested in, and thus creates more serendipity in recommendations; while content-based filtering only recommend restaurants that are very much like what you have browsed before, leading to less serendipity in recommendations.

Table 4. Manipulation of objective transparency in process stage.

Level	**Why is the advice suitable for users**	**Why is the advice better than other alternatives**	**Manipulation**
Level 1	Indicate the type of input data that generates the advice.	Justify that some particular features of the advice are better than other alternatives.	Customers who are similar to you also like… (*A list of recommended restaurants will be shown here.*) Compared to other restaurants, the recommended restaurants are more suitable for you in that your predicted ratings of these restaurants are higher than those of other restaurants.
Level 2	Indicate the type of input data that generates the advice. Show the content and features of the input data.	Justify that some particular features of the advice are better than other alternatives. Show the values of these features of the generated advice.	The following customers who are similar to you also like… *(A list of recommended restaurants and a list of customers who are similar to the target user will be shown here.)* The restaurants liked by these users were once also liked by you. (*Information of which restaurant was liked by which users will be shown here.*) Compared to other restaurants, the recommended restaurants are more suitable for you in that your predicted ratings of these restaurants are higher than those of other restaurants. Your predicted ratings have been converted into matching scores, which can be seen in our recommendations. (*The matching scores will be shown together with the recommended restaurants, e.g. "This restaurant is a 92% match with your interest"*.)
Level 3	Indicate the type of input data that generates the advice. Show the content and features of the	Justify that some particular features of the advice are better than other alternatives. Show the values of these features of both the generated advice and the al-	The following customers who are similar to you also like… *(Both a list of recommended restaurants and a list of customers' names will be shown here.)* The restaurants liked by these users were once also liked by you. (*Information of which restaurant was liked by which users will be shown here.*) These users' ratings of the recommended restaurants are shown below. (*Information of the ratings of the recommended restaurants given by those users will be shown here.*) Compared to other restaurants, the recommended restaurants are more suitable for you in that

	input data. Show correlations between the features of input data and the features of the generated advice.	ternatives, indicating that the values of the generated advice are higher than those of the alternatives.	your predicted ratings of these restaurants are higher than those of other restaurants. Your predicted ratings have been converted into matching scores, which can be seen in our recommendations. (*The matching scores will be shown together with the recommended restaurants, e.g. "This restaurant is a 92% match with your interest"*.) We only show you the restaurants with matching scores equal to or higher than 80%, while filtered out the restaurants whose matching scores are below 80%.

Table 5. Manipulation of objective transparency in output stage.

We will recruit 400 participants who will be randomly assigned into one of the 10 groups. They will be asked to imagine that they are going to go out for a dinner on this Sunday, and choose one restaurant using the experimental AGS. During the experiment, participants will be first asked to rate five restaurants, after which they can ask the system to show recommendations by clicking a "Show me recommendations" button in the homepage. In input stage conditions, the objective transparency information will be presented on the homepage right after users finish rating the restaurants. In process and output conditions, the objective transparency information will be presented to users together with the recommended restaurants. All the participants in groups 1 to 9 will be required to read the provided information. Participants' actual choice of restaurants will be recorded. After the experiment, we will use a questionnaire to measure the dependent variables and moderators. The measurements of users' perceived understanding of AGSs will be adapted from Zhu et al. (2018). The measurement of users' trust in AGSs will be adapted from Wang and Benbasat (2005; 2007; 2008). The measurements of users' domain knowledge will be adapted from Wang and Benbasat (2007) and Al-Natour et al. (2008). The measurements of the consistency between users' expectations of AGSs and the way AGSs work will be adapted from Al-Natour et al. (2008). The subjective transparency will be measured using the following items based on a seven-point Likert scale: a) I can access a great deal of information which explaining how the system works; b) I can see plenty of information about the system's inner logic; c) I feel that the amount of the available information regarding the system's reasoning is large. For the data analysis, we will use a regression model, which includes a quadratic term of users' subjective transparency, to test the hypothetical inverted U-shape relationship and other hypotheses.

5 Conclusion

Providing information of AGSs' reasoning has been proved to be effective in enhancing users' trust in AGSs (Diakopoulos and Koliska, 2017; Tintarev and Masthoff, 2007). Despite fruitful research findings, little attention has been paid to the potential inconsistency between how much information revealed by AGSs and how much users feel they understand about AGSs. We argue that while providing information of AGSs' inner logic in a modest level of detail can be helpful to users, providing excessively detailed information may hurt users' understanding and trust. Through conducting a lab experiment, we are expecting to find an optimal way for AGSs to revealing information, which can lead to the highest level of users' understanding of and trust in AGSs. Our study could contribute to the literature by exploring the potential inverted U-shape relationship among AGS transparency, users' perceived understanding of and trust in AGSs. Our study could contribute to the practice by providing suggestions on designing trustworthy AGSs.

References

Al-Jabri, I. M. and N. Roztocki. (2015). "Adoption of ERP systems: Does information transparency matter?" In: *Telematics and Informatics*.

Al-Natour, S., I. Benbasat and R. T. Cenfetelli. (2008). "The effects of process and outcome similarity on users' evaluations of decision aids." *Decision Sciences*.

Amalia, F. (2017). "Socio-technical analysis of Indonesian government e-procurement system implementation: barriers to enhance information transparency and accountability." *Asian Academic Accounting Association 2016*.

Ananny, M. and K. Crawford. (2018). "Seeing without knowing: Limitations of the transparency ideal and its application to algorithmic accountability." *New Media and Society*.

Arnold, V., S. G. Sutton, N. Clark, P. A. Collier and S. A. Leech. (2006). "The Differential Use and Effect of Knowledge-Based System Explanationsin Novice and Expert Judgement Decisions." *MIS Quarterly*.

Beliefs, E. and S. Al-natour. (2011). "The Adoption of Online Shopping Assistants : Perceived Similarity as an antecedent to Evaluative Beliefs." *Journal of the Association for Information Systems*.

Benbasat, I. and W. Wang. (2005). "Trust In and Adoption of Online Recommendation Agents." *Journal of the Association for Information Systems*.

Bilgic, M. and R. J. Mooney. (2005). "Explaining Recommendations: Satisfaction vs. Promotion." In: *Proceedings of Beyond Personalization 2005: A Workshop on the Next Stage of Recommender Systems Research at the 2005 International Conference on Intelligent User Interfaces*.

Cho, B., S. Y. Ryoo and K. K. Kim. (2017). "Interorganizational dependence, information transparency in interorganizational information systems, and supply chain performance." *European Journal of Information Systems*.

Cramer, H., V. Evers, S. Ramlal, M. Van Someren, L. Rutledge, N. Stash, … B. Wielinga. (2008). "The effects of transparency on trust in and acceptance of a content-based art recommender." *User Modeling and User-Adapted Interaction*.

Davidson, J., B. Livingston, D. Sampath, B. Liebald, J. Liu, P. Nandy, … M. Lambert. (2010). "The YouTube video recommendation system." In: *Proceedings of the fourth ACM conference on Recommender systems - RecSys '10*.

Davis, F. D. (1989). "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology." *MIS Quarterly*.

Dhaliwal, J. S. and I. Benbasat. (1996). "The Use and Effects of Knowledge-based System Explanations: Theoretical Foundations and a Framework for Empirical Evaluation." *Information Systems Research*.

Diakopoulos, N. and M. Koliska. (2017). "Algorithmic Transparency in the News Media." *Digital Journalism*.

Friedrich, G. and M. Zanker. (2011). "A Taxonomy for Generating Explanations in Recommender Systems." *AI Magazine*.

Gedikli, F., D. Jannach and M. Ge. (2014). "How should i explain? A comparison of different explanation types for recommender systems." *International Journal of Human Computer Studies*.

Gefen, D., I. Benbasat and P. Pavlou. (2008). "A Research Agenda for Trust in Online Environments." *Journal of Management Information Systems*.

Gefen, D., D. W. Straub and M.-C. Boudreau. (2000). "Structural Equation Modeling and Regression : Guidelines for Research Practice." *Structural Equation Modeling*.

Gefen, Karahanna and Straub. (2003). "Trust and TAM in Online Shopping: An Integrated Model." *MIS Quarterly*.

Granados, N., A. Gupta and R. J. Kauffman. (2010). "Information transparency in business-to-consumer markets: Concepts, framework, and research Agenda." *Information Systems Research*.

Gregor, S. and I. Benbasat. (1999). "Explanations from Intelligent Systems: Theoretical Foundations and Implications for Practice." *MIS Quarterly*.

Guy, I., N. Zwerdling, D. Carmel, I. Ronen, E. Uziel, S. Yogev and S. Ofek-Koifman. (2009). "Personalized recommendation of social software items based on social relations." In: *Proceedings of the third ACM conference on Recommender systems - RecSys '09*.

Hedbom, H., T. Pulls, M. Hansen, J. Camenisch, S. Fischer-Hübner and K. Rannenberg. (2011). "Transparency Tools." In: *Privacy and Identity Management for Life*.

Hengstler, M., E. Enkel and S. Duelli. (2016). "Applied artificial intelligence and trust-The case of autonomous vehicles and medical assistance devices." *Technological Forecasting and Social Change*.

Herlocker, J. L., J. A. Konstan and J. Riedl. (2000). "Explaining collaborative filtering recommendations." In: *Proceedings of the 2000 ACM conference on Computer supported cooperative work - CSCW '00*.

Hernando, A., J. Bobadilla, F. Ortega and A. Gutiérrez. (2013). "Trees for explaining recommendations made through collaborative filtering." *Information Sciences*.

Hosseini, M., A. Shahri, K. Phalp and R. Ali. (2018). "Four reference models for transparency requirements in information systems." *Requirements Engineering*.

Jiang and Benbasat. (2007). "The Effects of Presentation Formats and Task Complexity on Online Consumers' Product Understanding." *MIS Quarterly*.

Kim, D. and I. Benbasat. (2006). "The effects of trust-assuring arguments on consumer trust in internet stores: Application of Toulmin's model of argumentation." *Information Systems Research*.

Kim, D. and I. Benbasat. (2009). "Trust-Assuring Arguments in B2C E-commerce: Impact of Content, Source, and Price on Trust." *Journal of Management Information Systems*.

Kim, D. and I. Benbasat. (2010). "Designs for effective implementation of trust assurances in internet stores." *Communications of the ACM*.

Kizilcec, R. F. (2016). "How Much Information?: Effects of Transparency on Trust in an Algorithmic Interface." In: *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems - CHI '16*.

Komiak and Benbasat. (2006). "The Effects of Personalization and Familiarity on Trust and Adoption of Recommendation Agents." *MIS Quarterly*.

Komiak, S. X. and I. Benbasat. (2004). "Understanding Customer Trust in Agent-Mediated Electronic Commerce, Web-Mediated Electronic Commerce, and Traditional Commerce." *Information Technology and Management*.

Komiak, S. Y. X. (2008). "A two-process view of trust and distrust building in recommendation agents: A process-tracing study." *Journal of the Association for Information Systems*.

Konstan, J. A. and J. Riedl. (2012). "Recommender systems: From algorithms to user experience." *User Modeling and User-Adapted Interaction*.

Lakkaraju, H., S. H. Bach and J. Leskovec. (2016). "Interpretable decision sets: a joint framework for description and prediction." In: *KDD '16 Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*.

Leape, L. L. (2009). "Errors in medicine." *Clinica Chimica Acta*.

Lehikoinen, J. and V. Koistinen. (2014). "In big data we trust?" *Interactions*.

Lim, B. Y., A. K. Dey and D. Avrahami. (2009). "*Why and why not* explanations improve the intelligibility of context-aware intelligent systems." In: *Proceedings of the 27th international conference on Human factors in computing systems - CHI 09*.

Mao, J. Y. and I. Benbasat. (2000). "The use of explanations in knowledge-based systems: Cognitive perspectives and a process-tracing analysis." *Journal of Management Information Systems*.

Marjanovic, O. and D. Cecez-Kecmanovic. (2017). "Exploring the tension between transparency and datification effects of open government IS through the lens of Complex Adaptive Systems." *Journal of Strategic Information Systems*.

McKnight, D. H., V. Choudhury and C. Kacmar. (2002). "Developing and validating trust measures for e-commerce: An integrative typology." *Information Systems Research*.

McSherry, D. (2005). "Explanation in recommender systems." *Artificial Intelligence Review*.

O'Donovan, J. and B. Smyth. (2005). "Trust in recommender systems." In: *Proceedings of the 10th international conference on Intelligent user interfaces - IUI '05*.

Pieters, W. (2011). "Explanation and trust: What to tell the user in security and AI?" *Ethics and Information Technology*.

Pu, P. and L. Chen. (2007). "Trust-inspiring explanation interfaces for recommender systems." *Knowledge-Based Systems*.

Pu, P. and L. Chen. (2010). "A user-centric evaluation framework of recommender systems." In: *CEUR Workshop Proceedings*.

Pu, P., L. Chen and R. Hu. (2012). "Evaluating recommender systems from the user's perspective: Survey of the state of the art." *User Modeling and User-Adapted Interaction*.

Ribeiro, M. T., S. Singh and C. Guestrin. (2016). ""Why Should I Trust You?"" In: *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining - KDD '16*.

Schnackenberg, A. K. and E. C. Tomlinson. (2016). "Organizational Transparency: A New Perspective on Managing Trust in Organization-Stakeholder Relationships." *Journal of Management*.

Shapira, B., F. Ricci, P. B. Kantor, L. Rokach, T. Bogers and A. Van Den Bosch. (2011). *Recommender Systems Handbook. CEUR Workshop Proceedings*.

Söllner, M., I. Benbasat, D. Gefen, J. M. Leimeister and P. A. Pavlou. (2016). "Trust : An MIS Quarterly Research Curation Focus of the Research Curation." *MISQ*.

Spagnuelo, D. and G. Lenzini. (2016). "Patient-centred transparency requirements for medical data sharing systems." In: *Advances in Intelligent Systems and Computing*.

Swearingen, K. and R. Sinha. (2002). "Interaction Design for Recommender Systems." *World Wide Web Internet And Web Information Systems*.

Symeonidis, P., A. Nanopoulos and Y. Manolopoulos. (2008). "Providing justifications in recommender systems." *IEEE Transactions on Systems, Man, and Cybernetics Part A:Systems and Humans*.

Symeonidis, P., A. Nanopoulos and Y. Manolopoulos. (2009). "MoviExplain: a recommender system with explanations." In: *RecSys '09: Proceedings of the third ACM conference on Recommender systems*.

Tintarev, N. and J. Masthoff. (2007). "A survey of explanations in recommender systems." In: *Proceedings - International Conference on Data Engineering*.

Tintarev, N. and J. Masthoff. (2012). "Evaluating the Effectiveness of Explanations for Recommender Systems." *User Modeling and User-Adapted Interaction*.

Vig, J., S. Sen and J. Riedl. (2008). "Tagsplanations: Explaining Recommendations Using Tags." *Proceedingsc of the 13th International Conference on Intelligent User Interfaces - IUI '09*.

Wang, W. and I. Benbasat. (2007). "Recommendation Agents for Electronic Commerce: Effects of Explanation Facilities on Trusting Beliefs." *Journal of Management Information Systems*.

Xiao, B. and I. Benbasat. (2014). "Research on the Use, Characteristics, and Impact of e-Commerce Product Recommendation Agents: A Review and Update for 2007–2012." In: *Handbook of Strategic e-Business Management*.

Xiao and Benbasat. (2007). "E-Commerce Product Recommendation Agents: Use, Characteristics, and Impact." *MIS Quarterly*.

Xu, D. J., I. Benbasat and R. T. Cenfetelli. (2017). "A Two-Stage Model of Generating Product Advice: Proposing and Testing the Complementarity Principle." *Journal of Management Information Systems*.

Xu, J. (David), I. Benbasat and R. T. Cenfetelli. (2014). "The Nature and Consequences of Trade-Off Transparency in the Context of Recommendation Agents." *MIS Quarterly*.

Xu, X., K. Dutta and C. Ge. (2018). "Do adjective features from user reviews address sparsity and transparency in recommender systems?" *Electronic Commerce Research and Applications*.

Yamazaki, Y. and J. Yoon. (2016). "A Cross-National Study of Fairness in Asia: How Perceptions of a Lack-of-Group Bias and Transparency in the Performance Evaluation System Relate to Job Satisfaction." *Human Resource Management*.

Ye, L. R. and P. E. Johnson. (1995). "The Impact of Explanation Facilities on User Acceptance of Expert Systems Advice." *MIS Quarterly*.

Yetim, F. (2008). "A Framework for Organizing Justifications for Strategic Use in Adaptive Interaction Contexts." *ECIS*.

Zhou, L., W. Wang, J. (David) Xu, T. Liu and J. Gu. (2018). "Perceived information transparency in B2C e-commerce: An empirical investigation." *Information and Management*.

Zhou, X., Y. Xu, Y. Li, A. Josang and C. Cox. (2012). "The state-of-the-art in personalized recommender systems for social networking." *Artificial Intelligence Review*.

Zhu, K. (2002). "Information Transparency in Electronic Marketplaces: Why Data Transparency May Hinder the Adoption of B2B exchanges." *Electronic Markets*.

Zliobaite, I., A. Bifet, M. Gaber, B. Gabrys, J. Gama, L. Minku and K. Musial. (2012). "Next challenges for adaptive learning systems." *ACM SIGKDD Explorations Newsletter*.

Zouave, E. T. and T. Marquenie. (2017). "An inconvenient truth: Algorithmic transparency & accountability in criminal intelligence profiling." In: *Proceedings - 2017 European Intelligence and Security Informatics Conference, EISIC 2017*.