Transparency in Advice-Giving Systems: A Framework and a Research Model for Transparency Provision

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ABSTRACT

Advice-giving systems (AGSs) provide recommendations based on users' unique preferences or needs. Maximizing users' adoptions of AGSs is an effective way for e-commerce websites to attract users and increase profits. AGS transparency, defined as the extent to which information of a system's reasoning is provided and made available to users, has been proved to be effective in increasing users' adoptions of AGSs.

While previous studies have identified providing explanations as an effective way of enhancing AGS transparency, most of them failed to further explore the optimal transparency provision strategy of AGSs. We argue that instead of setting a uniform rule of providing AGS transparency, we should develop optimal transparency provision strategies for different types of AGSs and users based on their unique features. In this paper, we first developed a framework of AGS transparency provision and identified six components of AGS transparency provision strategies. We then developed a research model of AGS transparency provision strategy with a set of propositions. We hope that based on this model, researchers could evaluate how to effect transparency for AGSs and users with different characteristics.

Our work would contribute to the existing knowledge by exploring how AGS and user characteristics will influence the optimal strategy of providing AGS transparency. Our work would also contribute to the practice by offering design suggestions for AGS explanation interfaces.

CCS Concepts

• Information systems→Decision support systems • Human-centered computing→HCI theory, concepts and models • Computing methodologies→Cognitive science • Applied computing→Online shopping

Author Keywords

Advice-giving systems; transparency; explanations; justifications; adoption.

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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). 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' adoptions of AGSs and their acceptances of AGS outcomes (Cramer et al., 2008; Pu et al., 2011). Previous studies have identified providing explanations as an effective way of enhancing AGS transparency (Bilgic and Mooney 2005; Gedikli et al. 2014; Herlocker 2000) and users' adoptions of AGSs (Arnold et al. 2006; Gregor and Benbasat 1999; Hernando et al. 2013; Mao and Benbasat 2000; Pu and Chen, 2007; Wang and Benbasat 2007; Ye and Johnson 1995). Despite the fruitful research findings in the IS literature, there is still a lack of attentions to the optimal transparency provision strategy of AGSs. In this paper, we define optimal AGS transparency provision strategy as a way of providing transparency which will maximize users' adoptions of AGSs and their outcomes. We argue that there is not a global optimal transparency provision strategy for all kinds of AGSs and users. Rather, local optimal transparency provision strategies should be developed based on different characteristics of both AGSs and users.

The provision of AGSs transparency has a number of features, the combination of which can form different provision strategies. For example, when providing transparency, AGSs can reveal to users what they do (e.g. how AGSs generate advice) and why they do it (e.g. why AGSs collect certain user data). The information revealed by AGSs can be either long or short, complex or simple, with higher or lower accessibility, use professional or plain languages, be provided before or after a certain behavior is done by AGSs, etc. The above features may be more effective in different contexts. For instance, it has been shown that feedforward explanations (i.e. explanations provided before advice-generating process) are preferred by novice users, and feedback explanations (i.e. explanations provided after advice-generating process) are preferred by expert users (Arnold et al. 2006; Dhaliwal and Benbasat, 1996). However, while some studies considered users' characteristics when designing explanations, very few studies have focused on how AGS characteristics might influence AGSs' transparency provision strategy.

In recent years, due to the rapid development of advice-generating technology, AGSs has transformed from traditional ones, which explicitly ask users to indicate their preferences or needs and generate advice accordingly, to more advanced ones, which employ AI-based techniques (e.g. collaborative filtering and content-based filtering) to generate advice based on implicitly collecting users' personal data (e.g. their age, location, browsing behaviors, etc.). Due to the implicit user data collection and high complexity of advice-generating techniques, users may have higher privacy concerns and be more confused about how the advice is generated when they use AGSs with advanced features. Consequently, the existing theories and rules of transparency provision that have been developed and tested in the context of traditional AGSs might need to be modified or redeveloped to adapt the usage of more advanced AGSs. In this paper, we argue a necessity of developing a comprehensive model for AGS transparency provision. Such a model will allow us exploring ways of providing transparency in different types of AGSs and for different kinds of users, which can lead to the highest level of users' adoptions of AGSs and their acceptances of AGS outcomes. Using this model, we would like to address the following research questions:

1. What are the components of AGS transparency provision?
2. How should we explore the optimal way of providing AGS transparency considering both AGS characteristics and user characteristics?

Our research would contribute to the existing knowledge by proposing how AGS and user characteristics will influence the optimal strategy of providing AGS transparency, and contribute to the practice by offering design suggestions on AGS explanation interfaces. The remainder of our paper is organized as follows: Section 2 defines transparency in AGSs and provides a literature review about AGS transparency. Section 3 develops a framework of AGS transparency provision. Section 4 develops a research model of AGS transparency provision strategy. Section 5 discusses the contributions, limitations and future research directions.

TRANSPARENCY IN ADVICE-GIVING SYSTMES

In the domain of 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). In other domains such as e-government and health care, 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 AGSs release information regarding what they do and why they behave in a certain way, and subjective transparency 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).

Providing transparency is generally considered to be beneficial to users. Some studies argued that systems with high transparency would inform users about who can collect, access, and use their personal data, and give users the right to control the utilization of their own personal data (Hedbom, 2008). Some other studies proposed that highly transparent systems would articulate the systems' goals (Zouave and Marquenie, 2017), why data is collected from users (Hedbom, 2008), and the rationale for system outputs (Cramer et al., 2008; Diakopoulos and Koliska, 2017; Hedbom, 2008; 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), reduce users' uncertainty (Diakopoulos and Koliska, 2017) and increase users' confidence (Sinha and Swearingen, 2002) when interacting with systems, 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).

Despite the great benefits brought by providing transparency, some researchers indicated that misuses of system transparency might occur if transparency was not provided in a proper way. Some studies argued that excessively detailed information with great transparency might reduce the efficiency of systems in that such information 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). In addition, Hosseini et al. (2018) and Xu et al. (2018) also warned that if the information provided by systems was not understandable/interpretable/ actionable to users, users' trust in systems might be reduced rather than being increased.

A FRAMEWORK FOR AGS TRANSPARENCY PROVISION

Before exploring how AGS transparency should be provided to users, we first defined what is AGS transparency provision by developing a framework. Drawn from the framework of knowledge-based system explanations developed by Dhaliwal and Benbasat (1996), we included the characteristics of both the provided information and information-providing interfaces into our framework. Specifically, our AGS transparency provision framework has six components, namely transparency provision stage, transparency type, the content of the provided information, the timing of transparency provision, the type of transparency provision interface, and the format of the provided information. Each component has a number of different values. The framework of AGS transparency provision is shown in Figure 1.

Transparency Provision Stage

Adapted from Xiao and Benbasat (2007; 2014), we divide the utilization of AGSs into input, process, and output stages. Input stage is the stage during which users' preferences or needs are elicited; process stage is the stage

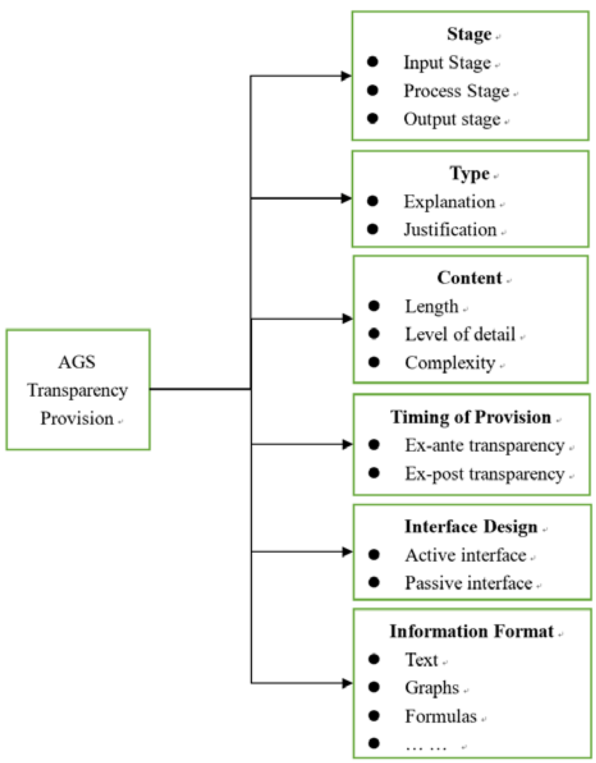

Figure 1. Framework of AGS Transparency Provision

during which advice is generated by systems based on the data collected in input stage, and output stage is the stage during which systems present the generated advice to users (Xiao and Benbasat, 2007; 2014). AGS transparency can be provided to users in each of the three stages. In input stage, AGSs can reveal the process and rational of their data collections from users. In process stage, AGSs can disclose and justify their advice-generating process. In output stage, AGSs can explain to users why they think the advice is a good one for users.

Transparency Types

In the field of AGSs, revealing explanations about how the system work is commonly considered to be one feasible way of providing system transparency to users (Tintarev and Masthoff, 2007). In addition to this, some studies have also proposed another way of conveying the idea of how advice is generated without elucidating precisely the mechanism of AGSs (Lipton, 2016), e.g. we recommended movie A to you because it is more suitable for you compared to 92% of the movies in our website. In this paper, we argue that AGSs can provide transparency to users through presenting two types of messages, namely explanations, i.e. what systems will do/are doing/have done, and justifications, i.e. information about why systems behave in a certain manner. Different from explanations, which offer users objective information regarding systems' behaviors, justifications enable AGSs to show users the advantages of their advice-generating technique and outcomes, and can thus make users feel less uncertain and more confident to accept the generated advice. In our framework, we suggest that AGSs can provide two types of transparency, i.e. explanations and justifications, in input, process, and output stage respectively. The content and examples are shown in Table 1[1].

[1] All the examples in this table are copied from Facebook's instructions for their customized ads.

Stage	Transparency	Examples
Input Stage	Explanation ● What data is collected ● How is the data collected Justification ● Why is this 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	Explanation ● How does the advice-generating algorithm work Justification ● Why is this 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	Explanation ● How does the advice meet users' needs Justification ● Why is this 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. Transparency Provision in Input, Process, and Output Stage

Content of Transparency Provision

In addition to stage and transparency type, the content of the information provided by AGSs, which aims to enhance systems' transparency, can also influence the effects of transparency provision. For example, the information provided by AGSs can be either long (e.g. one paragraph) or short (e.g. one sentence). The content of the information can be either complex (e.g. using profession language) or easy to understand (e.g. using plain language). The information regarding how systems work can be either very detailed (e.g. providing the formulas of calculating the similarity between users) or less detailed (e.g. briefly saying "users who are similar to you also bought…").

Timing, Interface, and Information Format of Transparency Provision

In addition to the above-mentioned factors, there are still some other factors that can be components of AGS transparency provision strategies, including timing of provision, interface design, and information format. Timing of provision refers to the fact that AGSs can choose to provide information to explain or justify their behaviors either before or after a specific behavior is performed by AGSs. The transparency provided before performing a specific behavior is called ex-ante transparency, while the transparency provided after a specific behavior is done is called ex-post transparency (Ananny and Crawford, 2018; Spagnuelo and Lenzini, 2016). Interface design is also an influential factor of transparency provision. Dhaliwal and Benbasat (1996) indicated that there were two types of AGS transparency-providing interfaces – one employs active strategy where the information is automatically presented to users, and the other one employs passive strategy where users have to make explicit requests to access the provided information. Finally, the format of the provided information may also make a difference on AGS transparency provision. AGSs can reveal information about their inner logic in a variety of formats, e.g. text, histogram, graph, matching score, or even formula, etc. Users may have different perceptions when the same information is provided by AGSs in different formats (Herlocker et al., 2000).

A RESEARCH MODEL OF AGS TRANSPARENCY PROVISION STRATEGY

In order to explore the optimal way of providing AGS transparency, which can help maximize users' adoptions of systems, we developed a research model for AGS transparency provision strategies (see Figure 2) for future studies to test. In this model, we take into consideration the characteristics of both AGSs and users. The model proposed in our research can be tested through conducting lab experiments and field studies. Through testing the propositions generated based on this model, we hope future research could find out the best ways of providing transparency in different types of AGSs and for different types of users.

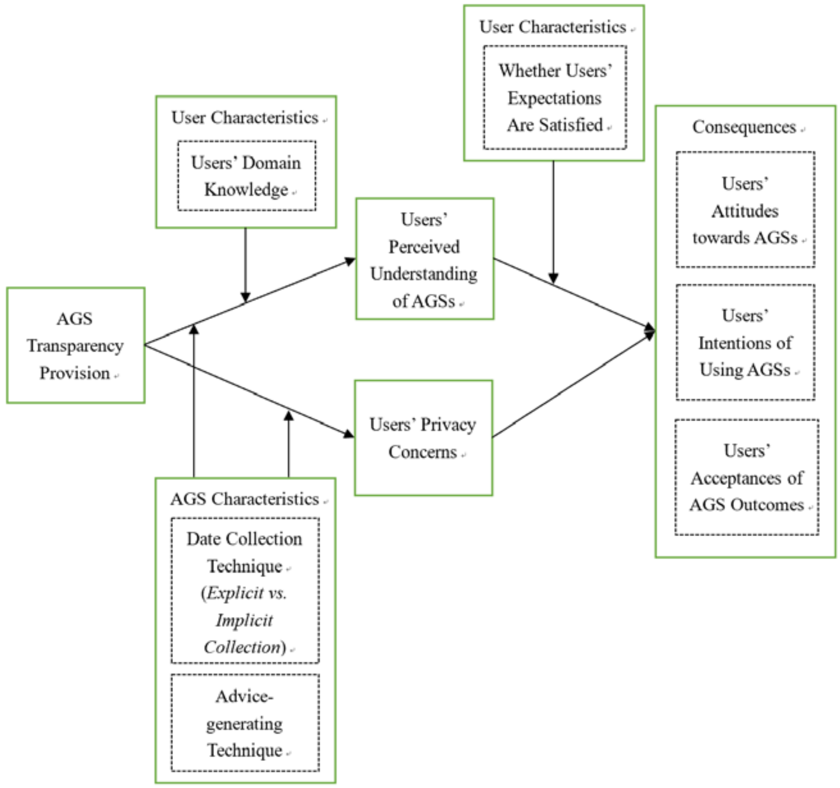

Figure 2. Research Model of AGS Transparency Provision Strategy

General Propositions

In this paper, we define users' perceived understanding of AGSs as the extent to which users perceive that they understand the meaning of the information provided by AGSs, which explains what AGSs do and justifies why they do it. We study users' subjective perception of how much they understand the inner logic of AGSs rather than their true level of understanding how AGSs work because it has been proved that compared to users' actual knowledge, users' subjective perceptions of their understanding of a website are more influential on their intentions to reuse the website (Jiang and Benbasat, 2007). Providing explanations regarding how AGSs work has been proved to be effective in improving users' perceived understanding and acceptance of AGSs (Hengstler et al. 2016; Lakkaraju et al. 2016; Lehikoinen and Koistinen 2014; Lim et al. 2009; Pieters, 2011; Wang and Benbasat 2007; 2008; Zliobaite et al. 2012). In addition, providing information regarding AGSs' data collection in input stage can help users know better about what kind of their personal data is collected and why it is collected, and thus have an effect on their privacy concerns.

P1: The provision of AGS transparency will improve users' perceived understanding of how AGSs work and why AGSs perform certain behaviors.

P2: The provision of AGS transparency will increase users' privacy concerns.

In our model, we assume that the effect of transparency provision on users' perceptions will be moderated by both AGS characteristics and user characteristics. When users have higher level of domain knowledge of AGSs, they will have the ability to process and comprehend more complex information provided by AGSs. In this case, providing information which is harder to process and understand will have a more positive influence on users with higher levels of domain knowledge compared to those who have lower levels of domain knowledge.

P3: User characteristics will moderate the influence of transparency provision on users' perceived understanding of how AGSs work and why AGSs perform certain behaviors.

In addition, the effect of transparency provision may be different in different types of AGSs. For example, compared to AGSs with explicit user data collection, input stage transparency may have a stronger effect on users' perceptions of systems in AGSs with implicit user data collection because users are less likely to know the details of how and why their data is collected when interacting with such AGSs, and may thus benefit more from the explanations and justifications provided by AGSs.

P4: AGS characteristics will moderate the influence of transparency provision on users' perceived understanding of how AGSs work and why AGSs perform certain behaviors.

P5: AGS characteristics will moderate the influence of transparency provision on users' privacy concerns.

Previous studies have proved that users' perceived understanding of AGSs will positively influence their attitudes towards AGSs, intentions of adopting AGSs, and acceptances of AGS outcomes (Cramer et al., 2008; Pu et al., 2011; Wang and Benbasat, 2007; 2008), while users' privacy concerns will negatively influence them (Hengstler et al., 2016; Wang and Benbsat; 2008; Yan et al., 2016). We also assume that whether or not users' expectations of AGSs can be met will moderate the effect of users' perceived understanding of AGSs on their attitudes towards AGSs, intentions of adopting AGSs, and acceptances of AGS outcomes. Users' expectations of AGSs include both process and behavior expectations, e.g. "Yelp should ask me where do I live" or "Yelp should make recommendations based on the restaurants that I have been to", and outcome expectations, e.g. "Yelp should recommend me some Chinese restaurants" (Wang and Benbasat, 2008). A higher-level perceived understanding of AGSs can help users know better how AGSs actually work, and can thus confirm users' perceptions of consistency/in-consistency between their expectations and the way AGSs work. Therefore, we assume that when there is a consistency, users' perceived understanding of AGSs will positively influence their attitudes towards AGSs, intentions of adopting AGSs, and acceptances of AGS outcomes 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 have negative influences in that users become more aware that the way AGSs work are different from their original expectations.

P6: The effect of users' perceived understanding of AGSs on users' attitudes towards AGSs, intentions of adopting AGSs, and acceptances of AGS outcomes 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 have positive influences. On the contrary, if there is an inconsistency, users' perceived understanding of AGSs will have negative influences.

P7: Users' privacy concerns will negatively influence their attitudes towards AGSs, intentions of adopting AGSs, and acceptances of AGS outcomes.

Transparency Provision Strategy Considering AGS Characteristics

Input Stage Characteristics

In the input stage, different AGSs have different ways of collecting user data. Some of them collect data through explicitly asking users to indicate their preferences or needs (e.g. a filter), while others collect data through implicitly tracking and recording users' interactive behaviors (e.g. browsing behaviors, transaction records, locations, etc.). It is traditionally thought that providing explanations and justifications in input stage will positively influence users' attitude towards AGSs (Wang and Benbasat, 2007) because this enables users to know more about data-collecting process. However, we propose in our model that we should also consider another "side effect" of doing so in AGSs with implicit user data collection – it makes users become more aware of the fact that their personal data is being collected by AGSs. In this case, providing explanations about what kind of data is collected and how it is collected may increase users' privacy concerns when interacting with AGSs.

P8: For AGSs with explicit input data collection, both input stage explanations (**P8a**) and justifications (**P8b**) will have a positive influence on users' perceived understanding of AGSs.

P9: For AGSs with implicit input data collection, both input stage explanations (**P9a**) and justifications (**P9b**) will have a positive influence on users' perceived understanding of AGSs.

P10: For AGSs with implicit input data collection, input stage explanations will increase users' privacy concerns.

Process Stage Characteristic

In process stage, different AGSs employ different techniques to generate advice. Some techniques have relatively easy inner logics (e.g. information retrieval), while some other techniques' logics are more like black boxes and may be beyond non-professional users' comprehensions (e.g. machine learning techniques). We assume that both process explanations and justifications of easily-understood advice-generating techniques will be comprehended by users, and can thus help users understand AGSs better. However, for complex advice-giving systems, while the process justifications can still be understood by users, the process explanations may not. We argue that the process explanations can help users understand AGSs only when users have enough time to process the explanations and enough ability to figure out the meaning of the explanations. Once the explanations are beyond a user's comprehension, users may feel more confused because they may become aware that their original ideas of how AGSs work are not accurate, and realize that they actually know very little about the real way AGSs work.

P11: For AGSs whose advice-generating techniques are easily understood by users, both process stage explanations (**P11a**) and justifications (**P11b**) will have positive effects on users' perceived understanding of AGSs.

P12: For AGSs whose advice-generating techniques are not easily understood by users, the process stage explanations can positively influence users' perceived understanding of AGSs only when users have the ability to process and comprehend the explanations. Once the provided explanations are beyond users' comprehensions, it will start to negatively influence users' perceived understanding of AGSs.

P13: For AGSs whose advice-generating techniques are not easily understood by users, process stage justifications will positively influence users' perceived understanding of AGSs

Transparency Provision Strategy Considering User Characteristics

In addition to AGS characteristics, we also assume that users' domain knowledge of AGSs will moderate the effect of the provision of AGS transparency on users' perceived understanding of AGSs. According to the Elaboration Likelihood Model (Petty and Cacioppo, 1986), users who have higher levels of domain knowledge will use a central route to process the provided information and thus focus more on explanations, which describe AGSs' behaviors. In contrast, users who have lower levels of domain knowledge will be more likely to use peripheral route to process information and focus more on justifications, which justify AGSs' behaviors through emphasizing the importance/advantages of doing so.

P14: For users with higher levels of domain knowledge, explanations will have stronger positive effect on their perceived understanding of AGSs (**P14a**), while justifications will have less positive effect on their perceived understanding of AGSs (**P14b**).

P15: For users with lower levels of domain knowledge, justifications will have stronger positive effect on their perceived understanding of AGSs (**P15a**), while explanations will have less positive effect on their perceived understanding of AGSs (**P15b**).

DISCUSSION

Conclusions

Providing information of AGSs' reasoning has been proved to be effective in enhancing users' adoptions of AGSs and acceptances of AGS outcomes. Despite fruitful research findings, little attention has been paid to the explorations of optimal transparency provision strategy for different types of AGSs and users. In this paper, we first defined transparency in the context of AGSs and summarized the existing research findings of AGS transparency. We then developed a framework of AGS transparency provision, identifying six components of AGS transparency provision strategies, i.e. transparency provision stage, transparency type, the content of the provided information, the timing of transparency provision, the type of transparency provision interface, and the format of the provided information. Finally, we developed a research model of AGS transparency provision strategy and proposed a set of propositions. Based on this model, we are expecting to find out the optimal way of providing transparency for AGSs and users with different characteristics.

Contributions

Our research has both academic and practical significance. It could contribute to the existing literature by indicating that the strategies of providing transparency should not be the same across all types of AGSs and users, and exploring the optimal ways of providing transparency for different types of AGSs and users. Our research could also contribute to the practice by offering design suggestions on AGS explanation interfaces.

Limitations and Future Research

Due to the limited time and cost, we have not yet conducted empirical studies to test the propositions in our research model. In addition, as an early-stage exploration of AGS transparency provision strategies, the model developed in this paper only considered the influence of a single factor (e.g. the complexity of advice-generation techniques, users' domain knowledge, etc.) on the selection of AGS transparency provision strategy. However, despite the limitations, our work figured out the possible rules of providing transparency for different types of AGSs and users. Future research could be conducted based on our work through refining and expanding our model by including more factors and considering the combined effects of multiple factors, as well as testing this model by conducting empirical research.

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