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Abstract:

Decision aids have enjoyed extensive use in various domains. While decision aid research and practice have largely focused on making these aids more functional and utilitarian, we propose that one should also purposefully design them as effective interaction partners, especially when one deploys them in contexts that require a “human touch”, such as finance or healthcare. In this paper, we report on the results from an experiment that investigates the effects of designing caring and informative decision aids on users’ evaluations of the aids and, subsequently, their satisfaction with the aids. Our results show that using explanations and expressive speech acts can enhance the extent to which users perceive decision aids as informative and caring. These strengthened beliefs subsequently enhance the extent to which users view decision aids as competent and as having integrity and improve the interaction atmosphere, which, in turn, increases users’ satisfaction with their overall interaction with the decision aid. We discuss the study’s contributions to theory and practice.

Keywords: Decision Aids, Virtual Advisors, Interaction, Satisfaction

Traci J. Hess was the accepting senior editor for this paper.

1 Introduction

Online decision aids (also known as recommendation agents or virtual advisors) have received extensive attention in both research and practice. These software-based tools typically act as tutors that educate users about decision attributes and as recommender systems that offer specific advice based on user-defined criteria (West et al., 1999). Consequently, research on decision aids has largely focused on understanding how one should design these aids to increase the extent to which users accept them (Xiao & Benbasat, 2014).

Practitioners have deployed decision aids in domains as varied as accounting and finance (e.g., Arnold et al., 2006), e-commerce (Xiao and Benbasat, 2014), employee interviewing (e.g., Pickard et al., 2016), and healthcare (e.g., Bouayad et al., 2020; Knops et al., 2013; Stacey et al., 2014). Understandably, depending on the context in which one uses them, decision aids may vary greatly in the type of questions they ask and the nature of their subsequent recommendations. They could range from product-specific requirements when seeking product recommendations to highly sensitive personal information when seeking more specialized advice. For instance, practitioners have used decision aids in healthcare not only as tools to screen, diagnose, and select treatment options (Skjøth et al., 2015) but also to educate patients and assist them in making informed decisions about their health, treatment, and wellness (Stacey et al., 2014). When deployed in such capacities, decision aids perform some functions that a human provider would traditionally perform and, hence, engage with users in often interpersonal and social interactions.

Despite their widespread deployment in many new settings, research on decision aids has largely only explored the utilitarian nature of their use and how one should design them to enhance their perceived benefits (Xiao & Benbasat, 2014). In doing so, this research has overlooked many social and relational dynamics associated with users' interactions with such aids (Schuetzler et al., 2020). Thus, users have unsurprisingly complained that their interactions with decision aids qualitatively differ from traditional patient-healthcare provider ones in that they feel superficial and devoid of all social norms (Knops et al., 2013; Skjøth et al., 2015; Stacey et al., 2014).

In contrast, in this study, we focus on the experience that users have when interacting with decision aids and examine the effects of various beliefs that users form during these interactions. While some studies have looked at decision aids' "social" aspects, in many instances, they have not examined how one can design these artifacts to manifest desired behaviors and the effect that such behaviors have on users' evaluations. In this study, we adopt Al-Natour and Benbasat's (2009) interaction-centric model and investigate how one can design decision aids to cue certain characteristics and manifest desired behaviors that influence how users subsequently design these aids. As such, we focus more on investigating the interaction-based determinants to users' evaluations of these aids, which could concern utilitarian or social aspects of the aid's characteristics and behaviors. Specifically, we focus on examining how one can design decision aids to convey appropriate emotion and concern (e.g., to manifest social behavior) (Schuetzler et al., 2020). Given their important role as means for educating users about the domain in which they work (Ghasemaghaei et al., 2019; Zhang & Curley, 2018), we further investigate how one can design decision aids so that people perceive them as informative.

As prior scholars have noted, identifying design-relevant antecedents for any number of proposed constructs deserves attention from the information systems (IS) scholars (Benbasat & Zmud, 2003; Benbasat & Barki, 2007). In this study, we identify and test the effect that a parsimonious set of three design elements (namely, why-explanations, how-explanations, expressive speech acts) have on users' perceptions. Consistent with Al-Natour and Benbasat's (2009) model, we further investigate the effects that these perceptions have on enhancing how users evaluate these aids and on increasing satisfaction with their use.

This paper proceeds as follows: In Section 2, we review the literature on decision aids. In Section 3, we present our research model and develop our hypotheses. In Section 4, we describe our research method. In Section 5, we outline the results from our empirical investigation. In Section 6, we discuss the results. Finally, in Section 7, we conclude the paper.

2 Literature Review

2.1 Decision Aids as Social Actors

As prior research has highlighted (e.g., Al-Natour & Benbasat, 2009), with the advent of new e-commerce artifacts that possess interactive and human-like characteristics, the utilitarian benefits users expect to achieve through their use (e.g., choosing an appropriate product) now parallel the benefits they obtain from engaging in satisfactory social interactions. In addition to being tools that help extend users' cognitive limitations in decision making, decision aids can use full sentences, communicate through voice, and assume anthropomorphic embodiments. As a result, these artifacts have human-like characteristics, which induce users' attributions of social action to them (Reeves & Nass, 1996). As a result, researchers have repeatedly suggested that decision aid users should view their interactions with these artifacts as social and interpersonal (Qiu & Benbasat, 2009).

Al-Natour and Benbasat (2009) formalized these ideas in their interaction-centric model, which they anchored in the theory of reasoned action (Fishbein & Azjen, 1975), to study user-artifact relationships (Figure 1 graphically depicts the model). They posit that the perceptions that users form about IT artifacts when interacting with them influence how they evaluate them. Consequently, one can use a decision aid's design characteristics to manifest certain characteristics in the aid, which users observe when interacting with it. Users will then form beliefs about these manifested characteristics (called object-based beliefs), which may be individualistic (beliefs about an IT artifact's characteristics and behaviors do not depend on how they relate to the user's characteristics and behaviors) or dyadic (beliefs about the IT artifact's characteristics and behaviors relate to the user's characteristics and behaviors). They further propose that these object-based beliefs affect how users subsequently evaluate an artifact and form cognitive, social, emotional, and relational beliefs. In this study, we adopt this view of the causal links between a decision aid's design, the characteristics it manifests, and the effect of users' perceptions of these characteristics on their evaluations of these aids.

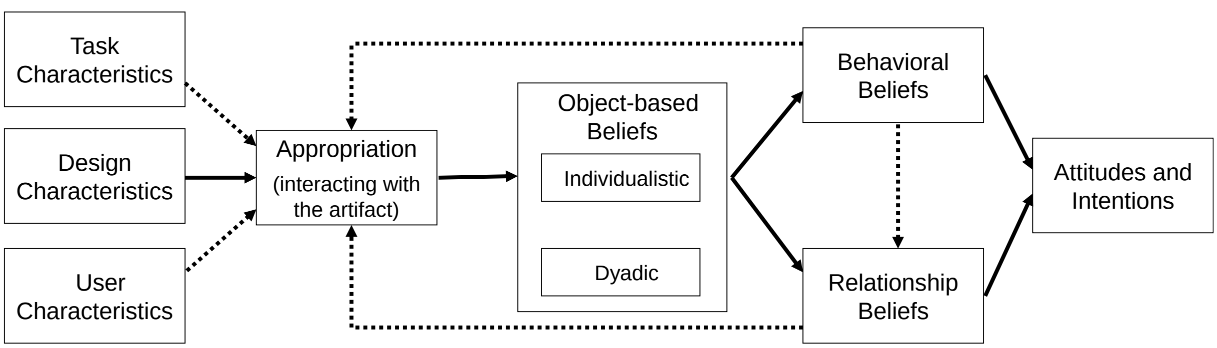

Figure 1. Al-Natour and Benbasat (2009) Model

Consistent with this view, researchers have demonstrated that individuals unconsciously attribute human-like characteristics (e.g., gender) to decision aids and apply social rules and expectations when interacting with them (e.g., Al-Natour et al., 2006; Hess et al., 2009). Empirical research suggests that one can use various design elements to induce social responses from users, such as language (Al-Natour et al., 2011a), interactivity (Al-Natour et al., 2006), and human embodiment and voice (Qiu & Benbasat, 2009). A main research substream has focused on the type of information that decision aids communicate. For instance, some research studies have investigated the effect that explanation facilities (Gregor & Benbasat, 1999) have in decision aid use contexts. Al-Natour et al. (2009) and Wang and Benbasat (2007) confirmed that one can use different types of explanations to manifest desired characteristics in decision aids. Similarly, other research has shown that the manner in which a decision aid communicates, such as the personality it manifests (e.g., Hess et al., 2009) or the types of speech acts it uses (Al-Natour et al., 2006, 2011a), can affect how users perceive the aid's various characteristics and subsequently, influence how they subsequently evaluate it.

Furthermore, the interaction-centric model that Al-Natour and Benbasat (2009) proposed for studying user-artifact relationships provides a theoretical framework for how applying these social categories and rules affect judgments about, and responses to, decision aids. Generally, studies in this research stream have 1) investigated the types of social characteristics that these aids can manifest and the conditions under which these manifestations will likely occur (e.g., Qiu & Benbasat, 2009) and/or 2) examined the ways in which users process how they perceive these characteristics and the effect that such perceptions have on their evaluations (e.g., Hess et al. 2006).

In the first substream, researchers have focused on examining characteristics that have been shown to be salient and influential in the interpersonal interaction context. Such characteristics have often included an aid's utilitarian characteristics (e.g., transparency; Wang & Benbasat, 2016) but also extended to "softer" characteristics such as the personality type that an aid manifests (e.g., Al-Natour et al., 2006; Hess et al., 2009). Other research has looked at how these manifested characteristics interact with users' characteristics, such as the interaction between the user's personality and the personality that a decision aid manifests (Al-Natour et al., 2006), or how much interdependence exists between them (Al-Natour et al., 2011b).

In the second research substream, studies have focused on investigating the ways in which users process these perceptions and how they affect their subsequent evaluations. Hence, beyond investigating the type of evaluations users likely form based on the perceived characteristics that decision aids manifest, such research has also looked at the mechanisms through which these perceptions affect how users subsequently evaluate these aids. This latter focus has led researchers to view user-aid relationships in various ways and apply psychological theories, such as social exchange and social penetration theories (Altman & Taylor, 1973) and the similarity-attraction hypothesis (Byrne, 1971), to understand how the way in which people perceive a decision aid's characteristics influence how they evaluate the aid and the most salient evaluation types. For instance, social penetration theories (e.g., Altman & Taylor, 1973) presuppose that both the utilitarian factors associated with an interpersonal interaction and the social cues and signals exchanged between the parties involved in these interactions jointly determine the success and assessment of these interactions (Clark & Reis, 1988). Hence, for decision aids to be effective as social partners, they need to demonstrate not only utilitarian benefits (e.g., expertise) but also social skills.

Consistent with Al-Natour and Benbasat's (2009) framework and building on prior findings that we summarize above, we focus on the experience that users have when interacting with decision aids by identifying new salient and influential beliefs that users form during these interactions. In explicating object-based beliefs that the interaction-centric model proposes, we gain an opportunity to capture new such beliefs that extend beyond an aid's utilitarian characteristics.

2.2 Evaluations of Decision Aids

Extant research has looked at myriad salient and deterministic evaluations that users form about decision aids. Understandably, such evaluations have included traditional adoption antecedents, such as perceived usefulness and ease of use, especially when research has examined the factors that influence users' intentions to adopt a decision aid (e.g., Al-Natour et al., 2011a). For instance, Al-Natour et al. (2011a) examined the effect that personality and process similarities (between users and decision aids) have on how users evaluate decision aids' use, usefulness, trustworthiness, social presence, and perceived interaction enjoyment. Similarly, Qiu and Benbasat (2009) found that endowing a decision aid with a humanoid embodiment and voice-based communication influences their perceptions about the aid's social presence, which, in turn, enhances users' trust in the aid, perceived enjoyment, and ultimately, their intentions to use it. Several other studies have looked at similar and additional evaluations (Xiao & Benbasat, 2014).

Understandably, given the decision aid use, some research studies have focused on examining the nature, antecedents, and consequences of trust in decision aids. Wang and Benbasat (2008) examined the means by which users form their trust in the decision aids with which they interact. They concluded that dispositional (general predisposition to trust other parties) and calculative (an evaluation of the benefits and costs associated with the aid acting in an untrustworthy manner) considerations partially drive trust in a decision aid. More significantly, they suggested that the interactive (based on assessing the aid's behavior and performance during their interaction) and knowledge-based (based on gaining knowledge about the aid that allows the user to interpret and predict the aid's behaviors) reasons for trusting a decision aid have much larger effects on users' trust in it. This logic concurs with our view that what transpires during an interaction forms the basis for users' beleiefs about these aids. These beliefs subsequently serve as the primary bases for their evaluations.

As other research has highlighted, trust in a decision aid can manifest as trust beliefs, such as beliefs about the aid's competence, integrity, and benevolence (e.g., Wang & Benbasat, 2007, 2008, 2016). These beliefs not only address the decision aid's ability as a trust object (i.e., competence) but also how the aid acts as an interaction partner (e.g., integrity). This approach adopted in these studies also concurs with our view that evaluations of decision aids extend beyond those addressing their inherent characteristics to beliefs that address relevant expectations about their behaviors (Wang & Benbasat, 2016). As we describe in Section 3, in this study, we focus on competence and integrity as two trusting beliefs that capture distinct aspects of trust in a decision aid both as an object and as an interaction partner.

3 Research Model and Hypotheses

3.1 Overview of the Model and Construct Selection

We depict our research model in Figure 2. Consistent with Al-Natour and Benbasat's (2009) model for studying user-artifact interactions, our model investigates the effect that two object-based beliefs that capture a decision aid's manifested characteristics have on how users subsequently evaluate the aid and the interaction with it. Understandably, users can form various object-based beliefs when interacting with decision aids. As the model depicts, we chose to focus on perceived caring and perceived informativeness for several reasons. First, given the role that decisions aids play as tools that educate users about the decision domain (e.g., health-related issues), perceived informativeness captures the extent to which they succeed in this primary role. We define this construct as the extent to which users perceive a decision aid to be knowledgeable about the decision domain and communicate this knowledge to the user. Hence, this belief captures a decision aid's utilitarian characteristic.

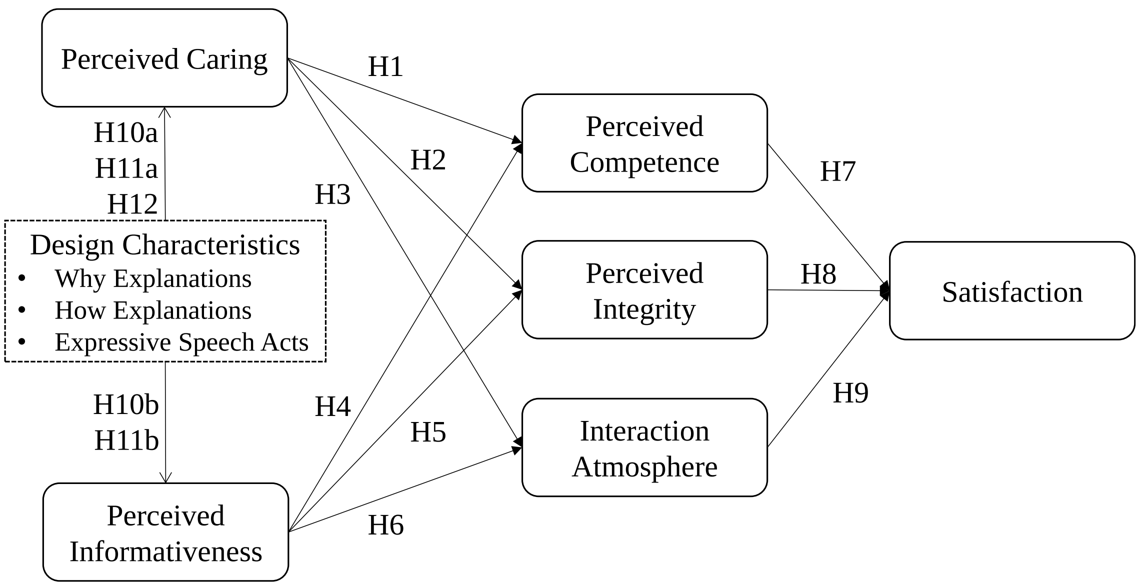

Figure 2. Research Model

Second, given our discussion about the need to view interaction with decision aids as social and interpersonal, we focus on perceived caring, a construct that researchers have proposed to capture how users perceive the extent to which the decision aid cares about them and their needs. Hence, perceived caring refers to the evaluation that a user makes about a decision aid's social aptitude and its ability to relate to its users at a human level. As such, it emphasizes the essential role that affective and responsive communication plays in successful social interactions (Altman & Taylor, 1973), especially in dyadic relationships that feature high levels of uncertainty about the other's intentions (Clark & Reis, 1988).

While user beliefs about a decision aid's informativeness and caring can potentially induce various subsequent evaluations, in this study, we focus on two trusting beliefs—competence (the extent to which the aid has the ability, skills, and expertise to perform effectively) and integrity (the extent to which the aid adheres to principles that the user finds acceptable) (McKnight et al., 2002; Wang & Benbasat, 2007)—to serve as example utilitarian and relational evaluations (Zhang & Curley, 2018). We further examine the effects of the perceived interaction atmosphere, which is a new construct that we propose to capture the interaction's socialness. We define it as the extent to which users perceive the interaction as friendly, cooperative, and conflict free. Subsequently, the model proposes that how users evaluate trusting beliefs and the interaction atmosphere influences their satisfaction, which refers to their overall affective attitude towards their interaction with decision aid.

To cue perceived caring and informativeness in decision aids, we used three design characteristics: 1) why explanations, which justify a decision aid's behaviors and, therefore, can demonstrate that it considers the user's needs and exhibits its expertise; 2) how explanations, which describe how a decision aid performs its task and, therefore, endow users with additional knowledge and demonstrate its openness; and 3) expressive speech acts, which express psychological states and, therefore, can allow a decision aid to directly communicate its empathy and concern towards users.

3.2 The Effects of Perceived Caring

As we discuss in Section 2, we need to distinguish interactive-based trust (Rousseau et al., 1998; Wang & Benbasat, 2008) from calculus-based and dispositional trust. Interactive-based trust builds on information obtained from interactions with a trust object. Research has also distinguished between two trust dimensions: cognition-based trust and affect-based trust (McAllister, 1995) to disentangle its intellectual/cognitive basis from the emotional/affective one. As Wang et al. (2016, p. 50) note:

> *Affect-based trust is the confidence one places in a partner on the basis of feelings generated by the level of care and concern the partner demonstrates and it is characterized by the feelings of security and perceived strength of the relationship.*

Alternatively, users' rational assessments that they develop when evaluating who to trust based on justified reasons anchored in evidence of trustworthiness drive cognition-based trust (Lewis & Weigert, 1985). In this study, we propose that users will form cognition-based trust based on rationally evaluating a decision aid's behaviors. Furthermore, users will form affect-based trust based on the emotional bond (i.e., their feelings and senses rather than their reasoning) that they perceive between themselves and the decision aid.

In this study, we propose that the perceived aid caring will prompt users to form cognition-based trust, which the experience that users have when interacting with a decision aid drives (i.e., interactive-based reason for trust). In its most general sense, perceived caring refers to a belief that captures information about a decision aid as an interaction partner. It represents users' familiarity level with some pertinent decision aid aspects, such as how well it understands and feels about their needs and concerns since a decision aid that exhibits perceived caring affords users a window into the aid and its intentions. This familiarity then serves as an appropriate context to interpret the decision aid's other behaviors (Luhmann, 1979). At minimum, it lessens confusion about some of the aid's intentions and, subsequently, reduces users from feeling that they are being taken advantage of (Gefen et al., 2003). In fact, researchers have viewed expressions of care and concern in social interactions as trusting behavior in and of itself, which consequently works to enhance the extent to which individuals view the actors who communicate these affective responses as trustworthy (Altman & Taylor, 1973).

When a decision aid communicates appropriate emotions in response to users' expressions of needs and concerns, it strengthens users' belief that the aid has the competence to understand these needs and, subsequently, use them as inputs for the decision process. In addition, users would perceive a caring aid as one more invested in and committed to helping them, which could further enhance the extent to which they view it as competent in generating personalized advice.

A decision aid that portrays care and concern also strengthen users' belief in its integrity. Essentially, displaying commitment to adhere to acceptable behavior behaviorally marks integrity (Mayer et al., 1995). By being more caring, a decision aid communicates more information (more cues) about its intentions and what it understands and will do. In addition, by conveying its feelings to users, the aid invariably communicates concern for users' welfare, its commitment to assist them, and its commitment to its advice-giving role. These propositions concur with the social penetration theory, which closely ties self-disclosure to responsiveness (Altman & Taylor, 1973). For example, as Berg and Archer (1980) show, people like others more when the latter manifest concern to the former's intimate disclosures compared to when the latter reciprocate such disclosures with their own.

In summary, when expressing concern for a user, a decision aid demonstrates openness. Thus, the aid communicates not only that it understands what the user "says" but also that it cares about the user. While the first can work to enhance the extent to which a user views a decision aid as competent, the latter can increase the extent to which the user perceives it as having integrity. Hence, we also expect perceived caring to have a positive effect on these two trusting beliefs. As Wang and Benbasat (2016) suggest, when users lack access to performance cues that help them assess a decision aid's competence or integrity, they use the experiences they have had interacting with it to form these beliefs. Hence, perceived caring acts as an interactive reason for users to trust a decision aid based on which users form their competence and integrity beliefs. Accordingly, we hypothesize:

H1: A decision aid's perceived caring positively influences its perceived competence.

H2: A decision aid's perceived caring positively influences its perceived integrity.

A decision aid that manifests care can further improve how well users perceive their interactions with it. Essentially, perceived caring influences the extent to which users perceive their interactions with a decision aid as free from conflict and anxiety, and it acts as a comforting a factor. Perceived caring further enhances the interaction atmosphere by making it to appear friendly and more cooperative. Similarly, by expressing feelings and emotions, a decision aid can foster richer and more intimate interactions in which partners can better relate to one another.

These propositions have support in social psychology literature that looks at the "intimacy process". Generally, this literature has shown that individuals perceive interactions that are characterized by friendliness and attentiveness as low maintenance and more enjoyable (Tickle-Degnen & Rosenthal, 1990). Researchers have observed similar results in consumer contexts. For instance, Ashforth and Humphrey (1993) suggest that a sense of genuine interpersonal sensitivity and concern drives good service. Similarly, LaBahn (1996) has shown that the extent to which customers perceive a company as friendly and diligent determines the extent to which they perceive their relationship as having the right "chemistry" and enjoyable. Gremler and Gwinne (2000) found that both interaction enjoyment and personal connection exerted effects on customer satisfaction and loyalty intentions.

Researchers have also recognized the related construct empathy, which refers to the ability to accurately infer other people's feelings and respond compassionately to their distress (Ickes, 1993), as an important phenomenon in interpersonal interaction. Ickes (1993) recognized two main elements of empathy: 1) empathic accuracy, which refers to the ability to accurately infer other people's thoughts and feelings, and 2) supportive response, which refers to responding compassionately to another person's distress (Coke et al., 1978). When investigated in the computer-mediated communication context (i.e., text-based instant messaging), Feng et al. (2004) found that both empathic accuracy and response type had significant effects on online interpersonal trust. Similarly, Peiris et al. (2000) found that empathetic responses received from a computer-simulated human conversational style to affect how much enjoyment users gained from and their interest in interactions (Peiris et al., 2000).

H3: A decision aid's perceived caring positively influences the perceived interaction atmosphere.

3.3 The Effects of Perceived Informativeness

As we discuss in Section 2, when a decision aid lacks performance cues that users can use to form calculative-based trust assessments, they can use their knowledge and understanding of the aid to form their trusting beliefs (Wang & Benbasat, 2016). Hence, perceived informativeness can afford users the knowledge basis on which to form their trusting beliefs and, thus, act as a knowledge-based reason (Wang & Benbasat, 2008) that they rely on to form their cognition-based trust (Wang et al., 2016).

An informative decision aid communicates pertinent information to users and educates them about the decision context. As Al-Natour et al. (2011a) have proposed, informativeness on the part of the aid reduces the knowledge gap between both and, subsequently, increases users' trust in the aid. Furthermore, a decision aid can communicate information relevant about a decision task to demonstrate its expertise, which can increase the extent to which users perceive it as competent (Wang & Benbasat, 2007). Alternatively, by describing what it does, a decision aid can help bridge the "intentions gap" that may arise due to users' uncertainty about its intentions (Wang & Benbasat, 2007). Similarly, by providing pertinent information, a decision aid can bridge the "knowledge gap" (Wand & Benbasat, 2016) that exists between users and the aid (Wang & Benbasat, 2016), which conveys goodwill toward users and enhances the extent to which they perceive the aid as having integrity (Wang & Benbasat, 2007).

H4: A decision aid's perceived informativeness positively influences its perceived competence.

H5: A decision aid's perceived informativeness positively influences its perceived integrity.

Finally, by providing pertinent information about the decision domain, a decision aid can enhance the extent to which users interact with it. In essence, by communicating information to the user and attempting to educate them about the decision context, the aid encourages user involvement and conveys its importance. In doing so, it enhances the extent to which users feel a sense of cooperation and, as such, to which they perceive the interaction as cooperative, friendly, and conflict free.

H6: A decision aid's perceived informativeness positively influences the perceived interaction atmosphere.

3.4 The Effects on Satisfaction

The model further proposes that the three evaluative beliefs competence, integrity, and interaction atmosphere enhance users' satisfaction with their overall interaction with a decision aid. Research on trust in online contexts has extensively confirmed that trust and individual trusting beliefs have a positive effect on people's intention to reuse IT artifacts, on how they evaluate them, and on their satisfaction with them (e.g., Gefen, 2002; Gefen et al., 2003; McKnight et al., 2002), which includes decision aids (e.g., Wang & Benbasat, 2007). Hence, we examine these established effects in the decision aid context with the following hypotheses:

H7: A decision aid's perceived competence positively influences users' satisfaction with it.

H8: A decision aid's perceived integrity positively influences users' satisfaction with it.

As we discuss in Section 2, users' interactions with decision aids constitute an interpersonal social interaction that involves some uncertainty. Whether such interactions succeed depends in part on the extent to which both parties perceive one another as interdependent (Emerson, 1976). Hence, users perceiving an interaction with a decision aid as friendly, cooperative, and conflict free should enhance their overall satisfaction with that interaction. Similarly, research on the intimacy process has shown that harmonious and conflict-free interactions (or interactions in which one party feels a personal connection toward another) signal relationship growth and well-penetrated interactions (Altman & Taylor, 1973; Tickle-Degnen & Rosenthal, 1990).

H9: The perceived interaction atmosphere positively influences users' satisfaction with a decision aid.

3.5 Designing a Decision Aid to Cue Desired Characteristics

In this study, we focus on investigating how one should design decision aids so that they manifest desirable characteristics and solicit positive perceptions, such as perceived caring and informativeness. While many different design elements may help cue these perceptions, we focus on two types of design elements that prior research has shown to affect how users perceive decisions aids: explanations and speech acts. As we describe in Section 4, we used pilot studies to examine various additional design elements that could potentially cue the desired characteristics. For parsimony, in the final data collection, we focused on only three elements to show that one can design decision aids to cue certain characteristics and manifest desired behaviors with only a small set of design elements.

First, we focus on explanation facilities, which researchers have long considered an essential component in decision support systems (Gregor & Benbasat, 1999). Similar to the explanations that human decision makers provide to explain their choices, explanation facilities provide users with information about these systems' inner workings. Researchers have also investigated explanations in relation to decision aids and shown them to increase users' trust in and the extent to which they accept decision aids (Wang & Benbasat, 2007). Specifically, explanations can inform users about decision attributes and why a decision aid considered them (termed why explanations) or, alternatively, about how the aid generated its recommendations (termed how explanations) (Wang & Benbasat, 2007, 2009).

When applied to the decision aid context, why explanations justify a decision aid's actions. In doing so, these explanations educate users about the decision-making task and, subsequently, enhance the extent to which users perceive it as informative. Similarly, why explanations manifest a decision aid's willingness to transparently serve users and, hence, convey openness, diligence, and concern.

H10: Why explanations positively influence a decision aid's a) perceived caring and b) perceived informativeness.

Alternatively, how explanations describe how a decision aid uses the information available to it to generate its advice. Essentially, how explanations offer additional information to the information that why explanations offer about what the decision aid does and how certain inputs affected the generated advice. Thus, how explanations can enhance the extent to which users perceive a decision aid as wishing to educate them about the decision-making context and, hence, the extent to which they perceive it as informative. Similarly, how explanations communicate a decision aid's willingness, motivation, and commitment to help users and find personalized solutions that fit their specific condition. Such communication demonstrates the aid's care and, hence, enhances these perceptions.

H11: How explanations positively influence a decision aid's a) perceived caring and b) perceived informativeness.

Second, we focus on speech acts. Individuals express a speech act not only to present information to hearers but also to perform an action, such as making requests, making promises, or issuing orders (Searle, 1979). For example, by making the statement "I will provide you with personalized advice", the speaker commits to an action, which, in turn, affects the "hearer" (Searle 1969). Prior research on designing decision aids has confirmed that one can use certain speech acts to cue people to perceive these aids in certain ways (e.g., Al-Natour et al., 2006, 2009).

In particular, we focus on expressive speech acts, which a speaker can use to express personal feelings and emotions (Searle, 1979). Specifically, we propose that one can use expressive speech acts to cue individuals to perceive a decision aid as caring since such speech acts primarily communicate emotions, feelings, and concerns. For instance, when people disclose that they suffer from a certain condition to a decision aid, it could communicate emotions and help comfort and validate them (e.g., "Sorry to hear that you are experiencing this condition. There is nothing to worry about as this is very common."). Such speech acts manifest involvement and understanding and, hence, increase the extent to which people perceive it as caring. In other words, because expressive speech acts express emotions and feelings, a decision aid can use them to demonstrate its openness and concern for users' wellbeing and respond empathetically to their needs and situation.

H12: Expressive speech acts positively influence a decision aid's perceived caring.

4 Research Method

We used a between-subjects full-factorial experiment with three factors (2 * 2 * 2) and eight treatment conditions to test our model. We randomly assigned participants to interact with one of eight decision aids that differed only in whether they provided why explanations (first factor), how explanations (second factor), and expressive speech acts (third factor). Table A1 describes what treatment factors appeared in each treatment group and the order in which we presented each manipulated factor.

We designed the decision aid to help users seeking personalized skincare advice. We deployed the aid on a fictional website. We used an avatar to represent the aid, which communicated with users through text. During the task, the aid asked subjects 30 multiple-choice questions to determine their skincare needs and, subsequently, recommend personalized solutions. The questions varied in their sensitivity level: they ranged from asking about demographics to asking about sensitive habits and health conditions.

We used the skincare context due to various factors. First, consumers often seek health and personal care products/services online, and sales in this area have grown in double digits over the past several years (Koch, 2019). Second, health and beauty products are characterized by their high personal relevance, which enhances the need for personalized advice as our context presupposes. Finally, to determine one's skincare needs, a decision aid needs to solicit not only product-focused information and preferences but also health-related and socially sensitive information (e.g., sensitive habits, such as birth control use) from the user. This increases the social relevance and sensitivity of the task and enhanced the need for trust. Furthermore, the need for disclosure of sensitive information also creates a context in which users may provide socially undesirable answers, which provides a decision aid with an opportunity to express appropriate feelings and emotions.

To enhance their motivation, we informed subjects that we would offer monetary in the form of vouchers that they could redeem to purchase the recommended skincare solutions from the website. In proving these prizes, we motivated subjects to take the task seriously as they could actually receive the recommended solutions.

After completing the task, we asked subjects various attention questions to confirm that they gave the task due consideration (e.g., asked about the specific information that we solicited from them). Next, we asked subjects to evaluate the decision aid and their interaction with it. They completed this evaluation before we presented them with its recommendation's in order not to confound how they evaluated the aid with how they perceived its advice's quality. In other words, users evaluated the aid solely based on the experience they had interacting with it rather than on how they perceived its recommendations.

4.1 Treatment Conditions

The decision aids differed in whether they used 1) why explanations to justify their actions, 2) how explanations to describe their actions, and 3) expressive speech acts to convey feelings and emotions. Specifically, in conditions where a decision aid used a why explanation, the decision aid described why it needed certain information and that information's relevance to the decision task in detail (e.g., information about the effect that certain health conditions have on the skin, hormonal therapy's relevance to skincare, etc.). When a decision aid offered a how explanation, it described how it processed the information available to generate its recommendations. In this study, the decision aid generated how explanations dynamically based on the individual input that users provided. Hence, unlike how prior research has used static explanations (e.g., Wang & Benbasat, 2007), which generally describe how decision making incorporates the information that users provide, the how explanations that we used in this study described how the decision aid factored each specific input into its decision making and how that input affected its consequent recommendations. Similarly, the decision aid generated expressive speech acts dynamically based on the inputs from users. Depending on the option that the user selected, the aid expressed the appropriate emotion.

4.2 Measures

We measured all constructs that we used in this study using seven-point multi-item Likert scales that ranged from strongly agree to strongly disagree (we list all measurement items in Table 1). We measured perceived competence and integrity using the scales that McKnight et al. (2002) developed to measure trusting beliefs, which Wang et al. (2016) adapted to the decision aid context. We measured satisfaction using the scale developed by Cenfetelli et al. (2008). We developed three new scales to measure the three remaining constructs: perceived caring, perceived informativeness, and interaction atmosphere. We validated the measures via four pilot studies. As Wang and Benbasat (2007) suggest, many studies (e.g., Arnold et al., 2006) have demonstrated that domain knowledge influences how users evaluate decision aids. Therefore, we also measured users' skincare knowledge to act as a control variable.

4.3 Pilot Testing

We conducted four pilot studies to inform the design, script, and measurement instrument that we used in the final data collection. While the first pilot study used a sample that contained both males and females, we used only females in the remaining pilot studies and the final data collection for two main reasons. First, the results from the first pilot study showed that male and female participants exhibited the same relationship pattern across the research model. Second, focusing only on female subjects ensured that we introduced no confounding factors into the study due to its context (i.e., skincare). Had we used a mixed sample, we would have had to make changes to the gender-specific questions that the decision aid asked, which would have essentially resulted in confounding differences in the treatment for each gender. Based on the results from the second, third and fourth pilot studies, we modified the script that the aid used, the questions it asked, and the measurement items. As we describe in Section 3, we employed additional design elements and examined their effects on how users perceived the decision aid in some pilot studies. Such design elements included other speech act types, explanation types, and non-verbal cues. The results we obtained from these pilot studies showed that the three design elements employed in the final data collection exerted large and independent effects on the examined perceptions.

4.4 Sample

We conducted the study online using 195 female participants that we recruited from a panel that a market research company maintained. We sent an invitation to participate in the study via email to panel members. We provided participants with a point-based incentive for their assistance in the study that they could redeem for various prizes available through the marketing firm.

5 Results

We assessed the measurement model and analyzed the structural model using partial least squares (PLS) with SmartPLS 3.

Table 1. Measurement Items

Construct (list of items)	Loading
Caring (CR = 0.96; CA = 0.95)*:	
The decision aid seems to care about the customer.	0.95
The decision aid shows concern for the customer.	0.95
The decision aid expresses empathy for the customer.	0.88
The decision aid is considerate of the customer.	0.95
Informativeness (CR = 0.97; CA = 0.95):	
The decision aid is knowledgeable about skincare	0.89
The decision aid educates the customer about skincare	0.96
The decision aid communicates a lot of information about skincare to the customer	0.96
The decision aid is overall informative.	0.94
Competence (CR = 0.95; CA = 0.92):	
The decision aid was effective in its role.	0.91
The decision aid performed its role well.	0.94
The decision aid was proficient.	0.92
Integrity (CR = 0.96; CA = 0.94):	
The decision aid seemed truthful in its dealings with the customer.	0.90
The decision aid seemed like it would keep its commitments.	0.91
The decision aid appeared to be honest.	0.95
The decision aid seemed sincere and genuine.	0.92
Atmosphere (CR = 0.95; CA = 0.93):	
The interaction with the decision aid is friendly.	0.91
The interaction with the decision aid is relaxed.	0.92
The interaction with the decision aid is cooperative.	0.93
The interaction with the decision aid is conflict free.	0.88
Satisfaction (CR = 0.96; CA = 0.94):	
Overall, how do you feel about your interaction with the decision aid?	
Satisfied.	0.92
Delighted.	0.89
Contented.	0.95
Pleased.	0.93
User knowledge (CR = 0.94; CA = 0.91):	
I consider myself an expert in choosing skincare products.	0.93
I am knowledgeable about skincare products.	0.93
I have extensive experience buying skincare products.	0.91
* CR = composite reliability; CA = Cronbach's alpha.	

5.1 Measurement Model

To assess individual item reliability, we examined how strongly the individual measurement items loaded on their intended constructs. As Table 1 shows, the loadings for all items on their intended constructs exceeded the recommended threshold 0.70 (Barclay et al., 1995).

Table 2 depicts the correlations between the model's constructs; the diagonal elements represent the square root of the average variance extracted (AVE). A rule for assessing discriminant validity requires that the square root of AVE be larger than the correlations between the constructs (Barclay et al., 1995). As Table 2 shows, the model met this criterion. Another criterion for discriminant validity requires that indicators load on their respective latent variables more strongly than other indicators load on these variables and these indicators load on other variables. As Table B2 in Appendix B shows, the model met this condition. We also report composite reliability and Cronbach's alpha in Table 1. Since these values exceeded the suggested minimum 0.70 (Fornell & Larcker, 1981), the model met internal consistency criteria.

Table 2. Construct Correlations

	M (St. Dev)	CA	IN	CO	IG	AT	SA	UK
Caring (CA)	4.86 (1.19)	0.93						
Informative (IN)	4.87 (1.17)	0.63	0.94					
Competence (CO)	5.29 (0.90)	0.56	0.50	0.92				
Integrity (IG)	5.14 (0.99)	0.57	0.52	0.76	0.92			
Atmosphere (AT)	5.20 (0.94)	0.69	0.53	0.58	0.58	0.91		
Satisfaction (SA)	4.89 (1.19)	0.63	0.68	0.62	0.61	0.66	0.92	
User knowledge (UK)	3.46 (1.29)	-0.02	-0.05	-0.12	-0.11	-0.11	-0.13	0.92

M = mean; st. dev. = standard deviation.
Diagonal elements show the square root of AVE.

To address potential common method variance (CMV), we followed the procedures that Podsakoff et al. (2003) recommend. We first conducted an exploratory factor analysis and applied Harman's (1967) one-factor extraction test. The results showed five factors with eigenvalues greater than one with the first factor accounting for 41.2 percent of the total variance. Second, as Kock (2015) suggests, one can also CMV in PLS through a collinearity assessment where a variable inflation factor (VIF) value greater than 3.3 indicates CMV (Hair et al., 2017). The results from a full collinearity test indicated that all VIF values were lower than three with the highest VIF being 2.88. These results indicate that collinearity does not influence the results (Tabachnick & Fidell, 1996).

Finally, following Lindell and Whitney's (2001) and Malhotra et al.'s (2006) recommendations, we used a post hoc approach to estimate CMV (Wang & Benbasat, 2016). Since the user knowledge variable did not theoretically relate to any constructs in the model, we used it as a marker variable. Accordingly, we could subsequently estimate CMV based on the correlations (r_M) between this marker variable and the other constructs. We calculated the correlations between all the constructs in the model (shown in Table 2) and selected the smallest correlation—the correlation between user knowledge and perceived caring (r_M = -0.0173)—as the estimate for the method variance. We calculated the corrected correlations among the constructs that partialed out CMV using the formula that Malhotra et al. (2006) provide and present them in Table B2 in Appendix B. The corrected correlations remained significant ($p < 0.01$), and we observed small differences between the uncorrected and corrected correlations. We also conducted a sensitivity analysis by assuming r_M = 0.10, 0.15, 0.20, and 0.30 (Wang & Benbasat, 2016). Even when we assumed the correlation that CMV caused to be 0.30, the smallest adjusted correlation (between informativeness and competence) remained statistically significant ($r = 0.290$; $t = 4.203$).

5.2 Structural Model Results

We depict the structural model results, which include the standardized path coefficients and the corresponding significant values, in Figure 3. We computed standard errors using a bootstrap procedure with 500 resamples.

Consistent with H1, H2, and H3, we found that the extent to which users perceived the decision aid as caring enhanced the extent to which they perceived it as competent and as having integrity ($\beta = 0.40$, $p < 0.01$; $\beta = 0.40$, $p < 0.01$, respectively) and improved how well they perceived the interaction atmosphere ($\beta = 0.59$, $p < 0.01$). Similarly, the extent to which users perceived the decision aid as informative enhanced the extent to which they perceived it as competent and as having integrity ($\beta = 0.25$, $p < 0.01$; $\beta = 0.27$, $p < 0.01$, respectively) and improved how well they perceived the interaction atmosphere ($\beta = 0.16$, $p < 0.01$). Thus, we also found support for H4, H5, and H6.

We found that competence and integrity exerted statistically significant effects on satisfaction (β = 0.21, p < 0.01; β = 0.21, p < 0.01, respectively). Perceived interaction atmosphere exerted a much larger effect on satisfaction (β = 0.41, p < 0.01). Thus, in line with prior research, we found support for H7, H8, and H9.

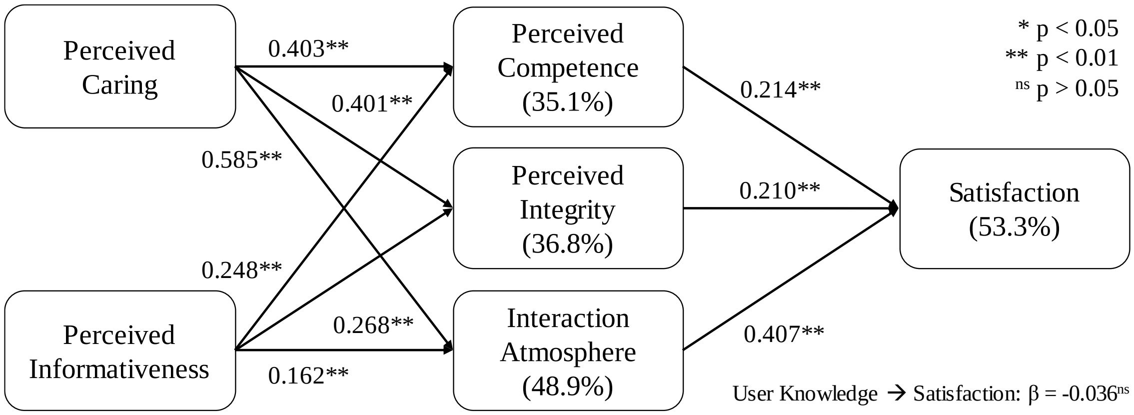

Figure 3. Structural Model Results[1]

Jointly, the two exogenous variables explained 35.1 percent of the variance in competence, 36.8 percent of the variance in integrity, and 48.9 percent of the variance in interaction atmosphere. These latter three variables explained 53.3 percent of the variance in satisfaction.

5.3 Treatment Effects

We show the mean scores and the standard deviations for the two exogenous variables perceived caring and perceived informativeness across the eight treatment groups in Table 3. To examine the effects of the design elements of the two exogenous variables, we performed a MANOVA that used the three design elements as fixed factors and perceived caring and informativeness as the dependent variables.

Table 3. Treatment Means

Why	How	Exp.	Caring	Informativeness	*N*
No	No	No	3.83 (1.14)	3.96 (1.09)	20
		Yes	4.90 (1.26)	4.27 (1.28)	25
	Yes	No	4.74 (1.15)	4.64 (1.03)	30
		Yes	5.29 (0.82)	4.86 (0.79)	21
Yes	No	No	4.22 (1.34)	5.13 (1.47)	25
		Yes	5.48 (0.88)	5.43 (0.86)	22
	Yes	No	5.01 (1.05)	5.41 (0.96)	29
		Yes	5.37 (0.87)	5.12 (1.03)	23
Note: “yes” and “no” indicate whether the design element appeared in the treatment group. Number outside parentheses is mean score; number inside the parentheses is the standard deviation.					

The results indicate that why explanations (F = 15.58, p < 0.01), how explanations (F = 4.93, p < 0.01), and expressive speech acts (F = 18.08, p < 0.01) influenced the extent to which users perceived the decision aid as caring and informative. In testing the between-subjects effects (see Table 4), we found that why explanations enhanced the extent to which users perceived the decision aid as caring (F = 4.41, p < 0.05) and informative (F = 28.42, p < 0.01). Hence, we found support for both H10a and 10b. Similarly, how

[1] Note that the original model that we analyzed included several demographical control variables. The results indicated that none had significant effects on any of the other endogenous variables, so we removed them from the model.
To ensure that the modeling tool we chose did not affect the results, we ran an additional model using AMOS 25 and further performed several independent linear regressions (see Appendix B). These additional analyses revealed almost exactly the same results to the ones we observed in the PLS model.
Figure B2 depicts the results from an additional structural model in which we included perceived benevolence as another satisfaction predictor. As the results show, benevolence had a nonsignificant effect on satisfaction in the presence of the other two trusting beliefs and interaction atmosphere.

explanations had a large effect on the extent to which users perceived the decision aid as caring ($F = 9.90$, $p < 0.01$) and a more modest effect on the extent to which they perceived it as informative ($F = 3.82$, $p < 0.05$). Hence, we also found support for H11a and H11b. Finally, expressive speech acts had a large effect on the extent to which users perceived the decision aid as caring ($F = 26.38$, $p < 0.01$) but not on the extent to which they perceived it as informative ($F = 0.73$, $p > 0.10$). Hence, we found support for H12. Overall, the three design elements successfully cued users to perceive the decision aid as caring and informative as we hypothesize.

Table 4. MANOVA Results

Effect on perceived caring			Effect on perceived informativeness		
Effect	F	**Sig.**	**Effect**	**F**	**Sig.**
Why explanations [WE]	4.406	0.037	Why explanations [WE]	28.424	<0.001
How explanations [HE]	9.901	0.002	How explanations [HE]	3.815	0.049
Expressive speech acts [EA]	26.379	<0.001	Expressive speech acts [EA]	0.734	0.393
WE * HE	0.972	0.325	WE * HE	4.289	0.040
WE * EA	0.000	0.999	WE * EA	0.648	0.422
HE * EA	5.128	0.025	HE * EA	1.166	0.282
WE * HE * EA	0.336	0.563	WE * HE * EA	0.620	0.432
R^2 (adjusted)	0.156		R^2 (adjusted)	0.139	

Furthermore, from testing the between-subjects effects, we found a significant two-way interaction between how explanations and expressive speech acts in predicting perceived caring ($F = 5.13$, $p < 0.05$). We show this interaction graphically in Figure 4. As one can see, the interaction indicates that expressive speech acts had the most significant effect in the absence of how explanations.

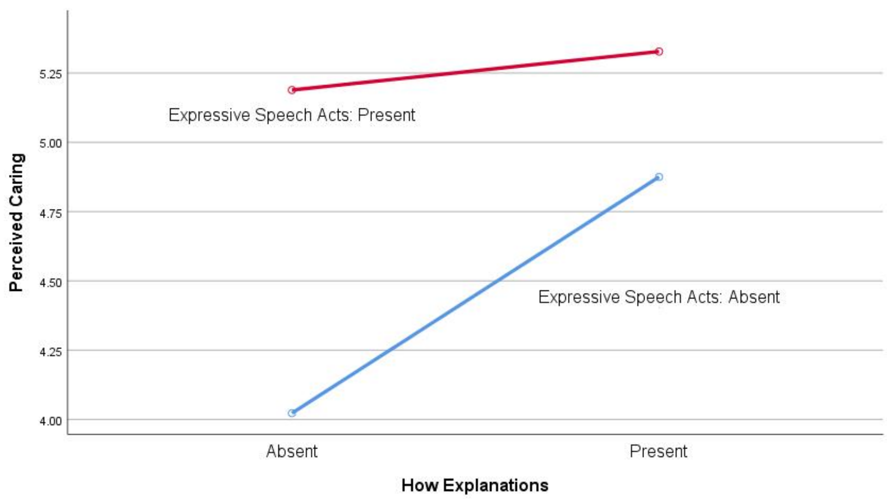

Figure 4. Interaction between How Explanations and Expressive Acts

The results also highlight another statistically significant two-way interaction (see Figure 5) between why and how explanations in predicting received informativeness ($F = 4.29$, $p < 0.05$). Similar to the earlier interaction, we observed how explanations to have the strongest effect in the absence of why explanations.

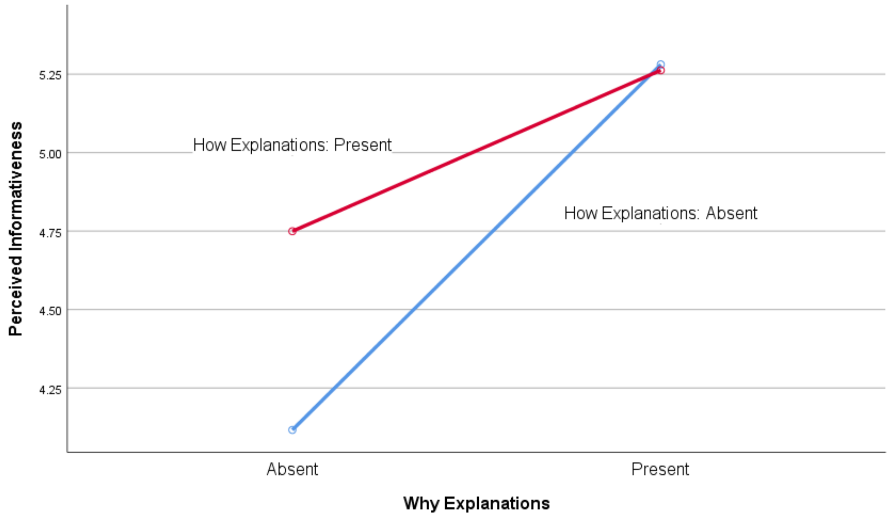

Figure 5. Interaction of Why and How Explanations

6 Discussion

Our results provide support for the need to design interactions with decision aids that exhibit caring and informativeness. The relatively large effect that perceived caring had on the extent to which users evaluated the decision aid as competent and as having integrity strongly support that people view interacting with these aids as social and interpersonal. While most studies that have examined the factors that determine trust in decision aids have focused on utilitarian factors (Wang & Benbasat, 2016), our results highlight the likely dominant role that the social interaction aspects play in predicting the different trusting beliefs. Hence, one needs to design these aids so that they manifest appropriate social characteristics for their use context to enhance users' trust in them. Similarly, the results also highlight that endowing a decision aid with explanation facilities enhance its perceived informativeness. This subsequently enhances its perceived trustworthiness via enhancing the extent to which people perceive it as competent and as having integrity. Therefore, utilitarian factors remain significant considerations when designing decision aids.

The large effect that perceived caring had on interaction atmosphere and that interaction atmosphere had on satisfaction lend support to the view that user-aid interactions resemble interpersonal ones. Other than the expected benefits and costs associated with their use, users' experiences during their interactions with these aids play a significant role in affecting their overall evaluations. This logic concurs with Al-Natour and Benbasat's (2009) framework, which advocates that users' experiences when interacting with IT artifacts shape how they eventually evaluate these artifacts. Future research should attempt to examine other aspects of this social interaction and identify other variables that affect users' evaluations.

The results indicate that perceived informativeness also exerts a modest yet statistically significant effect on improving how well users perceive the interaction atmosphere. As for why, many probable explanations exist. We believe that the enhanced interaction atmosphere results in large part from "novelty", which, in the online shopping context can satisfy users' innate need for exploration or information (Hui et al., 2006). In essence, the information that a decision aid provides acts to satisfy users' cognitive curiosity (Malone, 1981), which increases their affective responses (Steenkamp & Baumgartner, 1992) and subsequently enhances how well they view the interaction. Also, as we discuss in Section 3, providing pertinent information about the decision domain can enhance user involvement in the interaction, which allows for friendlier and more cooperative interactions with decision aids.

While our main model did not include perceived benevolence, the results in Figure B2 in Appendix B highlight that including benevolence as an additional factor that predicted satisfaction had a negligible effect on the proportion of variance explained in satisfaction in the original model. However, the relatively large bivariate correlation between satisfaction and benevolence (r = 0.59), which was similar in magnitude to the bivariate correlation between satisfaction and competence (r = 0.64) and satisfaction and integrity (r = 0.61), highlights that this variable remains important even though other predictors may subsume its effects.

The results concerning the effect that three design elements had on the exogenous variables indicate that one can use a small set of design elements to cue desired social and utilitarian beliefs. Interestingly, some design elements exhibited synergetic effects that demonstrate their complex relationship and, hence, warrant further investigation. Future research should identify other types of design elements and examine their effect in cueing other desired characteristics in decision aids.

The large proportions of variance that all examined constructs explained indicate these constructs' salience and sufficiency to understand the antecedents to users' satisfaction with decision aids employed in an advice-giving capacity.

6.1 Contributions

With this paper, we make several contributions to research and practice. First, theoretically speaking, we expand our knowledge on the factors that influence users' satisfaction with decision aids. Specifically, we identify and confirm the important role that the social characteristics that a decision aid manifests plays and their effects on how users evaluate these aids in a relational (e.g., trusting beliefs) and situational sense (e.g., interaction atmosphere). In doing so, we further corroborate that one can see decision aids as social actors and interactions with them as interpersonal.

Second, we identify variables that can enhance satisfaction with a decision aid that concur with its tutoring and the advice-giving role and that one can cue through its design. The results reveal that an aid's caring and informativeness that can be cued through its design exert significant effects on utilitarian and non-utilitarian evaluations of the aid. Such findings concur with Al-Natour and Benbasat's (2009) model, which posits that one can design an IT artifact to cue certain design characteristics that subsequently affect users' behavioral, relational, and social beliefs about interacting with an artifact and its outcomes.

Third, we contribute to HCI research by showing how one can use a parsimonious set of design elements to manifest desired characteristics in decision aids. From a research perspective, we identify two theoretical bases—explanation facilities and speech act theory—to illustrate how established theories and ideas can inform decision aids' design.

With this study, we also make at least two practical contributions. First, the significant effect that perceived interaction atmosphere had on satisfaction highlights the need to design harmonious, friendly, and conflict-free user-aid interactions. Indeed, we found that perceived interaction atmosphere more prominently drove users' satisfaction with our decision aid than perceived trust. Hence, decision aid designers should think carefully about the "interaction" as a whole as an important factor that drives satisfaction and strive to find ways to enhance that interaction atmosphere. As our results show, one can do so by enhancing the extent to which users perceive a decision aid cares. Therefore, decision aid designers should think carefully about the social characteristics that their aids manifest and whether they help to enhance the overall interaction atmosphere. Second, the significant effect that utilitarian-based beliefs had on satisfaction also highlights that one should *not* design a decision aid to focus on social aspects at the expense of its utility. The significant effect that our decision aid's competence had on satisfaction and the effect that perceived informativeness had on all three mediators highlight the need to also tailor how one design decision aids so that users perceive them as credible and experts.

6.2 Limitations and Future Research

Notwithstanding its contributions, the study also has several limitations. Had we used a mixed-gender sample and various product contexts, we could have better understood how females and males may respond differently to such decision aids. Furthermore, while we could isolate the effects of individual design elements due to the experimental design's factorial nature, examining other individual elements and element combinations may allow scholars to identify other desired beliefs that may further enhance satisfaction with these decision aids. A longitudinal study would allow one to examine how the way in which users perceive a decision aid evolves with repeated interactions and as the user-aid relationship progresses.

While we examine a small set of satisfaction antecedents and characteristics that a decision aid can manifest, other influencing perceptions potentially exist. Future research should focus on identifying other salient antecedents of satisfaction with decision aids and examine what effect already established ones have in contexts where these aids operate in socially sensitive advice-giving settings. Future research could further investigate other desired characteristics that a decision aid's design could cue and their impact on trust in the aid and enhancing the interaction atmosphere.

As we discuss in Section 1, in this study, we focus on decision aids contexts in which users would likely feel somewhat vulnerable due to the specialized nature of the decision task or the need to disclose sensitive personal information. Subsequently, to design our experimental manipulations, we focused not only on enhancing our aid's perceived utilitarianism but also on reducing users' perceived vulnerability. Future research should explore the extent to which the social characteristics that a decision aid manifests are salient and influence subsequent evaluations in a purely utilitarian context.

7 Conclusion

Motivated by the need to understand how to design interactions with social and rewarding healthcare decision aids, we identified and examined the effect that several design elements had on cueing desired characteristics in such aids. These characteristics enhanced how users evaluated the aid, subsequently, their satisfaction. With this study, we contribute to the research that views decision aids as social actors and ongoing research attempting to understand the factors that drive how users evaluate decision aids.

With the upsurge in patient portal and intelligent tool use in healthcare and other specialized advice-giving settings, in this study, we also contribute to explaining how users view, use, and evaluate these tools. We also identify several elements that the individuals who design these tools can use to manifest desired characteristics.

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Appendix A: Study Information

Sample Manipulation: Question 6

Table A1. Sample Manipulation

Why explanation	Unlike the conditions we discussed on the previous page, cold sores will need to be treated with medication. You apply this medication directly onto the sore. Cold sores can be brought on by stress and hormonal changes. The active ingredient needed to treat the sore is Aciclovir.
Question (and answer options)	Do you suffer from outbreaks of cold sores? Not at all Yes, rarely (once every few months) Yes, frequently (more than once a month)
How explanation (assuming "yes, rarely" is chosen)	Nowadays many products exist that can help treat cold sores and reduce the frequency with which they appear. I will make sure to include a number of these products in my final recommendations for you to choose from.
Expressive speech act (assuming "yes, rarely" is chosen)	Thanks for letting me know. There is no need to worry at all. Cold sores are more common than most people think.

Treatment Conditions

Table A2. Descriptive Statistics for Exogenous Variables

				Expressive speech acts	
				No	**Yes**
How explanation	**No**	**Why explanation**	**No**	Treatment condition 1: Question Answer options	Treatment condition 5: Question Answer options Expressive speech act (dynamic)
			Yes	Treatment condition 2: Why explanation Question Answer options	Treatment condition 6: Why explanation Question Answer options Expressive speech act (dynamic)
	Yes	**Why explanation**	**No**	Treatment condition 3: Question Answer options How explanation (dynamic)	Treatment condition 7: Question Answer options How explanation (dynamic) Expressive speech act (dynamic)
			Yes	Treatment condition 4: Why explanation Question Answer options How explanation (dynamic)	Treatment Condition 8: Why explanation Question Answer options How explanation (dynamic) Expressive speech act (dynamic)

Appendix B: Study Results

Loadings and Cross-loadings

Table B1: Item Loadings and Cross-loadings

	M	St. dev.	1	2	3	4	5	6	7
CA1	4.90	1.25	**0.770**	0.283	0.110	0.298	0.286	0.224	0.009
CA2	4.87	1.30	**0.800**	0.271	0.121	0.231	0.286	0.165	-0.001
CA3	4.64	1.31	**0.850**	0.215	0.166	0.093	0.122	0.163	0.027
CA4	5.01	1.23	**0.769**	0.296	0.156	0.228	0.299	0.183	0.010
IN1	5.03	1.14	0.230	**0.761**	0.153	0.195	0.158	0.257	-0.022
IN2	4.84	1.27	0.251	**0.871**	0.106	0.200	0.111	0.211	0.035
IN3	4.73	1.32	0.243	**0.872**	0.095	0.182	0.166	0.204	0.024
IN4	4.88	1.27	0.239	**0.823**	0.108	0.155	0.193	0.281	-0.064
CO1	5.25	1.03	0.166	0.141	**0.729**	0.406	0.140	0.264	-0.096
CO2	5.42	0.97	0.178	0.162	**0.746**	0.390	0.255	0.239	-0.047
CO3	5.31	0.97	0.255	0.226	**0.709**	0.455	0.238	0.105	-0.028
IG1	5.19	1.10	0.142	0.117	0.262	**0.766**	0.234	0.233	-0.088
IG2	5.04	1.02	0.191	0.183	0.170	**0.835**	0.135	0.175	-0.025
IG3	5.19	1.06	0.234	0.231	0.204	**0.834**	0.153	0.197	0.024
IG4	5.13	1.15	0.175	0.212	0.276	**0.779**	0.229	0.155	-0.084
AT1	5.14	1.04	0.469	0.221	0.054	0.256	**0.728**	0.232	-0.061
AT2	5.22	0.98	0.209	0.186	0.166	0.160	**0.821**	0.251	-0.098
AT3	5.13	1.07	0.316	0.197	0.076	0.318	**0.772**	0.189	-0.029
AT4	5.30	1.04	0.168	0.123	0.245	0.146	**0.828**	0.204	-0.002
SA1	5.30	1.21	0.141	0.337	0.175	0.158	0.231	**0.784**	-0.103
SA2	4.38	1.38	0.380	0.246	0.090	0.262	0.237	**0.727**	-0.046
SA3	4.93	1.29	0.191	0.283	0.182	0.256	0.265	**0.781**	-0.056
SA4	4.95	1.30	0.204	0.359	0.208	0.277	0.241	**0.717**	-0.019
UK1	3.23	1.34	0.071	0.021	-0.020	-0.053	-0.104	-0.039	**0.926**
UK2	3.79	1.38	0.010	-0.038	-0.040	-0.020	-0.029	-0.088	**0.929**
UK3	3.35	1.48	-0.057	0.002	-0.036	-0.034	0.026	0.001	**0.907**

CA: caring, IN: informativeness, CO: competence, IG: integrity, AT: atmosphere, SA: satisfaction, UK: user knowledge.
Extraction method: principal component analysis. Rotation method: Varimax with Kaiser normalization.

Common Method Variance

Table B2. Adjusted Correlations

Correlation	r_U	r_A	Adjusted correlations (r_U) sensitivity analysis			
			(r_M = 0.10)	(r_M = 0.15)	(r_M = 0.20)	(r_M = 0.30)
r (caring, competence)	0.560	0.552 (9.181)*	0.511 (8.242)	0.482 (7.632)	0.450 (6.985)	0.372 (5.546)
r (caring, integrity)	0.570	0.563 (9.430)	0.522 (8.490)	0.494 (7.880)	0.463 (7.233)	0.386 (5.798)
r (caring, atmosphere)	0.688	0.682 (12.929)	0.653 (11.947)	0.633 (11.318)	0.610 (10.656)	0.554 (9.217)
r (informativeness, competence)	0.503	0.494 (7.882)	0.448 (6.943)	0.416 (6.33)	0.379 (5.675)	0.290 (4.203)
r (informativeness, integrity)	0.521	0.513 (8.280)	0.468 (7.342)	0.437 (6.731)	0.402 (6.079)	0.316 (4.620)
r (informativeness, atmosphere)	0.532	0.524 (8.524)	0.480 (7.586)	0.450 (6.975)	0.415 (6.325)	0.332 (4.872)
r (competence, satisfaction)	0.615	0.608 (10.623)	0.572 (9.674)	0.547 (9.061)	0.519 (8.413)	0.450 (6.988)
r (integrity, satisfaction)	0.613	0.606 (10.561)	0.570 (9.613)	0.545 (9.000)	0.516 (8.352)	0.447 (6.927)
r (atmosphere, satisfaction)	0.658	0.652 (11.902)	0.620 (10.937)	0.597 (10.316)	0.572 (9.663)	0.511 (8.234)

RU = uncorrected correlation.
RM = correlation resulting from CMV.
RA = CMV-adjusted correlation between the variables under investigation. We calculated it as $(r_U - r_M)/(1 - r_M)$ (Malhotra et al., 2006, p. 1868).
* Number between parentheses is the t-statistic for the adjusted correlation. We calculated it as $\frac{r_A}{\sqrt{(1-r_A{}^2)/(n-3)}}$ where *n* equals sample size (Malhotra et al., 2006, p. 1868).

AMOS Model

To ensure that the modeling tool we chose did not affect the results (i.e., PLS), we also assessed the structural model using AMOS 25. We show the results for that model in Figure B1, which nearly exactly matched the results for the PLS model that we describe in the paper. The model demonstrated a good fit (χ2 = 501.4, df = 281, SRMR = 0.057, CFI = 0.960, RMSEA = 0.054).

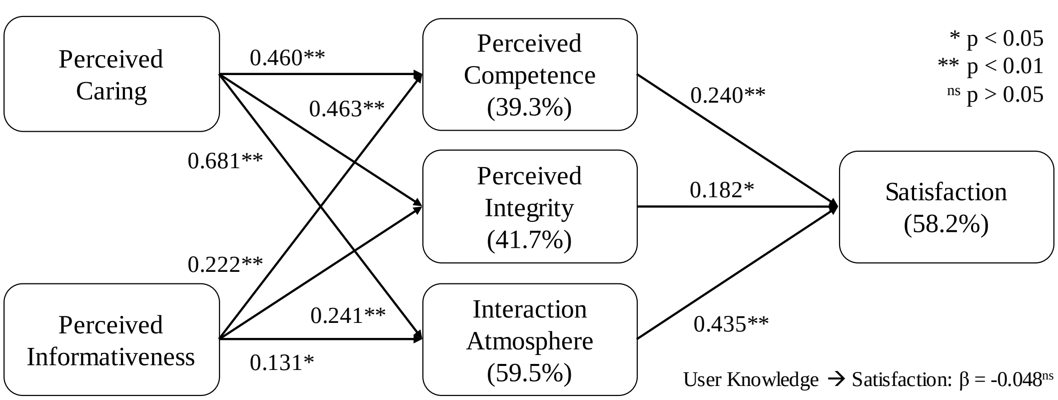

Figure B1. AMOS Model Results

Regression Analysis

Given the concerns that researchers have raised about using PLS[2], we also confirmed the results by performing several independent linear regressions. In essence, PLS equates to testing several regression models at the same time.

In the first step, we ran a regression model where satisfaction served as the dependent variable, which perceived competence, integrity, and interaction atmosphere predicted. In doing so, we essentially tested the model's right-hand side. As the results below show, the regression results almost exactly matched the ones we obtained from the PLS model.

The regression results indicated that the R^2 was 0.530 and the adjusted R^2 was 0.523—values that closely matched how much variance satisfaction explained in the PLS model (53.3%). The results also indicated that the three predictors had a similar effects to those observed in the PLS model: 1) competence → satisfaction: $\beta = 0.218$ in the regression and $\beta = 0.214$ in the PLS model, 2) integrity → satisfaction: $\beta = 0.211$ in the regression and $\beta = 0.210$ in the PLS model, and 3) atmosphere → satisfaction: $\beta = 0.407$ in the regression and $\beta = 0.407$ in the PLS model.

In the second step, we also ran three separate regression models to examine the effect that caring and informativeness (served as predictors in the three models) had on competence (model 1), integrity (model 2), and atmosphere (model 3). Again, as the results below show, the results resembled to what we obtained from the PLS model.

The regression results showed that caring had an effect on competence ($\beta = 0.396$), integrity ($\beta = 0.389$), and atmosphere ($\beta = 0.568$). These effects resemble the effect that caring had on these three variables in the PLS model (0.403, 0.401, and 0.585, respectively). We observed the same for the effect that informativeness had on competence ($\beta = 0.252$), integrity ($\beta = 0.275$), and atmosphere ($\beta = 0.171$)—they all resembled the effect that responsiveness had on these three variables in the PLS model (0.248, 0.268, and 0.162, respectively). The adjusted R^2 was 0.339 when predicting competence (35.1% in the PLS model), 0.355 when predicting integrity (36.8% in the PLS model), and 0.468 when predicting interaction atmosphere (48.9% in the PLS model).

Structural Model with Benevolence Included

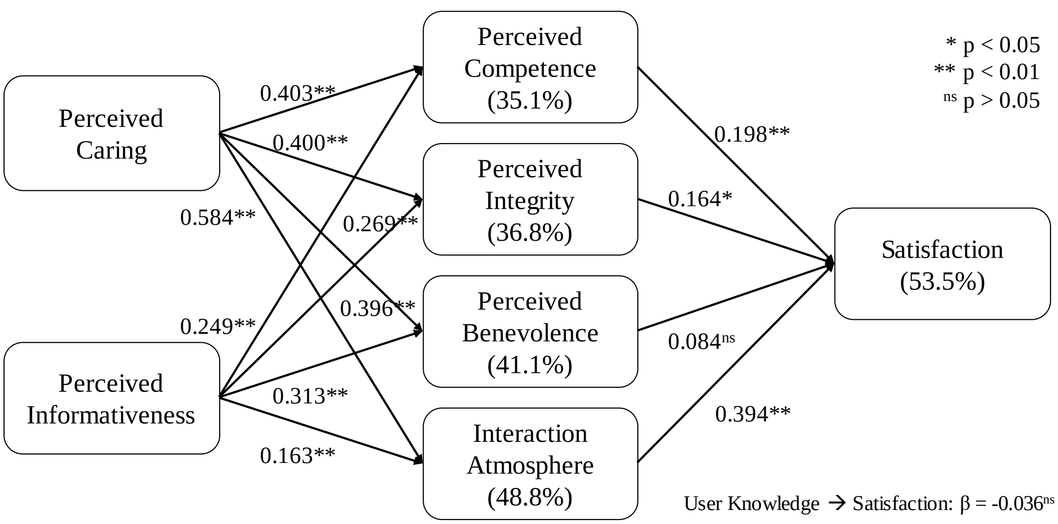

Figure B2. Structural Model with Benevolence

[2] Note that we did not have these concerns about PLS itself but rather with how researchers employ it, especially when testing atypical models. The model we tested, we believe, concurs with many other models in IS in terms of number of constructs and the degree of causal links that we tested.

Figure B2 depicts the results from additional structural model in which we included perceived benevolence as another satisfaction predictor. As the results show, benevolence had a nonsignificant effect on satisfaction in the presence of the other two trusting beliefs and interaction atmosphere.

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