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User acceptance of knowledge-based system recommendations: Explanations, arguments, and fit

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ABSTRACT

Knowledge-based systems (KBS) can potentially enhance individual decision-making. Yet, recommendations from KBS continue to be met with resistance. This is particularly troubling in the context of deception detection (e.g., border control), in which humans are accurate only about half the time. In this study, we examine how the fit between KBS explanations and users' internal explanations influences acceptance of KBS recommendations. We leverage cognitive fit theory (CFT) to explain why fit is important for user acceptance of KBS evaluations. We also compare the predictions of CFT to those of the person–environment fit (PEF) paradigm. The two theories make conflicting predictions about the outcomes of fit when it comes to KBS explanations. CFT predicts that explanations with a higher cognitive fit will have more influence and be evaluated faster whereas PEF predicts that individuals will take more time in evaluating explanations with greater fit. In our deception detection scenario, we find support for CFT in the sense that people are influenced more by cognitively fitting explanations, however PEF is supported in the sense that people take more time to evaluate the explanation.

1. Introduction

Knowledge-based systems (KBS) have the potential to enhance the way people make decisions. In cases in which a KBS's accuracy is much higher than the decision maker's—such as IBM's Jeopardy-playing Watson [1] —the decision makers are missing out on the potential value created by the KBS if they do not use them [2]. Nonetheless, in many domains, such as credibility assessment [3] and medical informatics [4], acceptance of KBS decisions often still falls below 60%. The potential value of accepting a correct decision from a KBS can be particularly meaningful in cases where individuals are attempting to discern whether or not someone is being deceptive, such as in border crossings [3] and auditing [5]. Therefore, if researchers can better understand why users do or do not accept the decisions of a KBS, the potential value of KBS for decision making in practice can be improved.

One unique aspect of KBS is the use of lines-of-reasoning explanations [6]. These explanations attempt to assist the user in evaluating the KBS's decision by helping the user understand how the KBS came to a certain conclusion (e.g., showing the logic by which the system arrived at the conclusion). Explanations have been studied since the introduction of MYCIN (a medical KBS) in the 1970s [7] to today [e.g., 8–10]. Notably, researchers continue to explore ways to present lines-of-reasoning explanations to users to increase acceptance of KBS recommendations [6]. Ye & Johnson [5] proposed that “one future direction may be to assess the impact of different kinds of justification and to identify the appropriate conditions under which each should be employed” (p. 169).

In addition to differential impacts of justifications, research also indicates that differing representations of information can alter the amount of KBS influence. For example, Papamichail and French [11] found that users preferred certain information formats over others. Users performed better with their preferred formats, and the preferred formats were not consistent among users (i.e., some users preferred formats rejected by other users). This finding suggests that a matching, or fit, between users and information format is needed for the KBS to be perceived favorably and thus adopted. When we combine this with the suggestion that certain justifications (i.e., lines of reasoning) are stronger than others [12], it logically leads us to propose that providing justifications that fit with user preferences should be valuable for increasing KBS recommendation acceptance. Accordingly, the following research question guides our study:

RQ: How does fitting KBS justifications to a user's cognitive preferences influence the user's acceptance of KBS recommendations?

To address our research question, we first review the explanation literature to build a foundation for our research. Then, we leverage CFT to explain why fit is important for understanding the influence of

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KBS recommendations on users. We also employ the PEF paradigm to provide an alternative explanation of how KBS recommendations will influence user behavior. Our theoretical model is then tested by an experiment in which we examine the processing of explanations provided by a KBS—focusing on explanations in a credibility-assessment task that will allow us to compare the two theories. Finally, we address the results and contributions of this experiment with respect to improving KBS acceptance.

2. Theory and hypotheses for KBS recommendations

We examine KBS explanations through two bodies of literature. First, we examine the KBS explanation literature. The KBS explanation literature provides constructs such as explanation quality and explanation influence (see Fig. 1). Second, we combine the KBS literature with theories of fit literature. In particular, we look out how fitting the explanation to the user will impact explanation quality and explanation influence. Fig. 1 depicts the overall theoretical model that we propose and further justify in this section. Before explaining our specific hypotheses, we define our null hypothesis:

H0. Fitting KBS justifications to a user's cognitive preferences does not influence the user's acceptance of KBS recommendations

2.1. Knowledge-based system explanations

KBS have been an important theme in information systems (IS) research for quite some time. Topics include adoption of early medical information systems [e.g., 7], loan evaluation systems [e.g., 13], and more recently, deception detection systems [e.g., 3]. One continuing theme in KBS research is the use of explanations. An explanation is a description of the reasoning processes the KBS uses to solve problems and make recommendations [5,14].

Explanation use is an important determinant of the influence and user acceptance of the KBS's decision [15–17]. Explanations help the user understand the situation or how the KBS came up with its results. Understanding a KBS can influence the user to believe the KBS, thus causing the user to agree more with the KBS [18].

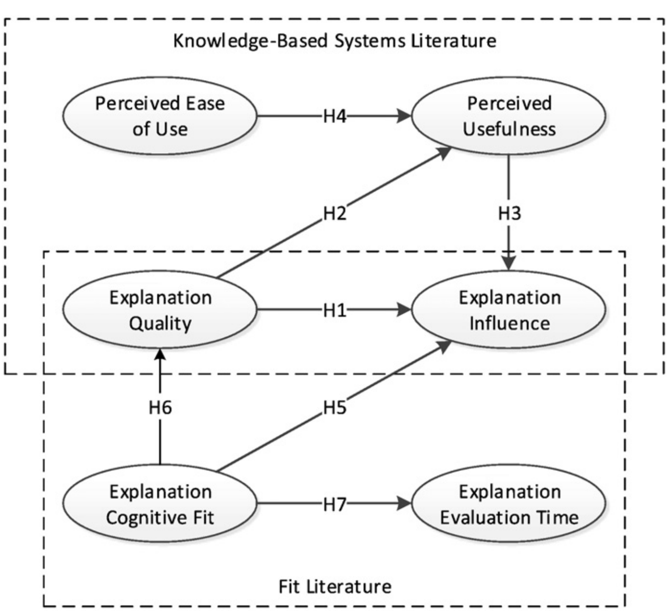

Fig. 1. Hypothetical model.

Because convincing the user to agree with the KBS is the goal of a KBS (assuming that the KBS recommendation is correct), we use two metrics to evaluate the KBS regarding this goal: explanation influence and explanation evaluation time. *Explanation influence* is the amount of change from what a user would have decided before the explanation to what the user decides after the explanation. This is often measured as the accuracy of the user [19]. *Explanation evaluation time* is the amount of time the user spends reading the explanation and coming to a decision [19].

Many types of explanations are possible, from emotion-based explanations to probability-based explanations [20–24], and people process explanations in different ways [25–28]. When people process explanations they aggregate their thoughts, feelings, and the argument made by the explanation into a perceived explanation quality. *Explanation quality* is a user's perception of the explanation's strength and adequacy. Measuring this allows researchers to collect and remove individual differences in scientific studies. An explanation with high quality is perceived as well written and understandable, whether or not the user agrees with it. Evidence of strong, persuasive arguments leading to attitude and belief change has been well supported in the literature [29–31] (see Fig. 1). When a user perceives an explanation to be strong and of high quality, he or she is more likely to have favorable message-oriented thoughts that cause the user to believe the message [32]. These message-oriented thoughts occur because high-quality explanations motivate a reader to understand and process the explanation [30].

H1. Explanation quality will increase explanation influence.

The perceptions and influence of a KBS explanation are tightly integrated with the KBS that provides the explanation to the user. Specifically, explanation quality will increase the user's perception of the system's competence. Explanations can cause users to perceive a KBS as more competent [10] than a KBS without an explanation. KBS are seen as competent when users believe that KBS have the ability, skills, and expertise to act [33]. Explanations make the reasoning process of the KBS transparent, allowing the user to judge the ability, expertise, and usefulness of the system [10]. The *perceived usefulness* of the KBS is a user's belief regarding its ability to enhance job performance [34].

H2. Explanation quality will increase perceived usefulness of the KBS.

When users perceive KBS as more useful, they will have more confidence in the output and decisions made by the KBS [35]. This confidence is due to users perceiving KBS as accurate and reliable, which in turn leads them to trust KBS to make more correct decisions then the user would have made without the KBS [10,35]. When users believe that KBS will provide more correct decisions, they will follow the recommendation of KBS, thereby increasing the influence of outputted explanations on the user.

H3. Perceived usefulness of the KBS will increase explanation influence.

The perceived usefulness of a KBS is not complete without considering the influence of how easy the KBS is to use. *Perceived ease of use* is the degree to which a user believes using the KBS is free from effort [34]. When a KBS is easier to use, all other things being equal, it has greater potential to be useful [34]. This positive relationship has been replicated in a large number of studies [e.g., 34,36]. We add this relationship to our model simply for nomological completeness.

H4. Perceived ease of use will increase perceived usefulness.

2.2. Applying theories of fit to KBS

The combination of the task and the style and wording of the explanation can influence the effectiveness of the explanation [37]. Therefore, the fit between the explanation given and the person receiving it is an important factor of the influence, the evaluation time, and even the perceived quality of the explanation. To understand these relationships, we look to theories of fit. We highlight two theories of fit: CFT [38] and stage-environment fit (SEF) [39], with the latter being part of the PEF paradigm [40].

Fig. 1 introduces the hypotheses that we have covered so far, plus the extension we are introducing using theories of fit. Our extension of current literature adds the cognitive fit leading to explanation quality, explanation influence, and explanation evaluation time. Each piece of this extension will be discussed in detail after we discuss theories of fit.

Cognitive fit indicates the degree to which a task's environmental factors—such as programming language [41] and visual representation [42]—match the nature of the task [38]. When there is good cognitive fit, a person does not have to transform his or her mental understanding of a task into a representation of the task [38]. When cognitive fit does not exist, a person has to perform multiple tasks simultaneously, increasing cognitive load [43] and decreasing task speed and task accuracy [44]. Consequently, CFT proposes that decision makers can be faster and more accurate in their decisions when their mental representation matches the task representation (see Fig. 2), that is, whenever there is cognitive fit [38,45]. For examples of CFT research in the IS literature see Appendix A.

According to CFT, the *task representation* is the format and manner of presenting the task. The nature of the problem changes an individual's mental representation of the task [38,46,47] because individuals acquire information based on how it is presented [42,48]. Task instructions often define the task as well as provide a mental model of the task that can influence the mental representation [49,50].

A *mental representation* is a person's knowledge or understanding of how a task functions and how to attempt to obtain a solution to the task. A mental representation allows a person to retrieve, store, analyze, and use information [51]. A person's mental representation can take form on the basis of various sources: task-related skills, abilities possessed by the individual that facilitate the task [52], decision style [53], cognitive style [54,55], and experience with the domain and the tool [44,56–58].

CFT explains that the task and mental representations are part of the *task space*, which is "a set of points, or nodes, each of which is a knowledge state" [46 p. 108]. A *knowledge state* "is the set of things the problem solver knows or postulates" [46 p. 108]. Consequently, what an individual knows or perceives changes the individual's model of the problem. Even isomorphs—two tasks in which "the solution path of one may be translated step by step into a solution path of the other and vice versa" [59 p. 22]—change the ability of an individual to accomplish the task [59].

CFT also proposes that individuals have a limited capacity to process information and that, because of this limitation, they are more effective at problem solving when task-environment complexity is reduced [38]. Because processing information is influenced by how the information is received, factors related to the problem-solving environment, such as problem representation, tools, and techniques, can reduce complexity if the environment supports the strategies required to perform the task [38]. That is, if an environment facilitates the cognitive processes necessary to transform the problem into a solution (i.e., fit), then task complexity is reduced [41]. This reduction is due to the fact that when the cognitive processes the individual uses to acquire information from the task match the cognitive processes required to complete the task, the task will be facilitated by the task representation [38]. This happens because there is no need to transform the mental representation generated by the processes used to acquire the information into a mental representation that can use the processes needed to accomplish the task [38]. Thus, cognitive load is decreased [43].

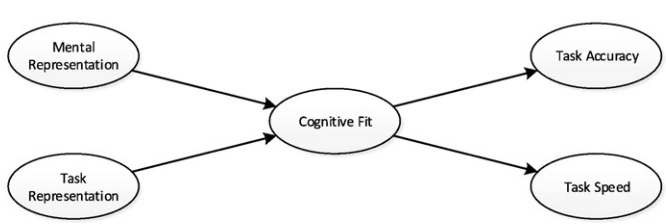

Fig. 2. Cognitive fit theory.

Conversely, where there is no fit—as a result of either under- or over-fit [60] —the processes used to acquire information cannot be used to accomplish the task [38]. When the same process cannot be used, individuals have to perform two subtasks: acquiring information and transforming the information to perform the task. The problem with having two subtasks is that individuals typically either form a mental representation based on the information and will need to transform the representation to accomplish the task, or they form a mental representation based on the task and will need to transform the information to accomplish the task [38]. Therefore, when the information does not have to be transformed, individuals will be able to internalize information in an explanation and apply it directly to the task, allowing the explanation to have more influence.

Specifically, in the context of this paper, we look at the fit between classification explanations and propensity to stereotype. A classification explanation is one that makes a conclusion about a specific instance based on a general population (in other words, such explanations are stereotypes). A propensity to stereotype (PtS) is a cognitive style defined as the "inferential logic by which people translate easily detected information about demographic attributes into best-guess hypotheses about personal attributes of a stranger" [61, p. 56]. For hypotheses 5–7, we focus on the fit between an individual's PtS and whether or not they receive a classification explanation.

H5. Explanation cognitive fit will increase explanation influence.

The reduction of complexity by cognitive fit will cause individuals to perceive the argument as a stronger and better one, because the user will be able to focus on the explanation itself and will not have to spend time trying to understand the explanation. That is, the user does not have to transform the explanation into something usable [38]. Because the user does not have to transform the explanation, the user will be able to perceive more readily the benefits of using the explanation.

H6. Explanation cognitive fit will increase explanation quality.

CFT explains that when an individual tries to perform multiple tasks simultaneously, the person's performance (task speed and accuracy) of the tasks worsens [44]. When an individual's mental representation and task representation differ, it is as though the person is performing multiple tasks simultaneously. This mismatch causes degradation in task accuracy and speed [45,62]. The degradation is increased in complex tasks where increased cognitive effort is needed just to accomplish a single task [45]. To recap, CFT states that decision makers can be faster and more accurate in their decisions when the individual's mental representation matches the task representation, that is, whenever there is cognitive fit [38,45]. Therefore, the less complex the KBS explanation, the more rapidly the user should be able to process and evaluate the explanation.

H7. Explanation cognitive fit will decrease explanation evaluation time.

3. Methodology

3.1. Study context

The context for this study is deception detection. Deception detection is a common decision-making task for security and law enforcement. Furthermore, because accuracy in deception detection tasks is often as low as 50% [3,63,64], it is a decision-making context that has room for improvement.

3.2. Participants and demographics

A total of 263 upper-division students from a large southwestern U.S. university participated in this study. We chose university students because deception detection is a common, if not daily, activity for most adults and deception detection rates for untrained populations and trained professionals are similarly poor [3]. Moreover, because the task was a simple decision-making task, the use of student participants allowed us to generalize to most young decision-making adults [65]. The average age range of the participants was 18–24 years, with 109 participants (41.44%) being female.

3.3. Research stimulus and task

Participants were recruited from a large introductory IS course required for all business school students. Participants were given course credit for completing the study. Upon recruitment, participants were directed to an online pre-survey that we used to measure demographics and various personality measures, including the PtS[1]. Participants were also asked to sign up for a time (roughly a week in the future) to participate in the second portion of the study.

For the second portion of the study, participants came to a large computer lab on campus. This setting was chosen to introduce a sense of seriousness to the study. In the computer lab, participants were once again directed to an online survey that informed them they would be watching some videos, their input is needed to help determine whether the person in the video is telling the truth or lying, and their input will help determine the legal actions that should be taken against each person.

Participants then watched three of four randomly ordered two-minute videos of subjects in another study who could have cheated or stolen a ring. In the videos (e.g., Fig. 3) the people are interviewed regarding whether or not they cheated or stole the ring. Two of the videos are of females from a cheating study, one being truthful (did not cheat) and one being deceitful (cheated). The other two videos are of two males from a ring-theft study, one being truthful (did not steal the ring) and one being deceitful (stole the ring).

The participants in our study were then directed to make a judgment and indicate whether they thought the person in the video was truthful or deceptive (binary), how deceptive or truthful the person was (Likert-type scale from 1, “deceptive”, to 7, “truthful”), and how confident they were in their response (Likert-type scale from 1, strongly unconfident, to 7, strongly confident).

After they made this judgment, participants were shown the KBS's decision (see Fig. 4). The KBS's decisions were always accurate. The participants were also given an explanation of how the KBS arrived at that answer. The explanation randomly fit or did not fit the participant's cognitive style (i.e., the explanation was about classifying stereotypes or it was not). Each participant received either all fitting explanations or all nonfitting explanations. Consequently, the match between PtS and classification explanations was used as the measure of fit. Participants were also asked to rate the explanation quality of each explanation.

To give the participants the opportunity to modify their original judgments, they were asked the same judgment questions previously given. The first two rounds were used as a practice to accustom participants to the environment. After watching all videos, the participants were given the post-experimental survey.

[1] As stated above with respect to hypotheses 5, 6, and 7, a PtS cognitive style is being matched with a classification argument, under the assumption that people who engage in classification by way of stereotyping will see a classification explanation as better fitting.

3.4. Measurement

We used previously validated scales for perceived ease of use, perceived usefulness, and explanation quality but modified them to fit the context. Both perceived ease of use and perceived usefulness were measured with four items from Venkatesh and Davis [34]. Explanation quality was measured with four items from Andrews and Shimp [32].

For our context, we measured fit as the match between PtS and whether or not the person received a classification explanation. PtS was measured with six items from Shrivastava and Gregory [66]. The cognitive fit is between the cognitive style of a person and the cognitive style used in the explanation. The interaction of the two was used as the measure of fit. Therefore, participants scoring high on the PtS scale who also received a classification explanation had high fit, whereas everyone else had low fit. For a complete list of scale items see Appendix B.

Explanation evaluation time was calculated by the survey software using the time that participants spent on the page with the explanation before making their final judgments. Explanation influence was calculated by comparing the movement from the initial judgment (binary scale, truthfulness scale, and confidence scale) to the final judgment (binary scale, truthfulness scale, and confidence scale). If the explanation was more influential, there was more movement toward the accurate judgment. We also included a manipulation check to verify that the participants were reading the explanations given to them. Five participants failed the manipulation check, meaning that they did not read any of the explanations (or completely disregarded them), and therefore were not included our analysis. Also, it has been shown that when a user already agrees with the decision of the KBS there is no incentive to read an explanation [67]. Users who agreed with all decisions were not evaluated. This left us with 140 usable responses.

4. Analyses

We chose to analyze our model using a covariance-based structural equation (CB-SEM) using SAS 9.3 software [68] because we were testing a path model (Fig. 1) containing multiple endogenous and exogenous variables with reflective indicators including mediating effects. Before evaluating our model, we needed to verify that our instruments were valid and captured our intended constructs (i.e., construct validity). Therefore we start our analysis with our instrument validation before moving on to the evaluation of the model.

4.1. Instrument validation

Prior to evaluating the model, we conducted five analyses to ensure that the latent constructs exhibited factorial validity and reliability. First, we ran an exploratory factor analysis to verify the convergent validity of the constructs. Second, we also checked the Cronbach's alpha values of each construct to examine reliability (see Appendix B). We removed items that did not load well or cross-loaded on more than one construct, leaving us with the items presented in Table 1. Third, we checked for common-method bias by examining our correlations. As all of our correlations were low, common-method bias is less likely a concern than if our correlations were high [69,70]. Fourth, we checked for discriminant validity by examining the square root of the AVE in comparison to construct correlations [71]. The constructs showed strong discriminant validity by having low correlation between constructs and having all correlations below the square root of the AVE. Finally, we checked for multicollinearity by running a regression of all the constructs to predict explanation influence and checking the variance inflation factors (VIF) [72,73]. All VIF values were close to 1 (with a range of 1.06–1.18) and therefore showed no signs of multicollinearity. We present the means, standard deviations, and correlations in Table 2.

Fig. 3. Sample video.

4.2. Model evaluation

We tested all of the hypotheses in one model (as shown in Fig. 1). We used CB-SEM to test our model using SAS 9.3 software [68]. CB-SEM estimates all of the paths in the model simultaneously and provides model fit statistics [74], whereas attempting to analyze such a path model with regression techniques results in several statistical issues, including model misspecification [75]. The resulting model provides the regression beta coefficient and significance for each path. Before testing the hypotheses in the model, it is best to measure how well the model fits the sample data [76]. To check goodness-of-fit, the first thing we check for was a non-significant chi-square, a high goodness-of-fit index (near 1.0), and a high adjusted goodness-of-fit index (near 1.0). Our chi-square was non-significant (0.79), the goodness-of-fit index was high (0.99), and the adjusted goodness-of-fit index was also high (0.97) indicating that our model fits the sample data. Fig. 5 presents the results of our model testing. Fig. 5 shows that many of our hypotheses were significant. In particular, Fig. 5 shows that the knowledge-based system literature and the fit literature come together to create a more comprehensive explanation of the causal mechanisms behind explanation influence. We will examine the results of the specific hypotheses in more detail in the discussion.

5. Discussion

The purpose of this study was to address the research question, "how does fitting KBS justifications to a user's cognitive preferences influence the user's acceptance of KBS recommendations?" The overall answer is that fit, as predicted by CFT, causes the KBS to influence the user more than when there is no fit as demonstrated by the support for hypotheses 1 and 6. Therefore, we can reject the null hypothesis (H0) and declare that fitting KBS justifications to a user's cognitive preferences influences the user's acceptance of KBS recommendations. While increasing acceptance, explanation evaluation time is increased as predicted by the PEF paradigm. Table 3 summarizes our tested hypotheses.

Although most of the hypotheses were supported, two of them were not. H5, cognitive fit will increase explanation influence, was predicted by CFT but was not supported in our analysis. This non-significant result could have been caused by a small sample size. The result might also have been caused by the mediation of explanation quality, however explanation fit failed the first test for mediation (a significant direct relationship to explanation influence) with a p-value of 0.192. Therefore, we conclude that explanation fit likely only has an indirect relationship on explanation influence by first affecting explanation quality and then letting explanation quality affect explanation influence.

H7, cognitive fit will decrease explanation evaluation time, was predicted by CFT but was not supported. We believe that the PEF paradigm suggesting fit increases explanation evaluation time, may provide a strong explanation. The PEF paradigm [40] states that when a lack of fit exists among the skills, knowledge, characteristics, or needs of a person and the environment, the person will experience increased stress or strain [77,78]. This stress can cause a withdrawal from the technology [79]. Conversely, lack of stress due to fit can cause an increase in motivation to perform the task and in the satisfaction associated with performing the task [80].

As the use of KBS can be viewed not only as decision support, but also as an opportunity for the user to learn [9], we examine an educational aspect of the PEF paradigm: SEF. As part of the PEF

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DECEPTION DETECTION SYSTEM OUTPUT

The system's judgment is that the person in the video is:  Deceptive

A majority of people when acting deceptively are in a protective stance. What is true for
the majority of liars will probably be true for this person. Most people are affected by
the same psychological rules, and this person generally shares the attributes of most
people. Therefore, this person's protective stance is because of deception. Unless this
person does not share the same psychological rules of most people.

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Fig. 4. Sample displayed explanation.

Table 1
Factor loadings of scale items.

Items	PTS	PEU	PU	EQ
PTS1	0.552	0.036	0.227	0.010
PTS2	0.623	0.047	0.117	0.043
PTS3	0.719	0.042	0.164	0.077
PTS5	0.647	0.123	0.084	0.122
PEU2	0.057	0.647	0.112	0.055
PEU3	0.084	0.706	0.443	0.123
PU1	0.217	0.200	0.757	0.225
PU3	0.213	0.285	0.840	0.268
PU4	0.103	0.278	0.797	0.260
EQ1	0.067	0.130	0.286	0.901
EQ2	0.081	0.083	0.301	0.944
EQ3	0.116	0.119	0.274	0.951
EQ4	0.098	0.113	0.268	0.930

paradigm, SEF is an educational theory [39] that posits that when there is a fit and relatedness between an environment and a student, engagement (e.g., positive behavior and motivation) increases [81,82]. Increased engagement will result in increased time spent absorbing the information in the fitting environment, because the person has the capabilities and available resources to adopt the arrangements [40]. SEF opposes CFT in that SEF predicts that a user will be more engaged and will spend more time reading and evaluating the explanation when there is fit. Consequently, whereas CFT predicts an increase in explanation evaluation speed, SEF predicts a decrease in explanation evaluation speed.

5.1. Contributions to research

This study has three main contributions to research: 1) explanations that fit influence users but indirectly through explanation quality, 2) explanations that fit will likely increase the amount of time the users spends evaluating the explanation, and 3) an integrated model, leveraging system and cognitive components, is necessary to understand the impact of explanations in KBS. Here, we discuss each of these contributions in turn.

First, the main theoretical contribution of this study, the one that most directly answers our research question, is that explanations that fit with the user will influence the user more than non-cognitively fitting explanations, but that it is not a direct relationship and only indirectly affects explanation influence through explanation quality. CFT would predict that the explanation should have more influence and users should evaluate the explanation faster when the explanation fits with the user than when the explanation does not fit with the user. However, the results suggest two findings contrary to CFT: 1) that the value of the cognitive fit comes through perceived explanation quality by making users think that the explanation is of higher quality, and 2) contrary to CFT and consistent with PEF, explanation fit increase

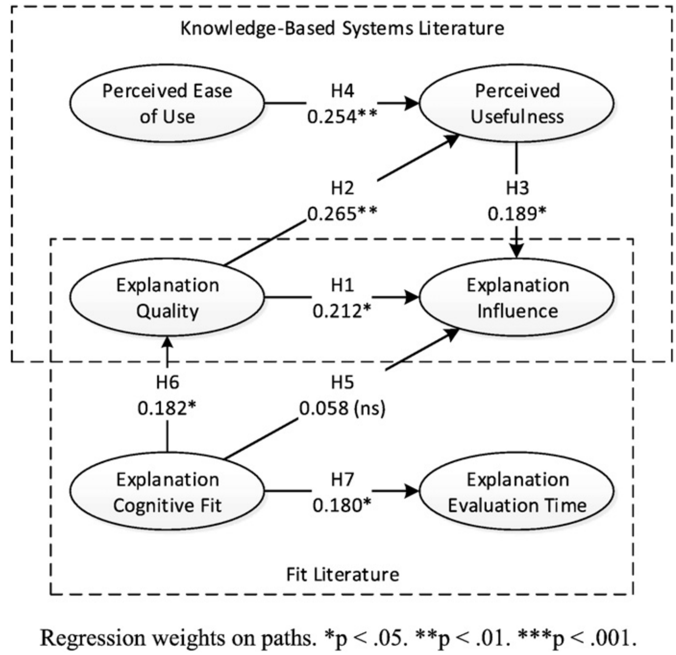

Fig. 5. Model results.

the time the user spends evaluating the explanation. In answering our research question, we conclude that users of KBS will spend more time evaluating and be influenced more by explanations that fit with the users through explanation quality. Future research in KBS needs to consider that fit works through explanation quality.

Second, CFT may be unable to explain evaluation time in the context of a KBS and that evaluation time is better explained by the PEF paradigm. This is important for KBS researchers, because explanations that cognitively fit with a user are likely to be engaging and increase the amount of time that a user spends with an explanation. Therefore, research aimed at optimizing evaluation time, such as credibility screening, needs to look at antecedents other than fit. This is an important finding as it provides a theoretical insight into dividing KBS into those that do not need fast response times that will benefit from explanations that fit with users and KBS that need fast response times and will not benefit from explanations that fit with users. KBS that need fast response times will benefit more by providing quick summary decisions than providing detailed explanations to users.

Last, this study provides an integrated model of KBS-level elements (perceived ease of use and perceived usefulness) and explanation elements (cognitive fit and explanation quality). This model helps answer outstanding research questions about how different types of explanations affect users and different conditions in which these

Table 2
Construct correlations.

Latent construct	Mean	SD	AVE	(1)	(2)	(3)	(4)	(5)	(6)
(1) Explanation cognitive fit	1.03	1.69	NA	**NA**					
(2) Explanation influence	9.81	10.36	NA	0.109 (0.196)	**NA**				
(3) Explanation evaluation time	19.92	9.03	NA	0.187 (0.027)	0.105 (0.213)	**NA**			
(4) Explanation quality	3.59	1.63	0.868	0.189 (0.025)	0.285 (0.001)	0.026 (0.756)	**0.932**		
(5) Perceived ease of use	5.15	1.20	0.458	−0.082 (0.333)	0.049 (0.564)	0.017 (0.838)	0.099 (0.246)	**0.677**	
(6) Perceived usefulness	4.18	1.28	0.638	0.050 (0.555)	0.254 (0.002)	0.062 (0.465)	0.288 (0.001)	0.278 (0.001)	**0.799**

p-Value is reported beneath correlations; square root of the AVE is on the diagonals.
SD = Standard Deviation;' AVE = Average Variance Extracted.

Table 3
Summary of hypotheses.

Hypothesis	Findings
H1: Explanation quality will increase explanation influence.	Supported
H2: Explanation quality will increase perceived usefulness of the KBS.	Supported
H3: Perceived usefulness of the KBS will increase explanation influence.	Supported
H4: Perceived ease of use will increase perceived usefulness.	Supported
H5: Explanation cognitive fit will increase explanation influence.	Not supported
H6: Explanation cognitive fit will increase explanation quality.	Supported
H7: Explanation cognitive fit will decrease explanation evaluation time.	Significant in opposite direction

explanations should be used. Furthermore, this model can now be extended to investigate additional personal traits and states that could influence the interactions of system elements and explanation elements.

5.2. Limitations and future research

Our implications should be viewed in light of the limitations of our study. Along with the task-performance measures of task speed and task accuracy, CFT has been used to explain an increase in perceived ease of use and in perceived usefulness due to enhanced information processing caused by cognitive fit [83–85]. Because perceived ease of use is the amount of effort the user believes is required to use the KBS or tool and cognitive fit reduces cognitive effort, improved perceived ease of use is a direct result of fit [86]. We did not test these constructs, because we believe that the fit of the explanation (explanation level) and the perceived ease of use and perceived usefulness of the KBS (system level) are on two different conceptual levels and it would not be correct to analyze them together.

Conducting this study in a deception detection environment may have limited the generalizability of the findings. Because deception detection is inherently difficult and complex for users, CFT may have a larger influence in a less complex task. One of the criticisms and limitations of CFT is that the theory is usually tested in simple tasks [62,87,88]. CFT has been extended to complex tasks that involve interruptions, social dimensions, multiple tasks, or extra analysis [89,90], but empirical evidence shows that certain types of complex tasks may not benefit from cognitive fit [45]. Deception detection may be one of those complex tasks for which CFT does not have a strong impact. Future research should study this phenomenon in another domain with other tasks.

Last, in terms of assessing fit, we only looked at propensity to stereotype as our measure of fit. Future research should look into other measures of fit combined with explanations from KBS. One such research study could be to examine explanation fit with different types of tasks (such as buying a replacement product versus buying a new product to fulfill a need).

5.3. Implications for practice

The results of this study show that a universal explanation will not work for all types of users. Although this is partially in line with previous research, this study takes another step toward understanding what needs to be done to develop adaptive KBS. An explanation from a KBS that cognitively fits with the user will increase the perceived quality of the explanation to the user. For example, when an officer is interacting with a KBS designed to look for deception in a border environment, the officer will want the KBS to explain the signs of deception that the KBS recognizes in the individual rather than telling about the cognitive behaviors observed in deceptive monkeys. Consequently, companies should try to learn more about their individual users when presenting them with information. One case of this would be using past purchase histories to help guide the KBS.

In the context of online shopping in which individuals are purchasing experience goods, such as books, a KBS that provides explanations for why the shopper will emotionally enjoy a book, or how others emotionally enjoyed a book, will perform better than an explanation touting the book's technical qualities. Conversely, structured tasks, like purchasing a printer, will need more of a sign-based explanation for why it is a good pick for the shopper. Explanations about how fast it can print compared to other printers will perform above those that discuss the printer's emotional qualities.

If companies can understand how their users process information, they can use that knowledge to build explanations of their KBS that fit with their users. Fitting the explanations to the user will engage the user and allow the user to evaluate the explanation more fully. Fitting the explanations will also increase the likelihood that the user will see the explanation as high quality leading to higher perceived explanation influence, and eventual action. However, we urge caution because fitting explanations may cause users to accept the explanations regardless of the accuracy of the system.

6. Conclusion

KBS help decision makers make high-quality decisions. This research study explored how cognitively fitting explanations can enhance the influence exerted by these KBS. We showed that when there is a cognitive fit between an explanation and a user, the user is more likely to spend more time reading the explanation and to be influenced more strongly by the explanation. Contrary to CFT that predicts faster response times, we found that explanations that fit with users lead to enhanced user engagement and longer response times. User engagement with explanations that fit is explained by PEF. Therefore, systems designed to increase user engagement with KBS that can afford longer decision time should use explanations that fit with the users.

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Appendix A. Uses of cognitive fit theory in IS

In addition to its use in studies of graphs and tables [91], CFT has been used to explain sense making in data-exploration tasks [92], efficient query building [93,94], online shopping [95,96], graphs and information load [97], graphs and uncertainty [98,99], geographical information systems [100–102], accounting visualization [88,103–105], spreadsheet usage and error correction [106], expert-data and self-organizing maps [107], maps [108,109], model comprehension [110–112], efficient database views [113], visual interactive simulations [114], multi-attribute data presentation [115], software development [116–118], hypertext and knowledge type [119], executive support systems [120,121], judgment strategies [122], system acceptance [123], multimedia effectiveness [124], interface design [125], decision aid features [126], pattern recognition [127], virtual reality [128], knowledge transfer [129], decision tables, trees, and rules [130], expertise and online reviews [131], as a special case of task-technology fit [132–135], and use of a joystick in tank simulations [136].

Appendix B. Scale items

Construct	Cronbach's Alpha	Code	Item (* = removed from analysis)
Propensity to stereotype [66]	Raw: 0.703 Std: 0.696	PTS1	I feel the nationality of a person can indicate a lot about the person.
		PTS2	I can tell a great deal about a person by knowing his/her age.
		PTS3	I can tell a great deal about a person by knowing the person's gender
		PTS4	*I can form an opinion about a person within the first few minutes of interacting with the person.
		PTS5	I find it easy to know what a person is like just by looking at him/her.
		PTS6	*When I first meet someone I tend to notice the differences between myself and the other person.
Perceived ease of use [34]	Raw: 0.661 Std: 0.668	PEU1	*My interaction with the system is clear and understandable.
		PEU2	Interacting with the system does not require a lot of my mental effort.
		PEU3	I find the system to be easy to use.
		PEU4	*I find it easy to get the system to do what I want it to do
Perceived usefulness [34]	Raw: 0.885 Std: 0.885	PU1	Using the system improves my performance in [the task].
		PU2	*Using the system in [the task] increases my productivity.
		PU3	Using the system enhances my effectiveness in [the task].
		PU4	I find the system to be useful in [the task].
Explanation quality [32]	Multiple measurements	EQ1	Weak … Strong
		EQ2	Unpersuasive … Persuasive
		EQ3	Unconvincing … Convincing
		EQ4	Bad Argument … Good Argument

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