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Degrees of Humanness in Technology: What Type of Trust Matters?

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ABSTRACT (REQUIRED)

Significant research has shown the impact of trust (i.e., trusting beliefs) in information technology (IT) settings. Most research has investigated trust between the consumer and the e-vendor. However, IT researchers have begun to investigate user trust in the technology artifact itself (*trust-in-technology*). This research has measured trust using both *interpersonal trust variables* (ability, benevolence, and integrity) and *system-like trust variables* (functionality, helpfulness, and reliability). Both measures seem to work. However, it is unclear when researchers should use *interpersonal* versus *system-like* trust-in-technology constructs. This study hypothesizes *interpersonal trust* will have a stronger influence on users' outcomes when the technology is *more human-like*. By contrast, *system-like trust* will have a stronger influence when the technology is *less human-like*. We validate this concept by measuring how both interpersonal and system-like trust predict user outcomes across three technologies: Facebook (high humanness), a recommendation agent (medium humanness), and Microsoft Access (low humanness).

Keywords

Trust, trust-in-technology, Facebook, recommendation agent, continuance intention, enjoyment, usefulness

INTRODUCTION

The literature regarding trust in information technology (IT) contexts shows compelling evidence that trust predicts technology usage intention. This literature has typically examined trust in the e-commerce environment, focusing on trust in an e-vendor or online firm (Gefen et al. 2003) and trust in virtual or online teams/communities (Hsu et al. 2007).

Recently, researchers have begun to explore users' trust in the technology artifact itself, including online recommendation agents (RA) (Wang and Benbasat 2005), manufacturing plant systems (Muir and Moray 1996), business information systems (Lippert 2001), m-commerce technologies (Vance et al. 2008), and websites (Lowry et al. 2008). Trust-in-technology is defined as the extent to which one is willing to depend on a technology because one believes the technology *itself* exhibits desirable attributes (McKnight 2005). Trust-in-technology research differs from the earlier literature because a *technology* is being studied as the trust object rather than another human entity (i.e., the vendor or organization). This research answers the call to study the IT artifact (Orlikowski and Iacono 2001).

While trust-in-technology research shows humans can and do trust technology artifacts for various reasons, it is not consistent on how to conceptualize trusting beliefs. Some researchers conceptualize trust-in-technology based on *interpersonal* trusting attributes such as ability, benevolence, and integrity (e.g., Wang and Benbasat 2005), while others conceptualize it based upon *system-like* or technical trusting attributes such as functionality, helpfulness, and reliability (Lippert 2001; Muir and Moray 1996). These divergent trust-in-technology concepts are not unexpected, as other disciplines have developed competing multi-dimensional constructs of trust (Corritore et al. 2003). However, IT researchers should investigate the differences between them, and the contexts in which one set may be more applicable than the other. *This research's goal is to empirically test the difference in predictive ability for these two sets of trust-in-technology constructs, and to determine when these constructs should be applied.* Knowing this will guide researchers to choose the appropriate constructs (and corresponding measures) for studying trust-in-technology.

Significant empirical research has found that people tend to attribute human qualities to technologies with which they interact socially (Kidd and Breazeal 2008; Reeves and Nass 1996). Based on this research, we investigate how trusting belief constructs differ in their predictive ability based upon how "human-like" a technology is. We examine three technologies that we predict differ in degree of humanness: Facebook, an online product recommendation agent (RA), and Microsoft Access. By humanness we mean the extent to which a technology is perceived to act like a person in its interfaces with people. Trust is important in studying these technologies because their use involves risk. For example, Facebook involves privacy risks, RAs involve product choice risks, and Access involves task completion risks. We contribute to the literature by identifying when trust-in-technology researchers should apply interpersonal- versus system-like trusting beliefs.

TWO TRUST-IN-TECHNOLOGY CONCEPTS: INTERPERSONAL AND SYSTEM-LIKE

While trust-in-technology is a relatively new and under-studied domain of IT research, scholars consistently find that trust-in-technology exists and that it is composed of multiple beliefs. Some trusting beliefs relate to the technology's human-like characteristics. For example, some researchers have used interpersonal trust beliefs—competence, integrity, and benevolence—to study trust-in-technology (Lowry et al. 2008, Vance et al. 2008, Wang and Benbasat 2005). Other researchers have used trusting beliefs that relate more to the technology's system-like characteristics, such as its functionality and reliability (Lippert, 2001; Muir and Moray, 1996; Thatcher et al. 2011).

Row	Interpersonal Trusting Beliefs	System-like Trusting Beliefs
1.	***Competence:*** Belief that the technology has the skills, competencies, and abilities to have influence with some specific domain. (Lowry et al. 2008, Vance et al. 2008, Wang and Benbasat 2005)	***Functionality:*** Belief that the technology will have the functions or features needed to accomplish one's task(s) (Lippert 2001, Muir and Moray 1996, Thatcher et al. 2011)
2.	***Integrity:*** Belief that the technology adheres to an acceptable set of principles. (Lowry et al. 2008, Vance et al. 2008, Wang and Benbasat 2005)	***Reliability:*** Belief that the technology will continually operate properly, or will operate in a consistent flawless manner. (Lippert 2001, Muir and Moray 1996)
3.	***Benevolence:*** Belief that the technology cares about and acts in users' best interests. (Lowry et al. 2008, Vance et al. 2008, Wang and Benbasat 2005)	***Helpfulness:*** Belief that the technology will provide adequate and responsive help (Thatcher et al. 2011).

Table 1. Major Trust in Technology Constructs

Prominent interpersonal and system-like trusting beliefs from prior trust-in-technology research can be grouped by conceptual similarity (Table 1). The two trusting belief sets fall under categories that represent conceptually similar, yet distinct constructs as presented in the Table 1 rows. For example in Row 1, competence beliefs relate more to human-like trusting characteristics of the technology, while functionality beliefs relate more to system-like trusting characteristics, yet both constructs relate to the trustee's abilities. While a person demonstrates ability by performing a task well or by providing timely information, a technology exhibits ability when it provides the functions or features a user requires to complete tasks. So a technology's ability is different from that of a human and refers to the technology's 'functional' capability to enable its user perform a task (McKnight 2005). Integrity and reliability (Row 2) are also conceptually-similar, yet distinct trusting beliefs. A person demonstrates integrity by keeping commitments and telling the truth. By contrast, a technology demonstrates integrity by being reliable or by consistently doing what it is supposed to do every time the technology is used. In Row 3, we categorize the interpersonal trusting belief benevolence with a system-like attribute called helpfulness. A technology cannot be benevolent per se because it does not have the moral agency to care for or act in another's best interest. However, technology can be 'benevolent' in a limited way by being helpful through its help function. Therefore, the system-like manifestation of human benevolence is called helpfulness.

Given the literature's to-date use of these trust-in-technology trusting beliefs, it is less than clear when a researcher should use the interpersonal versus the system-like beliefs. For example, interpersonal trust beliefs have been used to study RAs (Wang and Benbasat 2005), websites (Lowry et al. 2008), and m-commerce technologies (Vance et al. 2008). The system-like attributes have been used for example, to study automated manufacturing systems (Muir and Moray 1996), business information systems (Lippert 2001), and knowledge management systems (Thatcher et al. 2011). These systems represent a wide technology range. Next we suggest that the extent to which a technology is perceived to be human-like should determine which trusting beliefs to apply.

Human-Like Technologies

Early work on trust-in-technology was performed by Reeves and Nass, who found that people can and do treat technologies as if they are real people (e.g., Nass et al., 1996; Reeves and Nass, 1996). They found that people develop relationships with computer systems and applications such as websites. In these studies, people described technologies in human-like terms and responded to them as if they were people. The authors emphasize that people do not think technologies *are* human, but when people perceive a technology as close enough to being human they will respond socially to it "even though they believe it is not reasonable to do so" (Reeves and Nass 1996, p 7). This is especially true when computer systems encourage humans to interact socially by communicating, instructing, and taking turns interacting.

Corritore et al. (2003) explain that IT are social actors to the extent they have social presence. Social presence is defined as the extent to which a medium allows users to perceive others as being physically present (Fulk et al. 1987). A face-to-face medium is considered to have the most social presence, whereas written, text-based communication has the least. Web sites and other IT have been shown to have more social presence if they exhibit a strong social richness, incorporate personalization and human images, or incorporate human audio or video (Cyr et al. 2009; Gefen and Straub 2004; Lombard and Ditton 1997).

We follow Reeves and Nass by defining human-like technologies as those that are inherently communicative, instructive, and interactive. For example, RAs such as those Wang and Benbasat (2005) studied have human-like characteristics to the extent that they ask questions that allow humans to respond, provide information to humans, and sometimes mimic person-to-person communication. Further, the lens of human-like technologies extends to technologies that mediate human interactions. Reeves and Nass (1996) found that when people interacted with technology that provided representations of humans, such as television, people interacted with the technology as if it were a person.

By contrast, software systems like Microsoft Access do not interact with users in a very human-like fashion. Access interacts with its users in a limited way with its help function. For example, the help function for Access provides a place for one to search for help or browse help topics. The help function also has a Contact Us button that takes one to an Access Support website. At the website, one can choose among three options: email Support, Chat with Support, or Phone Support. Since these options are several clicks away from users, it is expected that Access users will perceive it as less human-like than an RA, which is often represented as a person-like figure on the screen. Thus, we expect that individuals will perceive a RA to be more human-like than Microsoft Access.

Hypothesis 1a. Users will rate a Recommendation Agent as more human-like than Microsoft Access.

We also expect users will perceive Facebook.com to be more human-like than an RA because Facebook enables users to find, invite, track, and communicate with friends. Reeves and Nass found that people perceive technology that mediates communication between humans *as* the communicator, and responded to it with typical human social responses. Even though an RA interface can contain human-like images or a playful avatar, it does not act as a mediator. Also, these are not one's friends. With Facebook, we are interacting with friends, and this interaction can be initiated by either party. The same is not true of a RA. RAs are not friends per se, and interactions with RAs are driven solely by the user. This means that an RA would be perceived to be less human-like than is Facebook.

Hypothesis 1b. Users will rate Facebook as more human-like than a Recommendation Agent.

In summary, we believe users will rate Facebook as the most human-like, followed by a RA, and then by Microsoft Access. Viewed from the other end of the human-like to technology-like continuum, Access will be considered the most system-like, followed by the RA and then Facebook.

Next we relate a technology's humanness to the predictive ability of interpersonal trust versus system-like trust. Our general proposition here is two-fold: (1) for more human-like technologies, interpersonal trust will be a better predictor than will system-like trust; (2) for less human-like technologies, system-like trust will be a better predictor than will interpersonal trust. We argue for this below based on the three technologies listed above.

Figure 1: Continuum of System-Likeness to Human-Likeness

We predict trusting beliefs should influence perceived usefulness (perceptions of the utility provided by an IT), continuance intention (readiness to continue using an IT), and enjoyment (perceptions that using an IT is enjoyable in its own right, aside from any performance consequences). We chose these constructs because prior work shows that they are important in the trust nomological network. Trusting beliefs have been found to influence usefulness and continuance intention (Gefen et al. 2003). Trust should predict enjoyment because trust predicts other affective response constructs such as job satisfaction (Dirks and Ferrin 2002). Also, liking and trust have been found to be strongly related in the communication literature (Walther and Bunz 2005). We also choose these constructs because they represent different psychological responses: enjoyment is an affective response, perceived usefulness is a cognitive response, and continuance intention is a willingness or determination.

Because RAs are likely to be more human-like than is Microsoft Access, users will associate the *interpersonal* trusting beliefs more with recommendation agents than with Microsoft Access. Because Microsoft Access is less human-like, its users will be more likely to associate the *system-like* trusting beliefs with it. For example, based on Table 1, respondents who use Microsoft Access will likely relate better to the functionality, reliability and helpfulness trusting beliefs than to the competence, integrity and benevolence beliefs.

Because of this, we predict that the more human-like a technology, the better the interpersonal trusting beliefs will predict its dependent variables (Figure 2). While we believe that some interpersonal trusting beliefs may be predictive in whatever technology context we study, we believe that for a technology that allows the user to interact more socially, to ask questions and receive answers, and to exhibit a greater social presence, interpersonal trusting beliefs will be more predictive. Given how H1a and H1b order the human-like degree of our three technologies, we predict:

Hypothesis 2a. The interpersonal trusting beliefs will be stronger predictors of enjoyment, perceived usefulness, and continuance intention for a Recommendation Agent than for Microsoft Access.

Hypothesis 2b. The interpersonal trusting beliefs will be a stronger predictor of enjoyment, perceived usefulness, and continuance intention for Facebook than for a Recommendation Agent.

As a technology's human-like properties decrease, the ability to interact socially with the technology also decreases. When these social cues are lacking, the user will evaluate the properties of the system itself. When utilizing a non-human like technology, the user views the technology less like a social entity, and more like a tool. As a tool, the user will perceive the technology's system-like aspects of functionality, reliability and helpfulness as more predictive than the interpersonal trust attributes (Figure 2).

Hypothesis 3a. The system-like trusting beliefs will be stronger predictors of enjoyment, perceived usefulness, and continuance intention for Microsoft Access than for a Recommendation Agent.

Hypothesis 3b. The system-like trusting beliefs will be stronger predictors of enjoyment, perceived usefulness, and continuance intention for a Recommendation Agent than for Facebook.

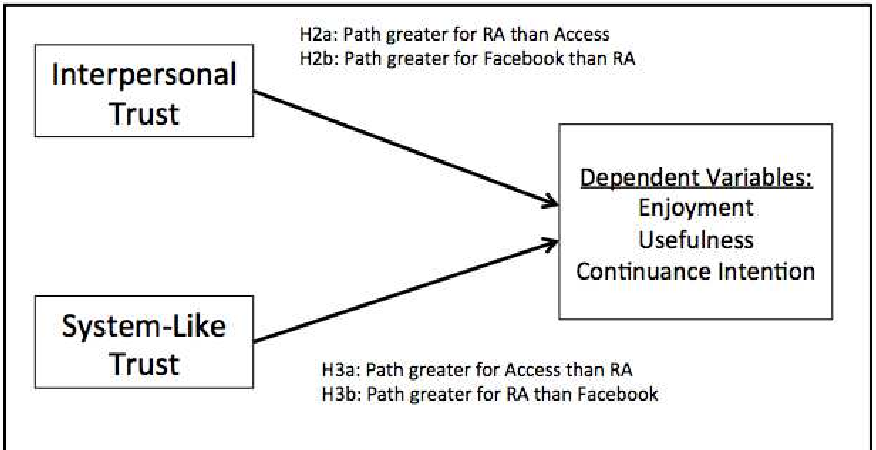

Figure 2: Research Model

METHOD

The research study was conducted via a survey of 495 undergraduate business students at a large US university. Class size was 511, for a response rate of 97%. Points were given for completing the survey, which was performed in an introductory information systems course, in which students had completed several weeks of Microsoft Access exercises. Since we also asked about Facebook usage, we excluded non-users of Facebook and incomplete responders for a final sample of 435. While this sample does not generalize to all Access, Facebook, and RA users, it is similar to those used in e-commerce trust studies (Gefen et al. 2003).

To introduce all students to a RA, we performed a pre-survey exercise in which they used myproductadvisor.com to receive recommendations for two different products. Myproductadvisor.com is an RA that interacts in a limited manner with the user. It utilizes a human-like character that asks questions on the screen and gives directions about how to use the site. Based upon answers to the user's questions it then provides several recommendations for the requested product.

The pre-survey exercise was developed by one of the authors, tested in three rounds by the other two authors, and then pretested using the teaching assistants from the course. First, the students were presented with a short description of RAs in general, and were directed to navigate to www.myproductadvisor.com. Next the students were taken through a series of steps to introduce them to the RA's features and to assist them to enter three different criteria for getting a recommendation for a new television. After guiding the students through interpreting the RA output, the students again added three criteria to receive a recommendation for a laptop computer. Research has found that new system users develop opinions quickly from such exposure (Tractinsky 1997).

The survey was administered to all students immediately following the RA exercise. All students responded to the same items about the same constructs (the three interpersonal trust beliefs, the three system-like trust beliefs, usefulness, enjoyment, and continuance intentions) for all three technologies. For example, all students responded to the interpersonal trusting belief, integrity item about keeping commitments three times: once for Facebook ["Facebook.com keeps its commitments"], once for the RA ["MyProductAdvisor.com keeps its commitments"], and once for Access ["Access keeps its commitments"]. All items used 7-point Likert scales, were adapted from earlier trust studies, and were piloted in previous semesters.

At the end of the survey, respondents were asked how human-like versus technology-like they felt each technology was (using the following 7-point scales anchored at 1-4-7): 1. "Much more Technology-like–Equal—Much more Human-like" 2. "Much more Machine-like—Equal—Much more Person-like" and 3. "Has many more Techno Qualities—Equal—Has many more Human qualities." We controlled for age, gender, and experience with the technology.

RESULTS

We found a clear distinction in how human the three technologies were perceived. On average, Facebook was perceived to be the most human (4.7/7.0), with the RA next (3.4/7.0) and then M/S Access (2.2/7.0). We tested these differences by pairs at the construct average level and found the RA was considered significantly more human than Access ($p<.001$), supporting H1a. FB was considered significantly more human than the RA ($p<.001$), supporting H1b. We then tested these differences at the item level (e.g., FB item 1 vs. RA item 1) with the same result. This provides evidence of the relative perceived humanness of these technologies.

We tested the remaining hypotheses using EQS's multi-group method that tests for parameter invariance (equivalence) across groups. EQS is a structural equation modeling program that can assess relationships for latent variables as well as for manifest variables. For our study, all constructs relating to the same technology were considered a different group or dataset. Before using EQS, we ran principal component analyses with direct oblimin rotation in SPSS to perform item culling. All items loaded between .70 and .99 except for two of the benevolence items in the recommendation agent dataset that loaded at .57 and .67. There were no cross-loadings greater than 0.30, so we retained these items.

Facebook	Mean	ICR	AVE	1	2	3	4	5	6	7	8	9
1. Usefulness	5.39	.97	.90	**.95**								
2. Enjoyment	5.64	.97	.92	.77	**.96**							
3. Usage Intention	5.87	.99	.96	.68	.77	**.98**						
4. Reliability	5.00	.95	.85	.46	.46	.41	**.92**					
5. Functionality	5.57	.94	.85	.63	.64	.59	.73	**.92**				
6. Helpfulness	4.41	.97	.91	.23	.22	.14	.51	.47	**.95**			
7. Integrity	4.68	.97	.92	.42	.27	.30	.58	.51	.48	**.96**		
8. Competence	6.03	.97	.92	.67	.69	.66	.54	.72	.22	.43	**.96**	
9. Benevolence	4.43	.92	.79	.38	.31	.22	.50	.42	.55	.73	.32	**.89**
Recommendation Agent	Mean	ICR	AVE	1	2	4	5	6	7	8	9	10
1. Usefulness	4.65	.95	.86	**.93**								
2. Enjoyment	4.78	.93	.82	.61	**.90**							
3. Usage Intention	4.15	.98	.95	.51	.59	**.98**						
4. Reliability	4.43	.88	.72	.55	.45	.41	**.85**					
5. Functionality	4.99	.94	.84	.62	.49	.38	.73	**.91**				
6. Helpfulness	4.99	.89	.74	.47	.46	.27	.56	.69	**.86**			
7. Integrity	4.71	.94	.84	.47	.46	.35	.57	.49	.49	**.92**		
8. Competence	5.00	.94	.85	.66	.56	.44	.64	.72	.69	.72	**.92**	
9. Benevolence	4.68	.88	.71	.57	.54	.40	.51	.58	.56	.73	.77	**.84**
Microsoft Access	Mean	ICR	AVE	1	2	4	5	6	7	8	9	10
1. Usefulness	5.30	.97	.93	**.96**								
2. Enjoyment	3.62	.97	.91	.44	**.96**							
3. Usage Intention	4.76	.97	.92	.67	.63	**.96**						
4. Reliability	5.44	.94	.85	.66	.45	.57	**.92**					
5. Functionality	5.53	.95	.87	.72	.47	.62	.79	**.93**				
6. Helpfulness	4.81	.95	.86	.43	.51	.50	.59	.56	**.93**			
7. Integrity	5.58	.97	.92	.50	.27	.39	.58	.54	.45	**.96**		
8. Competence	5.82	.96	.89	.68	.32	.52	.72	.72	.48	.66	**.94**	
9. Benevolence	5.07	.92	.78	.53	.42	.49	.63	.59	.60	.65	.63	**.89**

Table 2. Correlations, Validity Statistics

The measurement models for each dataset display adequate fit. For the three datasets, the non-normed fit index ranges from 0.95 to 0.97, the comparative fit index ranges from 0.96 to 0.97, and the root mean square error of approximation ranges from 0.05 to 0.07. These are within suggested guidelines for adequate fit statistics (Browne and Cudeck 1993; Hu and Bentler 1999).

These models also have adequate convergent and discriminant validity among the first-order factors. For the three datasets, the internal consistency reliability (ICR) for each construct exceeded 0.80 and each average variance extracted (AVE) exceeded the 0.50 standard (Fornell and Larcker 1981) (Table 2). Also, each square root of the AVE is greater than any correlation in that construct's row or column (Fornell and Larcker 1981) (Table 2), and no cross loadings in the SPSS factor analysis are greater than .30. We also tested for multicollinearity and common method variance, neither of which were a problem in our data. Finally, we evaluated the appropriateness of using a second-order model by employing the tests used in Tanriverdi (2006), and found that using the second-order model (versus the first-order model) is appropriate for our data analysis. The second-order factors also discriminate as the model with two second-order trusting belief factors (interpersonal and system-like) has significantly better fit than a model with one second-order factor representing overall trust (interpersonal and system-like trust combined).

Structural Model Results

We next tested for differences in the structural paths among the datasets. Table 3 shows the structural model results along with the LM group difference statistics used to test H2a, H2b, H3a, and H3b for each dependent variable. We find that H2a is supported for two of the three dependent variables as interpersonal trust is a stronger predictor of enjoyment and continuance intention for RAs than for Access. We find full support for H2b as interpersonal trust is a stronger predictor of the dependent variables both for Facebook versys RAs and for RAs versus Access. We also find full support for H3a as system-like trust is a stronger predictor of usefulness, enjoyment, and continuance intention for Access than RAs. Although Table 3 shows the numbers lie in the direction hypothesized, we find no support for H3b as there were no significant group differences between RAs and Facebook for the coefficients' system-like trust paths. We also found significant differences for the experience predictor between the RA and Facebook for all three dependent variables. No other significant differences were found.

Structural Path Coefficients *** p<.001; ** p<.01; * p<.05	**Access**	**RA**	**FB**	**LM Group Differences**
Interpersonal Trust → Usefulness	.24***	.50***	.81***	RA versus FB, p = .003 (H2b)
Interpersonal Trust → Enjoyment	-.17***	.53***	.83***	Access versus RA, p = .012 (H2a); RA versus FB, p = .000 (H2b)
Interpersonal Trust →Continuance Intention	-.05	.41***	.72***	Access versus RA, p = .006 (H2a); RA versus FB, p = .029 (H2b)
System-like trust → Usefulness	.71***	.40***	.02	Access versus RA, p = .002 (H3a)
System-like trust → Enjoyment	.68***	.23***	-.02	Access versus RA, p = .000 (H3a)
System-like trust → Continuance Intention	.76***	.18***	-.05	Access versus RA, p = .001 (H3a)
Control Variables				
Age → Usefulness	-.01	-.01	-.01	
Age → Enjoyment	.01	.01	.01	
Age → Continuance Intention	.03	.04	.05	
Gender → Usefulness	.00	.00	.00	
Gender → Enjoyment	.03*	.05*	.05	
Gender → Continuance Intention	.05*	.05*	.06*	
Experience → Usefulness	.01	-.05	.19***	RA versus FB, p = .031
Experience → Enjoyment	.07	-.06	.29***	RA versus FB, p = .033
Experience → Continuance Intention	.14***	-.01	.35***	RA versus FB, p = .048
Usefulness R^2	56.2%	41.6%	69.9%	
Enjoyment R^2	49.2%	34.4%	77.1%	
Continuance Intention R^2	60.4%	20.6%	64.7%	
NNFI	.927			
CFI	.935			
RMSEA	.077			

Table 3: Structural Model Testing Results

As a supplemental analysis, we also ran a group analysis to compare just Access (the least human-like technology) and Facebook (the most human-like technology). We find that all the structural paths between both trust constructs and the three predictors are significantly different with interpersonal trust being more predictive for Facebook and system-like trust being more predictive for Access. Note also that for Facebook, system-like trust was not a significant predictor of any of the dependent variables.

DISCUSSION, LIMITATIONS AND RESEARCH IMPLICATIONS

While prior research has investigated trust across a wide range of IT contexts, this is the first study to evaluate how common trust measures perform across multiple technology contexts. It addresses the important issue of which trusting beliefs to use when examining trust-in-technology. Prior research uses both *interpersonal* and *system-like* trusting beliefs. This study proposes that the predictive ability of interpersonal and system-like trust measures is significantly impacted by the technological context in which they are applied. We contribute to the IS literature by proposing and empirically testing a theoretical view that a person's trusting beliefs in IS contexts are significantly impacted by the humanness of the technology context. We provide empirical evidence of how technology humanness impacts the predictive ability of two alternative trust concepts. Overall, we find that trusting beliefs explain a significant amount of variance in usefulness, enjoyment, and continuance intention. For all three predictions, the variance explained by the trusting beliefs is greatest for Facebook and the least for the RA, perhaps because experience is high for FB and low for RA.

We find that the respondents consider the RA more human-like than Microsoft Access and Facebook more human-like than the RA. This was expected, since Facebook is a very socially-engaged context, and Access is not.

Given the relative humanness of these technologies (in order: Facebook, RA, Access), we tested how well both interpersonal and system-like trusting beliefs would predict. We find that the more human-like a technology is perceived to be, the better interpersonal trust predicts. The less human-like a technology is, the better system-like trust predicts. For the most human technology (Facebook), interpersonal trust predicts the three outcomes very well (mean of the three betas = .79), while system-like trust does not predict at all (mean of the betas [absolute value] = .03). Thus, predicting Facebook outcomes using system-like trust is not likely to work, whereas predicting outcomes using interpersonal trust will work very well. For the least human technology, Microsoft Access, almost the reverse is true. System-like trust makes an excellent predictor (mean of the betas = .72), whereas interpersonal trust does not predict nearly as well (mean of the betas =.15). This suggests one should use system-like trust constructs for Access. For the RA, interpersonal trust predicts quite well (mean beta = .48), while technical-like trust does not predict as well (mean beta = .27). This indicates one might use either set of measures, but that the RA outcomes are better predicted by interpersonal trust.

These results suggest that it was appropriate for Wang and Benbasat (2005) and other researchers to use interpersonal trust measures to predict outcomes related to an RA. However, RAs have different features (Xiao and Benbasat, 2007) that make them more or less human. Our research suggests that it is important to review the features of an RA before applying the interpersonal trust measures. The RA we chose was perceived as being more human than Access (H1a finding), but if an RA has fewer human-like features, it might be perceived less human-like. Our results also suggest that Lippert (2001), studying inanimate systems, appropriately defined technology trust in terms of technical-like attributes. The results also confirm that interpersonal trust will predict well for Facebook, while system-like trust will not, suggesting the latter should not be used. For Access and other less human technologies, the results suggest scholars should use system-like trust measures, not interpersonal measures.

One study limitation is that we did not examine trust or the dependent variables at the task level for each technology. Users may perceive different degrees of humanness for a technology depending on the task. Future research should investigate this issue in addition to how perceived humanness may differ between two or more technologies used to perform similar tasks.

Conclusion

In the future, researchers should consider how human a technology is before deciding whether to use interpersonal or system-like trust constructs. This should open up new areas for research. For example, very little research has been done on trust in less human technologies like Access. In part, this has occurred because it seemed unnatural to ask respondents about the benevolence or integrity of a non-social technology that did not have the volition or moral agency that is required to exhibit these traits (e.g., Friedman et al. 2000). This paper shows that one can still effectively measure trust in non-humanlike technologies without trying to unreasonably apply human attributes to that technology—but rather by using system-like trust attributes that better suit the technologies' nature. Knowing this, researchers will be able to effectively study trust in non-humanlike technologies and fill the gaps that still exist in the trust literature.

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