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Affect Infusion and Detection through Faces in Computer-mediated Knowledge-sharing Decisions

Dennis D. Fehrenbacher

Monash University

Dennis.Fehrenbacher@monash.edu

Abstract:

Faces are important in both human communication and computer-mediated communication. In this study, I analyze the influence of emotional expressions in faces on knowledge-sharing decisions in a computer-mediated environment. I suggest that faces can be used for affect infusion and affect detection, which increases the effectiveness of knowledge-management systems. Using the affect infusion model, I discuss why emotions can be expected to influence knowledge-sharing decisions. Using the two-step primitive emotional contagion framework, I found that emotional facial expression attached to a knowledge-sharing request influenced knowledge-sharing decisions. This influence was mediated by the decision maker's emotional valence in the facial expression tracked by Face Reader technology and held for females but not males. I discuss implications for designers of emotionally intelligent information systems and research.

Keywords: Face Reader, Affect Infusion, Affect Detection, Knowledge Sharing, Eye Tracking.

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1 Introduction

Our ability to recognize human faces is remarkably quick, precise, and effortless. Despite their complexity and similarity (e.g., they comprise the same objects such as a mouth, nose, and eyes), we can tell who someone is, whether we have seen someone before or not, and what someone's relationship to us is. With a short glance at a face, we can usually even tell someone's age, gender, and emotional state (Hole & Bourne, 2012; Zhao, Chellappa, Phillips, & Rosenfeld, 2003; Fridlund, 1991). In this study, I examine the influences of gender and emotional state on social interactions that involve knowledge-sharing decisions in an electronic communication environment that contains pictures of faces.

Studying knowledge sharing is important because knowledge is the foundation of a firm's competitive advantage (Spender, 1996). However, knowledge inherently resides in the individual, and individual knowledge does not always easily transform into organizational knowledge (Hahn & Subramani, 2000; Bock, Zmud, Kim, & Lee, 2005). Thus, determining mechanisms that influence individual knowledge sharing is an important step towards improving knowledge management.

I contribute to the knowledge sharing literature by exploring a mechanism based on affect. With that said, affect does not influence all judgments and decisions (Forgas, 1995). I suggest that affect influences knowledge-sharing decisions because the act of sharing knowledge is rather complex and strategic and can, thus, be infused by affect according to the affect infusion model (AIM) (Forgas, 1995).

Specifically, I examine whether facial expressions (happy vs. angry) can induce affect that influence knowledge sharing. Nowadays, individuals can easily communicate facial expressions in electronic communication and do so regularly. Research has also shown that facial expressions communicate and transfer emotions (Seidel, Habel, Kirschner, Gut, & Derntl, 2010). I draw on the two-step primitive emotional contagion theory (Hatfield, Cacioppo, & Rapson, 1994). This theory suggests that, in a first step people engage in mimicry behavior based on facial expressions, and, in a second step, they then begin to feel the emotions that they mirror in others.

Importantly, this research addresses the question of whether the two-step model differs by gender. Researchers see the role of gender differences as important to more completely understand user behavior in information systems (Gefen & Straub, 1997; Venkatesh & Morris, 2000; Riedl, Hubert, & Kenning, 2010b). Yet, research has found conflicting results of gender differences (Croson & Gneezy, 2009). As such, guided by the emotional contagion framework, I study 1) gender differences in individuals' tendency to "catch" the emotions displayed in the picture of a face and 2) gender differences in the way such emotions influence knowledge sharing.

To study this model, I use a 2 (requestor's facial expression) x 2 (receiver's gender) + 1 (control) experimental design. The stimuli of the requestor's facial expression comprise pictures that show either happy or angry faces. I used face-detection technology (Face Reader by Noldus) to test for the presence of the mimicking behavior. Research has shown facial-detection technology to serve as an acceptable proxy for facial electromyography (EMG), which directly captures the contractions of facial muscles by inserting the electrodes to the face (D'Arcey, 2013). In this study, I conducted an experiment in which I asked participants about their willingness to share knowledge with a colleague who showed "free-riding" behavior.

This paper proceeds as follows: in Section 2, I review the background literature and, in Section 3, develop the research model. In Section 4, I explain the method used. In Section 5, I present and discuss the results. In Section 6, I discuss the study's limitations. In Section 7, I discuss the study's contributions to research and practice.

2 Background and Hypothesis Development

2.1 Knowledge Sharing

According to the knowledge-based view of the firm (Spender, 1996), knowledge is the foundation of a firm's competitive advantage. However, knowledge inherently resides in the individual (Bock, Zmud, Kim, & Lee, 2005). Researchers have been interested in organizational knowledge sharing because the ability to integrate specialized individual knowledge into organizational uses and routines to produce a competitive advantage depends on effective knowledge-sharing behaviors (Sarma, Subramani, & Aldrich 2001; Whelan, 2007).

Organizations have formalized knowledge sharing through implementing organizational knowledge-management systems (e.g., knowledge repositories or intranet networks) (Hahn & Subramani, 2000). These technologies focus on improving knowledge sharing and largely coded forms of knowledge. However, individual knowledge does not always easily transform into organizational knowledge (Bock et al., 2005) partly because knowledge can comprise rich information that one cannot codify (Hislop, 2002) and the transfer of information often occurs informally through direct interactions and discussions. Thus, research has critically debated organizations' reliance on information technologies to share knowledge (Hislop, 2002). Researchers have also suggested that informal knowledge sharing depends on motivational factors in particular, which they have claimed we do not fully understand (Kalling & Styhre 2003). Consequently, we need to understand knowledge-sharing behavior and its determinants more completely.

Knowledge sharing comes with beliefs about expected costs and benefits. These beliefs are important in determining knowledge-sharing behaviors (Bock et al., 2005). If the benefits exceed the costs, then knowledge sharing is likely (or unlikely otherwise). The costs of knowledge sharing can relate to both time and effort (Lin, 2007), such as time taken and mental effort required to share knowledge. In an organizational setting, those who have the option to share knowledge may lose their unique value and power in the organization from sharing it (Kankanhalli, Tan, & Wei, 2005); they also face the risk that others will deem the knowledge they share to be inaccurate or irrelevant, which can damage their reputation (Bock et al., 2005). Benefits of sharing knowledge can come in the form of recognition and social capital and can provide benefits to individuals by enabling them to signal their competence (Haas & Hansen, 2007). Next to a simple cost-benefit view, one can also view knowledge sharing as a strategic decision.

Researchers have discussed a strategic view of knowledge sharing through the lens of a public goods dilemma (Cabrera & Cabrera, 2002; Wasko & Faraj, 2000). Defined as a product or good created by a group, a public good is accessible to all members of a group whether or not each individual contributed to its creation. For example, one can view a public park as a public good because all individuals can enjoy it—even those who do not pay taxes. Because knowledge and/or resource sharing between employees frequently leads to improved performance and the development of novel ideas, methods, and tools, it is often in the best interest of organizations for employees to share knowledge with each other regardless of whether they assisted in developing that knowledge or not.

Because of unrestricted access to public goods in organizations, "free-riding" (i.e., consuming the public good without having contributed to its creation) can often occur (Sweeney, 1973). Therefore, the highest individual utility occurs when organizations withhold cooperation among group members regardless of the remaining members' actions. Non-contributors can maximize their utility of the public good if the majority of the group members contribute to producing the public good. However, if all group members contribute little, a non-contributor can save the effort of useless contribution. Thus, from the perspective of maximizing economic utility (Dawes, 1980), a dominant strategy involves not contributing to a public good (e.g., knowledge) (i.e., defecting).

However, in reality, most group members are willing to sacrifice their individual contribution in order to enjoy the public good (compared to retaining their individual contribution and not using the public good). If all members in a group believed the others would all contribute equally, then the majority would actually contribute to creating the public good. This argument serves as the source of the dilemma. Individuals often perceive defecting as the dominant strategy (i.e., where all members of the group suffer by not being able to use the public good). As more individuals in the group defect, the individual incentive to contribute to the public good (and, therefore, reap the benefits) declines.

Thus, from both the cost-benefit perspective and the public goods perspective, knowledge sharing is a rather complex decision individuals make. The affect infusion model (AIM) (Forgas, 1995), which I introduce in more detail below, states that tasks that require little to no constructive thinking and processes, such as performing routine actions, should largely be impervious to affect infusion. However, emotions should readily influence complex and strategic tasks (Forgas & George, 2001).

2.2 Facial Expressions and Emotional Contagion

Body and facial expressions (and their effects) are of great interest to researchers (Fridlund, 1994; Hatfield, Cacioppo, & Rapson, 1994; Seidel et al., 2010) because they are vital methods of communicating and conveying information in a non-verbal manner. Facial expressions are specific configurations of the facial muscles' contracting and relaxing. Consequently, they are a key aspect of social interaction, communication, and information transmission because they contain information that can influence the behavior of others (Fridlund, 1994). Further, facial expressions can frequently provide insight into an individual's emotional state (Russell, 1994), which may partly explain the emotional labor mantra of "service with a smile" (Pugh, 2001), which assumes that service from positive, happy staff/employees leads to happy, satisfied customers.

The emotional contagion theory describes the way in which facial expressions can influence behavior (Hatfield et al., 1994), which relates to the flow of emotions from one person to another. Research that involves emotional contagion explores how emotions are transmitted between people in social interactions and how the flow (or "catching") of other individuals' emotions can alter behavioral patterns. Research has identified both conscious and subconscious processes to influence emotional contagion (Barsade, 2002). Conscious processes include social comparisons between people (Barsade, 2002), whereas people subconsciously mimic and match the facial expressions, vocal tones, and body movements of others to approach and enter the same emotional state (Hatfield et al., 1994). The subconscious, automatic process of contagion is the result of a two-step process.

First, the tendency to mimic the facial expressions and behaviors of others is believed to be innate. Researchers have observed such mimicry behavior in direct interactions between two or more individuals and in response to the presentation of photographs of expressive faces (Hatfield et al., 1994; Wild, Erb, & Bartels, 2001). Researchers have offered a neuroscientific explanation for this mimicry based on the actions of "mirror neurons" located in the human motor cortex, which they believe to be responsible for imitation behaviors. Mirror neurons are activated both when an individual observes an action and when they initiate the same action themselves (Rizzolatti & Craighero, 2004). Consequently, if individuals see a smiling, happy individual, they tend to mimic this behavior and display a smile ourselves. Therefore, the observation of others' behaviors and the realization of our own behaviors appear to be closely linked via neurological processes. Such processes underline the theory that mimicking behavior is innate and autonomic.

Second, when people engage in mimicry behavior, they then begin to feel the emotions that they mirror. This emotional shift results from physiological feedback from muscular, visceral, and glandular responses (Barsade, 2002; Hatfield et al., 1994; Horstmann, 2003). Consequently, observing a human smile can induce similar emotional states in the observer. Because emotions drive human behavior (Lazarus, 1991; Weiner, 1992), the behavioral effects of observing faces may result from the activation of emotional states in individuals' perceiving facial expressions (Fridlund, 1994; Seidel et al., 2010).

2.3 Emotions and Knowledge Sharing

Research on the interplay of feeling and thinking in relation to complicated cognitive processes such as decision making, learning, and memory has experienced a considerable rise in the last decade. Researchers have proposed several models to help explain the influence of affective states on cognition (Cohen, 2005; Forgas & Eich, 2013; Forgas & George, 2001). They have found that emotional processing interacts with (and, in some cases, overrides) cognitive decision making[1].

Researchers have identified that affect influences cognition in at least two ways. First affect can influence *what* people think (i.e., what kind of information people recall, attend to, select, interpret, and learn) through a greater availability and use of affectively colored information (the content of cognition; Bower, 1981). Second, affect may influence the process of thinking (i.e., *how* people deal with a given task) (Forgas, 1998). Some evidence suggests that positive affect promotes a more internally driven, top-down, flexible, and generative processing style, while negative affect facilitates a more externally oriented, bottom-up, and systematic thinking style (Bless, 2000; Fiedler, 2000).

Forgas' (1995) affect infusion model (AIM) provides an integrated model to explain in which circumstances feeling colors judgment. Affect infusion refers to the process whereby affectively loaded information exerts an influence on and becomes incorporated into a person's processes and deliberations, which eventually colors the person's decisions (Forgas, 1995). Affect infusion occurs because planning and executing complex social (and organizational) behaviors usually requires constructive cognitive processes for which pre-existing knowledge, memories, and associations play a part in interpretation and response (Forgas & George, 2001). The AIM argues that the extent of affect infusion critically depends on what kind of processing strategy one uses for a particular task.

[1] The literature differentiates between moods and emotions in terms of intensity and time. It describes emotions as more intense and shorter than moods. It often uses the term affect as a generic label to refer to both (Forgas & George, 2001). In terms of emotional states visible in human faces, the literature also regularly uses the term valence to describe whether the emotional state is "good" (positive) or "bad" (negative) (Loijens & Krips, 2014; Cowie et al., 2001).

The AIM identifies four processing strategies that vary by the degree of openness or constructiveness, effort involved in seeking a solution, and likelihood of affect infusion (Forgas & Eich, 2013; Forgas, 1995). While analyzing and reviewing the model in this paper falls outside its scope, we need to understand the model's main premises. The AIM states that tasks that require little to no constructive thinking and processes, such as performing routine actions, should largely be impervious to affect infusion. However, in contrast, affect should readily influence complex and strategic tasks (Forgas & George, 2001). The model posits that complex tasks require constructive thinking and interpretation of ambiguous or indeterminate information for which feelings can help guide interpretations and judgments, whereas simple processes follow a more automatic style of response. Research in the organizational setting has demonstrated the influence of affect infusion on a number of complex processes including work motivation, performance, judgments, group functioning, and withdrawal behaviors (Forgas & George, 2001). Thus, since knowledge sharing is a complex and strategic decision that depends several factors, we may expect feelings to influence knowledge sharing in a way consistent with the AIM. Having established that affect is likely to influence outcomes with regards to knowledge sharing, I turn to the question of whether gender moderates such influence.

2.4 The Moderating Role of Gender

IS research considers gender differences to be an important factor in understanding user behavior (Venkatesh & Morris, 2000), human-computer interaction (Sproull, Subramani, Kiesler, Walker, & Waters, 1996), and technology adoption in their entireties (Gefen & Straub, 1997). Recently, Riedl et al. (2010b) observed that women activated more brain areas in their study on decisions on trustworthiness of eBay offers. Similarly, Pavlou (2010) has called for more research into the moderating role of gender after observing brain activation for his constructs in relation to the perception of online product recommendation agents mainly for female rather than male users.

The academic literature at large and not just the IS literature also continues to debate whether men and women have any universally different social behaviors. While we have strong evidence that males and females differ in social preferences (for a review, see Croson & Gneezy, 2009), we have conflicting results about *how* men and women differ in their social preferences (Croson & Gneezy, 2009).

Regarding knowledge-sharing behavior, research has already shown that men and women differ. As such, we have established that gender roles influence knowledge sharing as a social behavior (Miller & Karakovsky, 2005). Further, Lin (2008) has found that the influences of courtesy and sportsmanship on knowledge sharing are stronger for men than for women and that the influence of altruism on knowledge sharing is stronger for women than for men. These findings generally suggest that men and women have different motivations to share knowledge. I take the lens of the emotional contagion framework (Hatfield et al., 1994) and examine whether men and women differ in knowledge-sharing behavior and suggest a mechanism through emotions for gender differences in knowledge sharing.

3 Hypotheses

First, I suggest that individuals exhibit emotional contagion when presented with a happy versus angry face along with a knowledge-sharing request and that gender moderates this emotional contagion such that men are less susceptible to the emotional stimuli from someone who requests them to share knowledge than women. Consistent with Croson and Gneezy (2009 p. 463) who state that "the cause of…conflicting [gender] results is that women are more sensitive to cues…than are men" and consistent with psychology research that suggests that women are more sensitive to social cues (Kahn, Hottes, & Davis, 1971), I suggest that women exhibit more emotional contagion.

> **H1:** A receiver's emotional valence response is more strongly associated with a requestor's facial expression (angry vs. happy) when the receiver is female rather than male.

Second, as I discuss above, knowledge sharing is a rather strategic and complex decision, and, thus, the AIM would predict that emotions are likely to play a role in knowledge-sharing decisions. In light of evidence that negative emotions can induce avoidance behavior, that positive emotions lead to approach behavior such as trust or cooperation (Forgas & Eich, 2012), and that individuals more often accept offers in strategic games accompanied by a smiling rather than a neutral or angry face (Mussel, Goeritz, & Hewig, 2013), one can derive that decision makers' emotional valence is associated with knowledge-sharing behavior. In particular, I expect that gender moderates this relationship.

Allen and Haccoun (1976) studied gender differences in emotional intensity and found gender differences in the "functional significance of emotions" (p. 711) whereby women experienced emotions at higher levels than men. Literature on emotional intensity generally agrees that "women report more intense experience of emotions than men" (Grossman & Wood 1993, p. 1010; see also Allen & Hamsher, 1974; Diener, Sandvik, & Larsen, 1985; Larsen & Diener, 1987). Psychophysiology evidence supports that woman and men experience emotions differently in that they activate different parts of the brain under the same mood (Blackhart, Kilne, Donohue, LaRowe, & Joiner, 2001).

Recall that, as derived from the AIM, infused affect is likely to color knowledge-sharing decisions. Drawing on the literature on differences in the functional significance of emotions in women and men (Allen & Hamsher, 1974; Allen & Haccoun, 1976), I predict that women experience the infused affect more strongly than men, which leads to a higher significance of the emotion for women than men in the decision making process and to a stronger emotional effect for women than men.

> **H2:** A receiver's emotional valence is more positively associated with a receiver's knowledge-sharing willingness when the receiver is female rather than male.

As such, H1 and H2 together describe an indirect effect of a requestor's facial expression on a receiver's knowledge-sharing willingness through a receiver's emotional valence. Gender fully moderates this indirect effect. The moderation in stage 1 draws on gender differences in the sensitivity to social cues (Kahn et al., 1971; Croson & Gneezy, 2009), and the moderation in stage 2 draws on gender differences in the intensity and the functional significance of the emotional experience (Grossman & Wood, 1993; Allen & Haccoun, 1976). Figure 1 depicts the research model.

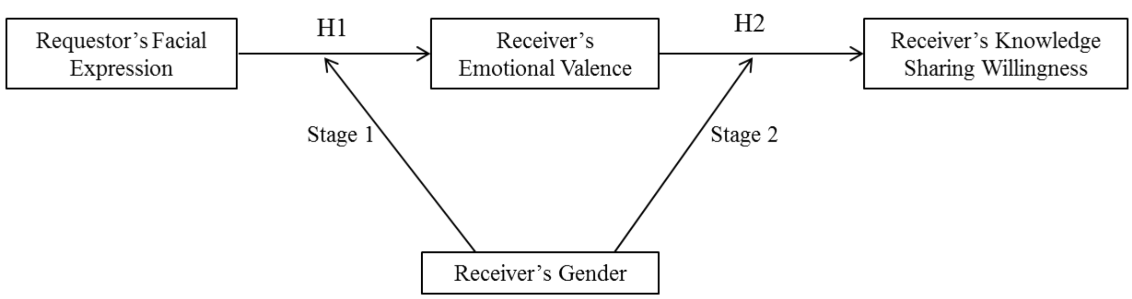


Figure 1. Research Model

4 Method

I conducted a scenario-based experiment in which I asked participants to work through a scenario and make a knowledge-sharing decision. I analyzed the experiment based on a 2 (requestor's facial expression) x 2 (receiver's gender) + 1 (control) design. I randomly assigned participants to either a positive or a negative requestor's facial expression condition. In all, I assigned an approximately equal number of female and male participants to each treatment condition. The control condition displayed a neutral emotion as I explain below.

4.1 Participants and Sample Description

I successfully collected face-reader, eye-tracking, and behavioral data from 56 participants. The 56 participants—students from a second-year accounting information systems class—took part on a voluntary basis. On average, the participants were 20.68 years' old; further, 44.6 percent were male and 55.4 percent were female.

4.2 Experimental Materials

I conducted the study in a laboratory of a large university. The laboratory contained separate cubicles with Tobii T120 eye trackers. Separate cubicles ensured that participants worked on the case material without disturbance. I asked participants to leave their belongings outside of the cubicles. The participants used 17-inch displays with eye trackers and video cameras built into their rims.

Figure 2 (next page) illustrates the two sensors (i.e., eye trackers and video cameras) and their role in the experimental set-up. I used the video cameras to produce video footage of participants' faces. I used the eye trackers to detect when participants fixated on the stimuli. Thus, by using the eye trackers in combination with the video footage, I could record the faces of the participants and the exact tracing of when they looked at the stimuli when completing the experimental scenario. The combination of the eye-tracking and face-reading technologies enabled the experimental set-up to overcome limitations of a variety of other systems in the context-dependent tracking and detection of facial emotions. In reviewing the state of the art of facial detection, Calvo and D'Mello (2010, p. 24) state: "almost none of the systems integrated contextual cues with facial feature tracking". My system could track the context (i.e., participants' interaction with the system) via tracking their eye movements.

I used the Tobii Studio 3 software package to analyze participants' gazes at the stimuli. I used the Face Reader 5 software package from Noldus to analyze their video footage. Research has shown this software to serve as an acceptable proxy for facial electromyography (EMG), which directly captures the contractions of facial muscles by inserting the electrodes to the face (D'Arcey, 2013). Rather than using electrodes, Face Reader identifies the face before creating a three-dimensional active appearance model (AAM) (Cootes & Taylor, 2004) of the face. During processing, it uses the AAM to compute scores of intensity and probability of facial expressions on a continuous scale from 0 to 1. van Kuilenburg, Wiering, and den Uyl (2005) describe the algorithms that the Face Reader uses in detail. Research has also shown the Face Reader to be as accurate as a human when it comes to correctly recognizing emotions (Lewinski, den Uyl, & Butler, 2014). Researchers have used the technology in psychology (He, Boesveldt, de Graaf, & de Wijk, 2014), marketing (Lewinski, Tan, Fransen, Czarna, & Butler, 2016), and information systems user experience research related to screen complexity (Goldberg, 2014).

The Face Reader classifies participants' facial expressions in line with the seven basic emotions that Ekman (1970) describes: happy, sad, angry, surprised, scared, disgusted, and neutral. Ekman classifies "happy" as a positive emotion and "sad", "angry", "scared", and "disgusted" as negative emotions. "Surprise" can be either positive or negative, whereas "neutral" is neither positive nor negative.

4.3 Procedure and Task

I asked participants to sit in a cubicle and read through case instructions and answer the presented questions. I adapted the case from Constant, Kiesler, and Sproull (1994). It asks participants to assume the role of a junior level programmer. Specifically, participants received the following information about the department the case asked them to assume they worked in:

> *You and Alex are junior-level computer programmers. You and Alex are in the same department and are assigned to the same programming project. About a month ago, Alex refused to help you fix a program bug.*

Then, they learnt that Alex had asked them for help. The knowledge they needed to share was codified knowledge (Wasko & Faraj, 2000); that is, a software program. Specifically:

> *You have just put 40 hours of work into a particularly difficult computer program to be used in your project. Now, Alex would love to have a copy of the program for a project you are not involved in and asks you for a copy.*

The public good in this case is the company's aggregate programming knowledge and expertise. Alex is a colleague who conducted free-riding in not sharing her knowledge in an earlier situation. Participants had to decide whether to *defect* as well or to contribute to the public good.

The subsequent page displayed a picture of Alex with either a happy or angry facial expression (stimulus). Below the picture, Alex asked: "Could you please send me a copy of your program?" (see Figure 3). Human faces are powerful stimuli and are increasingly employed in research studies (Wild et al., 2001; Furl, Gallagher, & Averbeck, 2012). I sourced the face pictures from the Radboud Faces Database. The database collects pictures of faces in different emotional states. Langner et al. (2010) confirmed the validity of the emotional expressions in the faces of the database. I chose Alex as the name because it is gender neutral. I chose an alternating design such that the system would choose either an angry/happy female or male in a random fashion such that it would match the sender's and receiver's gender about half the time. The randomization was successful, and there was no difference in the number of participants who received a request from the same or from the opposite gender across requestor's facial expression conditions ($p > .25$). The control condition displays a neutral emotion, and I designed it to receive half the number of participants than the treatment conditions.

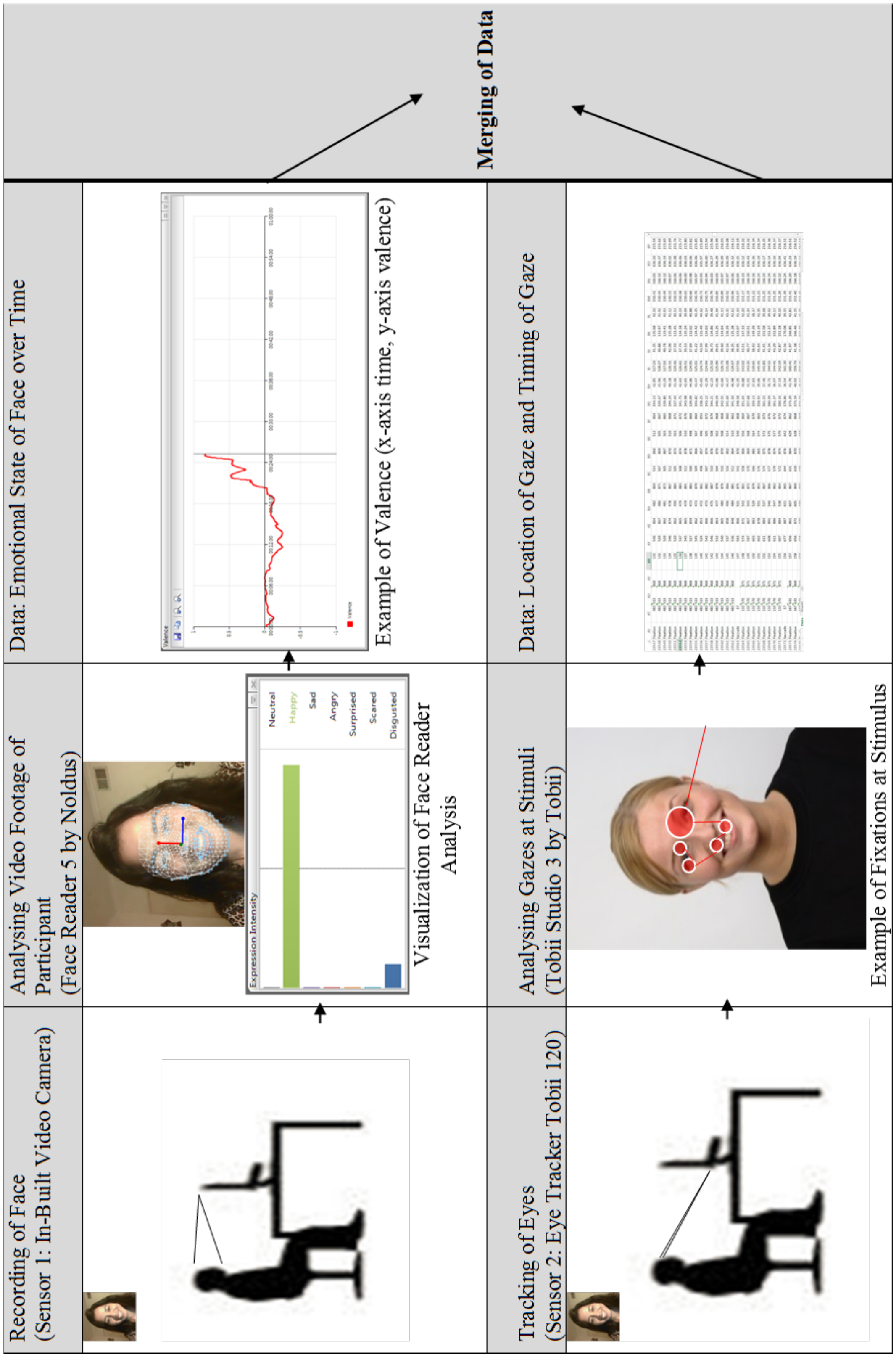


Figure 2. Illustration of Experimental Set-up (Lagnet et al., 2010; Tobii Technology AB, 2012)

Figure 3. Requestor's Facial Expression Manipulation (Langner et al., 2010; Microsoft Word 2010)

4.4 Measures, Manipulation Checks, and Control Analysis

The study used two independent variables. The first was the requestor's facial expression (angry, happy). In order to check whether participants perceived the faces as intended, I asked participants: "How happy do you think Alex is?". The responses were significantly different for the angry (N = 19, mean = 2.263) and happy treatments (N = 23, mean = 4.609, t = 5.185, $p < .01$). Responses to the question "How angry do you think Alex is?" were also significantly different between the angry (N = 19, mean = 5.105) and happy treatments (N = 23, mean = 2.565, t = 5.046, $p < .01$).

The second independent variable was participants' gender. The random assignment was successful, and about half of the male and female participants were in the angry and happy conditions (see Table 1). The Chi-square test of participants' gender per requestor's facial expression was not significant (Chi-square = .423, $p > .51$).

The study also used two dependent variables: emotional valence and the knowledge-sharing willingness of the individuals who received the knowledge-sharing request and responded to it (i.e., the receivers). I calculated the receiver's emotional valence by deducting the highest negative emotion (from sad, angry, scared, and disgusted) from the happy emotion, which follows Loijens and Krips' (2014) suggestion for calculating emotional valence. Accordingly, the valence values theoretically range from -1 to +1 (see also Figure 2). For instance, if there were no happy emotions (value 0) and one negative emotion reached 1, the valence would be -1. If the happy emotions reached 1 and all negative emotions were 0, the valence would be +1.

I used the Face Reader valence data from the point in time when participants looked at the stimuli for the first time (first fixation) until participants fixated the stimuli for the last time (last fixation). The size of the stimuli was 470 x 530 pixels across all conditions (Figure 3). Tobii T120 eye trackers recorded the first and last fixations. I used the time stamps of these fixations to calculate the valence between the time stamps frame by frame based on the video footage.

I captured knowledge-sharing willingness via a question adapted from Constant et al. (1994): "What is the likelihood you would give a copy of the program to Alex?" (1 = not at all likely to 7 = very likely).

In order to gain confidence that the differences in emotional valence were robust and actually resulted from the manipulations and not from individual differences in facial expressions, I conducted two further tests. First, I compared whether the valences in the happy and angry conditions were statistically different from the control condition. I found a difference in valence between the control condition (N = 14, mean = -.135) and the happy condition (N = 23, mean = -.039, t = 2.080, $p < .043$). Thus, the valence was higher in the happy condition as compared to the control condition. However, I found no statistical difference between the control condition and the angry condition (N = 19, mean = -.094, t = .843, $p > .403$), which may point to the circumstance that positive mimicking may have been stronger than negative mimicking behavior. I discuss this finding more below.

Second, I compared the valence of the participants in the happy and the angry conditions before I presented the participants with the facial stimuli. Before I presented them with the emotional stimuli, I should not have observed a difference in emotional valence. I used the first 30 seconds of the study—well before the emotion treatment took place. During this time frame, the mean valence of the angry condition was almost the same as of the happy condition (in both conditions, approximately -.05, untabulated data) and the difference was not significant $p > .86$. This result further supports Face Reader's validity since the difference in the receiver's emotional valence in response to the stimuli (requestor's facial expression) was significant (see below) whereas the difference in valence before I presented the stimuli was small and not significant.

5 Results

5.1 Analysis Method and Descriptive Statistics

Tables 1 and 2 show the means and standard deviations for the dependent variables by receiver's gender (male, female) and by requestor's facial expression (angry, happy). Table 1 shows the receiver's emotional valence; Table 2 shows the receiver's knowledge-sharing willingness. To test the hypotheses, I employed a partial least square (PLS) path approach using SmartPLS 3. The sample size was 42. This sample size satisfies the heuristic to be at least 10 times the largest number of paths directed at any one construct. The largest number of paths directed at any one construct was 4. PLS allows one to test all relationships of a proposed model (see Figure 1) simultaneously even under conditions of small to medium sample sizes (Chin, 1998). I used a bootstrapping resampling procedure of 500 samples to test the significance of the paths (Chin, 1998). I expected gender to moderate both paths of the mediation in the research model (see Figure 1), which constitutes a stage 1 (H1) and stage 2 (H2) moderation of mediation (Edwards & Lamberts, 2007). I tested the moderation by introducing two product terms into the PLS model as Chin, Marcolin, and Newsted (2003) suggest[2]. If a product term is significant in the PLS model, one can take this result as evidence for moderation (method 1 in Table 6). I further evaluated the model by splitting the sample according to gender and using the subgroup approach (method 2 in Table 6). Research in the methodological literature of moderation has recommended the subgroup approach in the context of mediations and structural equation modeling (Rigdon, Schumaker, & Wothke, 1998; Wegener & Fabrigar, 2000). In the subgroup approach, gender would moderate the mediation if the evidence for the mediation differed between the subgroups (i.e., for male as compared to female). I evaluated the statistical difference of the strengths of the paths between the subgroups using Wynne Chin's t-statistic described in Keil et al. (2000). I assessed evidence for the mediation using Sobel's test (Preacher & Leonardelli, 2001).

Table 1. Mean and Standard Deviation of Receiver's Emotional Valence per Condition

Receiver's gender	Requestor's facial expression	Mean	Std. deviation	N
Male (coded 0)	Angry (coded 0)	-.036	.045	8
	Happy (coded 1)	-.050	.158	12
	Total	-.045	.123	20
Females (coded 1)	Angry (coded 0)	-.136	.156	11
	Happy (coded 1)	-.026	.025	11
	Total	-.081	.123	22
Total	Angry (coded 0)	-.094	.130	19
	Happy (coded 1)	-.039	.114	23
	Total	-.064	.123	42

[2] I thank the anonymous reviewers for suggesting this approach.

Table 2. Mean and Standard Deviation of Receiver's Knowledge-sharing Willingness per Condition

Receiver's gender	Requestor's facial expression	Mean	Std. Deviation	N
Male (coded 0)	Angry (coded 0)	3.250	1.389	8
	Happy (coded 1)	3.583	1.505	12
	Total	3.450	1.432	20
Females (coded 1)	Angry (coded 0)	2.636	1.502	11
	Happy (coded 1)	3.455	1.635	11
	Total	3.045	1.588	22
Total	Angry (coded 0)	2.895	1.449	19
	Happy (coded 1)	3.522	1.534	23
	Total	3.238	1.511	42

5.2 H1: Requestor's Facial Expression and Receiver's Emotional Valence

H1 posits that a female receiver's emotional valence response to a requestor's facial expressions (angry vs. happy) is stronger than a male's valence response. My interest was not in general differences between men and women but in whether they would react differently to the happy and angry faces[3]. In statistical terms, I was interested in the interaction of a receiver's gender with a requestor's facial expression. In males, the difference in emotional valence between happy and angry was -.014; in females, the difference was larger: .11 (see Table 1). The PLS model presented in Table 3 shows that the path from the interaction term (requestor's facial expression x receiver's gender) was significant (beta = .445, t = 2.383, p <.01), which supports H1.

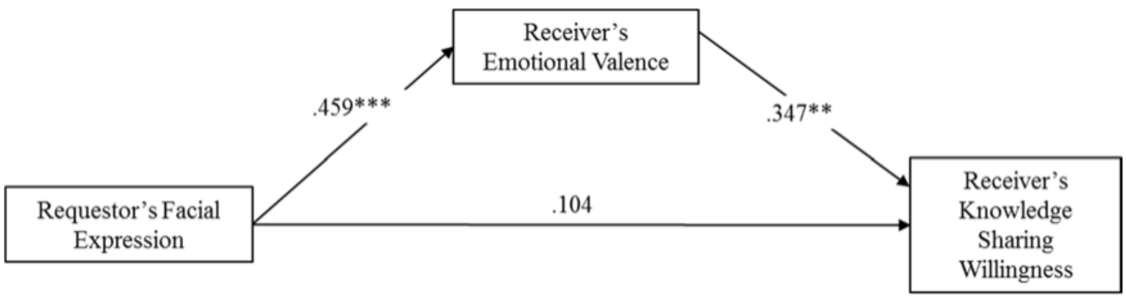
Table 2. Path Analysis

Variables	Path to	Path to	R square
	Receiver's emotional valence	**Receiver's knowledge-sharing willingness**	
Requestor's facial expression	-.051 (t = .256)	.107 (t = .676)	
Receiver's gender	-.409 (t = 2.280)**	.015 (t = .081)	
Requestor's facial expression x receiver's gender	.445 (t = 2.383)***		
Receiver's emotional valence		-.094 (t = .437)	.132
Receiver's emotional valence x receiver's gender		.362 (t = .557)	
Receiver's knowledge-sharing willingness			.121

Notes: the effects were one-tailed. One can term the form of the research model a "first and second stage moderated mediation model" (Edwards & Lamberts, 2007, p. 4). I included the main effect paths in the model because the analysis needs the main effect variables to predict interaction path coefficients (Chin et al., 2003). However, one does not need to evaluate them.
Variables: requestor's facial expression was binary with 0 = angry and 1 = happy; receiver's gender was binary with 0 = male and 1 = female; receiver's emotional valence captured the emotional state and ranged from -1 to +1; knowledge-sharing willingness ranged from 1 to 7.
*** denotes significant at the 0.01 level; ** denotes significant at the 0.05 level.

[3] In a PLS model without interaction terms using requestor's facial expression and receiver's gender as predictors and receiver's emotional valence as outcome, the t-statistic of the path requestor's facial expression → receiver's emotional valence was 1.465 (p > .142, two-tailed) and the t-statistic of the path receiver's gender → receiver's emotional valence was .866 (p > .386, two-tailed).

I also split the sample into female (Figure 4, Table 4) and male (Figure 5, Table 5). In the female-only model (Figure 4, Table 4), the path from a requestor's facial expression to a receiver's emotional valence was significant (beta = .459, t = 3.735, p < .01). In the male-only model (Figure 5, Table 5), this path was not significant (beta = -.055, t = .181, p > .42). These results support the interactive expectation of H1 that female emotional responses are stronger. From using Chin's t-statistic to compare paths strengths across samples, I found a statistical difference of the paths strengths at the 0.01 level (t = 25.82, Table 6, Keil et al., 2000). While the results for the male participants were not significant in the male-only path model, theory would not predict that there are no responses for male participants. Table 6 summarizes the results for both the product term and subgroup methods.



Note: *** denotes significant at the 0.01 level; ** denotes significant at the 0.05 level

Figure 4. Female-only model

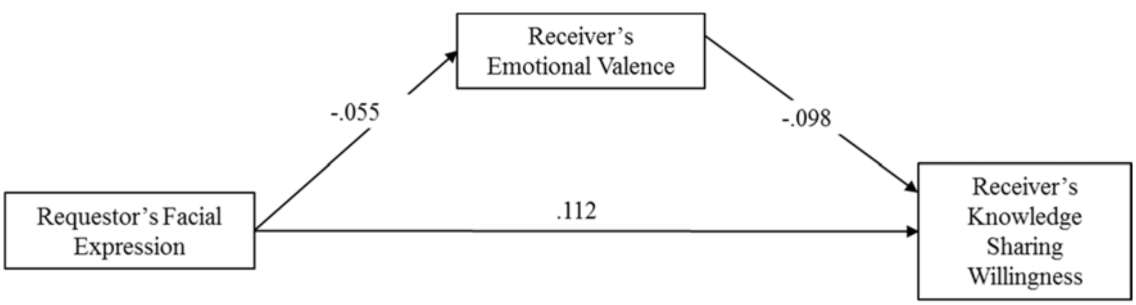


Figure 5. Male-only model

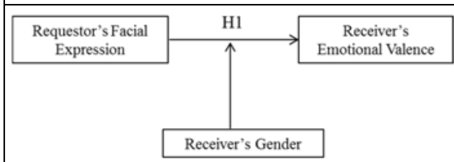
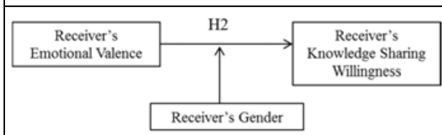
Table 3. Path Analysis: Female Only

Variables	Path to	Path to	R square
	Receiver's emotional valence	Receiver's knowledge-sharing willingness	
Requestor's facial expression	.459 (t = 3.735)***	.104 (t = .463)	
Receiver's emotional valence		.347 (t = 1.722)**	.133
Requestor's knowledge-sharing willingness			.185
Note: *** denotes significant at the 0.01 level; ** denotes significant at the 0.05 level.			

Table 4. Path Analysis: Male Only

Variables	Path to	Path to	R square
	Receiver's emotional valence	Receiver's knowledge-sharing willingness	
Requestor's facial expression	-.055 (t = .181)	.112 (t = .466)	
Receiver's emotional valence		-.098 (t = .654)	-.005
Requestor's knowledge-sharing willingness			.047

Table 5. Summary of Moderated Mediation Results based on PLS

	Method 1 Full-sample method (Chin et al. 2003)	Method 2 Subgroup method (Wegener and Fabrigar, 2000; Rigdon et al., 1998; Keil et al., 2000)
	Supported .445 (t = 2.383)***	Supported (stage 1) Female: .459 (t = 3.735)*** Male: -.055 (t = .181) n.s. Test for difference: t = 25.82***
	Not supported .362 (t = .557)	Supported (stage 2) Female: .347 (t = 1.722)** Male: -.098 (t = .654) n.s. Test for difference: t = 26.37***
Mediation test by subgroup	Supported Moderation of mediation supported by differences in Sobel's t- test: Female: t = 6.48*** Male: t = 1.06 n.s.	

Note: Method 1: to evaluate the moderation of the mediating paths, I used the product terms that are part of the model summarized in Table 3: (requestor's facial expression x receiver's gender) and (receiver's emotional valence x receiver's gender).
Method 2: I split the sample into subgroups based on gender. Gender moderates the mediation if evidence for the mediation differs between the subgroups. I assessed evidence for the mediation using Sobel's test. The methodological literature on moderation in the context of structural equation modeling (Rigdon et al., 1998) and mediation (Wegener & Fabrigar, 2000) recommends the subgroup approach. The test for statistical difference of path coefficients between samples is suggested by Wynne Chin and documented in Keil et al. (2000).
*** denotes significant at the 0.01 level; ** denotes significant at the 0.05 level.

5.3 Receiver's Emotional Valence and Knowledge-sharing Willingness

H2 posits that a receiver's emotional valence is more positively associated with knowledge-sharing willingness when the receiver is female rather than male. The PLS model in Table 3 shows that the path from the product term (receiver's emotional valence x receiver's gender) to a receiver's knowledge-sharing willingness was insignificant (beta = .362, t = .557, p > .55). Yet, the female-only model showed a significant path from valence to knowledge-sharing willingness (Figure 4, Table 4, beta = .347, t = 1.722, p <.05), whereas the male-only model again did not show a significant link (Figure 5, Table 5, beta = -.098, t = .654, p > .25). Thus, the subgroup method (Rigdon et al., 1998; Wegener & Fabrigar, 2000) supports H2 (i.e., that there is a difference in the way males and females translate their emotional experience into knowledge sharing). Chin's t-statistic also supports a significant difference of the strength of the path coefficients across samples (t = 26.37, p < .01, Table 6). Table 6 summarizes the results.

5.4 Moderated Mediation

In accordance with the emotional contagion framework, the hypotheses H1 and H2 together imply a mediation that gender moderates. To test the significance of the mediation paths, I used Sobel's t-test (Preacher &

Leonardelli, 2001). I found evidence for such a mediation for female participants (Sobel's t-test = 6.48, p < .01) but not for male participants (Sobel's t- test 1.06, p > .14). Figure 6 summarizes the research model.

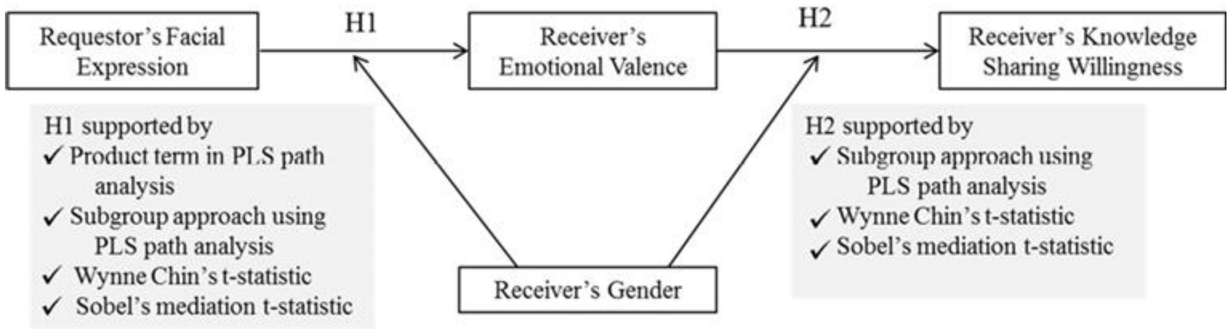


Figure 6. Research Model Evaluation

6 Limitations and Future Research

Next to the usual limitations of a laboratory experiment, some specific limitations of this study seem worth mentioning, which provide opportunities for future research. In this study, I used the face as an affect-detection channel. Calvo and D'Mello (2010) review six different affect-detection channels that emotionally intelligent systems can use: facial expressions, voice, body language and posture, physiology, brain imaging and EEG, and text. Thus, with regards to the affect-detection channel, I used only one channel in this study. However, as for affect's influence on knowledge-sharing decisions, this study may be more generalizable to other channels as well. For instance, if a system tells the affect of a decision maker through different means, the AIM would have the same prediction with respect to knowledge sharing.

Further, I examined knowledge sharing as a form of sharing codified knowledge. There can be different costs and benefits associated with sharing codified knowledge versus sharing personal advice in terms of improvements to work quality, signaling of competence, and time savings (Sproull, Subramani, Kiesler, Walker, & Waters, 1996; Haas & Hansen, 2007). Thus, it is important to examine emotional effects in different forms of knowledge sharing to refine our understanding of emotional effects in knowledge sharing.

Further, I observed mimicry behavior using face reader technology and observe theory-consistent behavioral responses in the knowledge-sharing domain. Thus, using face-reader technology, I could open the "black box" and observe objective data (as opposed to subjective self-reported data) directly from the human body (Dimoka et al., 2012). Doing so responds to calls for IS research to use more objective rather than self-assessed subjective data (Marsden, Pakath, & Wibowo, 2006). However, the objective data I observed still only reflects what occurs in the brain and is only one step towards unpacking the "black box" of human behavior. For instance, I show the second step of the emotional contagion framework only indirectly via showing theory-consistent behavioral consequences in knowledge sharing originating from the stimuli. Future research may work towards triangulating additional objective measures to support the findings.

In my control analysis, I found indication that positive mimicking might be stronger than negative mimicking behavior. While one might consider this finding to be good news from an organizational perspective because it is rather of interest to organizations to induce positive emotional conditions to support knowledge sharing than to induce negative emotional conditions, future research needs to explore this indication and potential implications for emotionally intelligent systems.

7 Discussion

Table 7 summarizes this study's contributions to research and practice. Table 7 references related literature and outlines previous findings that are associated with this study. I discuss contributions to research below in relation to the first two research areas in Table 7. I discuss contributions to and implications for practice below in relation to the latter two research areas in Table 7.

7.1 Psychological Motivations in Knowledge Sharing

First, this study contributes to the literature that examines the psychological motivations associated with knowledge sharing. Such a contribution is particularly important in light of the limited evidence on the role of emotions in knowledge sharing, which van den Hooff, Schouten, and Simonovski (2012, p. 148) stress in stating: "The connection between emotions and knowledge sharing…has not been the subject of much empirical research to date". The current study is arguably most closely related to van den Hooff et al.'s (2012) findings: they found that the emotions pride and empathy affect willingness to share knowledge. Admittedly, as compared to measurement scales such as pride and empathy, my measure of emotional valence as a composite measure of one positive and four negative emotional states seems quite crude. Still, I show that even a crude classification of valence on a continuum from negative to positive can predict individuals' tendency to share knowledge. Importantly, I perform this classification by observing physiological responses of humans (for a review on the use of neurophysiological tools in information systems, see, for example, Dimoka et al., 2012; Riedl et al., 2010a; Riedl, Davis, & Hevner, 2014a), which is important for our research perspective because much research in the literature doubts that questionnaires can capture gender differences in emotions because of social desirability response behavior. As such, Manstead (1992, p. 364) contends: "it is entirely possible (or even likely) that the way in which males and females respond to [emotion] questionnaires will, consciously or unconsciously, be influenced by their knowledge of sex stereotypes".

As a theoretical lens, I use the AIM to predict that emotions influence knowledge-sharing decisions because these decisions are strategic and rather complex in nature. In a real-life context, this complexity is magnified rather than mitigated, which is why these results are likely to be stronger in real life.

7.2 Gender Differences and Knowledge Sharing

Second, this study contributes to literature by exploring gender differences in knowledge sharing (Miller & Karakovsky, 2005; Lin, 2008) and offering another explanation why males and females can differ in their knowledge-sharing behavior (i.e., because of the different role of emotions in men and women). I draw on gender differences in the sensitivity to social cues (stage 1; Kahn et al., 1971; Croson & Gneezy, 2009) and on gender differences in the intensity and the functional significance of the emotional experience (stage 2; Grossman & Wood, 1993, Allen & Haccoun, 1976). I also draw on the theory of emotional contagion in predicting and evidencing gender differences in mimicry behavior and how emotions color subsequent knowledge-sharing behavior. Consistent with expectations, I found evidence that females exhibit stronger mimicry behavior than men and, thus, that, for women, this stronger mimicry behavior results in a knowledge-sharing behavior colored more by emotions.

Information systems scholars have observed gender differences in physiological responses. For instance, we have evidence that brain activation related to information systems tasks can be higher in females than in males (Riedl et al., 2010b; Pavlou 2010). Information systems scholars have also found evidence that gender has a moderating role in important behavior for information systems success. For instance, in the domain of technology acceptance, research has found that the relation between perception of usefulness and technology adoption is stronger in men than in women and that the relation between subjective norm and technology acceptance is stronger in women than in men (Venkatesh & Morris, 2000). The current study combines both: it evidences gender differences in physiological responses related to emotions and shows effects of these gender differences on behavior relevant to information systems management. As such, it particularly contributes to the knowledge-sharing literature.

Table 7. Contributions to Research and Practice

Research areas	Current thinking (closely associated and relevant findings)*	Contribution of this study
1: Psychological motivations in knowledge sharing	Pride and empathy influence knowledge sharing (Van den Hooff et al., 2012) Psychological climate and knowledge repository characteristics influence knowledge sourcing (Durcikova & Fadel, Forthcoming) Usefulness of neuroscience tools to use objective data from the human body to open the "black box" of human behavior (Dimoka et al., 2012)	Emotional valence influences knowledge sharing (theoretic perspective: affect infusion model) Use of emotional valence as an objective measure in the domain of knowledge sharing: step towards reducing the reliance on self-reported subjective measures
2: Gender differences and knowledge sharing	Gender moderates the influence of courtesy, sportsmanship, and altruism on knowledge sharing (Lin, 2008) Gender roles influences feedback-seeking in teams (Miller & Karakovsky, 2005) Gender moderates the influence the effect of perception of usefulness, ease of use, and social norm on technology use (Venkatesh & Morris, 2000) Women activate more brain areas than men to judge trustworthiness of eBay offers (Riedl et al., 2010b) Brain activation constructs in relation to the perception of online product recommendation agents higher for female than male users (Pavlou, 2010)	Emotional valence serves as a mediator to predict knowledge sharing for females (theoretic perspective: emotional contagion) Gender moderates the effect of facial stimuli on emotional valence Gender moderates the effect of emotional valence on knowledge-sharing willingness
3: Faces in information systems	Interfaces with faces change user perceptions (Sproull, Subramani, Kiesler, Walker, & Waters, 1996) Human faces are considered more trustworthy than faces of avatars (Riedl, Mohr, Kenning, Davis, & Heekeren, 2014b) Positive faces are associated with website loyalty (Gregor, Lin, Gedeon, Riaz, & Zhu, 2014)	Facial expressions accompanying knowledge-sharing requests can change knowledge-sharing behavior Use of faces can improve the effectiveness of knowledge-management systems
4: Affect detection channels and emotionally intelligent information systems	There are six ways of detecting affect. Almost none of the reviewed systems integrate contextual cues with facial feature tracking (Calvo & D'Mello, 2010) Development and demonstration of a neuro-adaptive information system supporting financial decision making (Astor, Adam, Jercic, Schaaff, & Weinhardt, 2014)	Demonstration of a system that detects affect context dependent by using the face as an affect detection channel and the eye tracker to detect human interaction with context Triangulating facial data with eye-tracking data can predict knowledge-sharing behavior
Note: I do not describe the references closely associated with this study that appear in this table in their entirety. I include the displayed findings as "relevant" not because they are generally the most relevant findings but because they are closely associated with this study. Accordingly, the categorization of references to particular research areas can vary according to which aspect of the references one stresses. Contributions to theory and research relate to the first two research areas. Implications for practice relate to the latter two research areas.		

7.3 Faces and Information Systems

Third, this study contributes to the investigation of faces in information systems. Research has shown that individuals consider human faces to be more trustworthy than faces of digital avatars (Riedl et al., 2014b), that faces influence website loyalty (Gregor et al., 2014), and that humanization of interfaces change user perceptions (Sproull et al., 1996). This study contributes to this literature in showing that facial expressions that accompany knowledge-sharing requests can change knowledge-sharing behavior. Surely, in reality, a simple smile with a picture attached to, for example, an email may not help in situations where individuals incur high costs from individual knowledge sharing. In organizations, a whole set of strategic considerations may be present, and face-to-face communication includes a lot of other non-verbal cues besides facial expressions, such as voice tones and body gestures, which may influence people's perceptions. Still, holding everything else constant, a smile—including a virtual smile—can make a difference. For instance, profile pictures that often accompany messages exchanged through communication and collaboration systems such as Skype, Slack, or Jammer can improve the nature of the information exchange with regards to participants' level of cooperation and helpfulness, which may become even more important in the future because of increasing virtualization and digitization of work. Generally, for information systems practitioners, the results underscore the importance of emotionally "positive" systems design.

7.4 Affect Detection Channels and Emotionally Intelligent Information Systems

Forth, and in part as a consequence of the above, this study informs designers of information systems in general and designers of knowledge-management systems in particular about how and in which contexts emotional stimuli in information systems may influence behavior. Thereby, it contributes to the literature of affect detection channels. Researchers have suggested several hybrid systems that process not only content data but also emotional data (for a review, see, for example, Cowie et al., 2001; Calvo & D'Mello, 2010). The potential of reliably telling important emotions in an automated and digital fashion is obvious because systems can use such information to interact with humans in an emotionally intelligent way. Information systems' capability of recognizing and adequately responding to emotions "can enhance the quality of the interaction, thereby making a computer interface more usable, enjoyable, and effective" (Calvo & D'Mello, 2010, p. 19). I suggest a set-up with a commercially available face reader and eye tracker (see Figure 2) that can overcome limitations of context dependence in affect detection (Calvo & D'Mello, 2010). In the case of knowledge-management systems, deploying affect information can support knowledge exchange in organizations, which is more important than ever in our knowledge-intensive environment, and can increase the effectiveness of users and organizations.

Moreover, the role of emotions in information systems will likely receive more and more attention with increasing technological possibilities. For instance, Kurzweil (2005, p. 37) states that "the human ability to understand and respond appropriately to emotion (so-called emotional intelligence) is one of the forms of human intelligence that will be understood and mastered by future machine intelligence". Some researchers are working on integrating emotions into information systems in order to use them as bio-feedback and to enhance dynamic learning environments (Astor et al. 2013). Therefore, we need to understand the possibilities and limits associated with tracing emotions via face readers. This study shows that simple facial stimuli can influence emotions and that resulting emotions can influence decisions highly important for organizations and communities (i.e., knowledge sharing). Importantly, this study contributes in showing a full path (that holds for females) from facial stimuli to an expression of knowledge-sharing willingness via the mediator valence.

8 Conclusion

This study examines affect infusion and affect detection in knowledge-sharing behavior. I show that face reader technology can detect affect infused by facial expressions and that this affect influences responses of a receiver of a knowledge-sharing request. The effects observed concur with the primitive emotional contagion and affect infusion models. Importantly, I found evidence that there are gender differences in the exhibition of mimicry behavior, the infusion of affect, and knowledge-sharing responses.

Thus, the appropriate use of faces to design systems and the appropriate detection of facial emotion can increase the effectiveness of knowledge-management systems. Pictures of faces can be used as part of information presentation in systems to make humans more responsive to information that computers present. In turn, systems can detect human faces to tell human affective states. These affective states can be factored into system behavior to make computers more responsive to humans.

Research has long stated that faces are very important to people in social and emotional communication (Darwin, 1872; James, 1884). With the advent of emotionally intelligent systems, faces will probably continue to play a crucial communication role, and the integration of facial information will provide opportunities for enhanced system designs in the future.

References

Allen, J. G., & Haccoun, D. M. (1976). Sex differences in emotionality: A multidimensional approach. *Human Relations*, 29(8), 711-722.

Allen, J. G., & Hamsher, J. H. (1974). The development and validation of a test of emotional styles. *Journal of Consulting and Clinical Psychology*, *42*(5), 663-668.

Astor, P.J., Adam, M. T. P., Jercic, P., Schaaff, K., & Weinhardt, C. (2013). Integrating biosignals into information systems: A neuroIS tool for improving emotion regulation. *Journal of Management Information Systems*, *30*(3), 247-278.

Barsade, S. G. (2002). The ripple effect: Emotional contagion and its influence on group behaviour. *Administrative Science Quarterly*, *47*(4), 644-675.

Blackhart, G. C., Kline, J. P., Donohue, K. F., LaRowe, S. D., & Joiner, T. E. (2002). Affective responses to EEG preparation and their link to resting anterior EEG asymmetry. *Personality and Individual Differences*, *32(*1), 167-174.

Bless, H. (2000). The interplay of affect and cognition: The mediating role of general knowledge structures. In J. P. Forgas (Ed.), *Feeling and thinking: The role of affect in social cognition* (pp. 201-222). New York, NY: Cambridge University Press.

Bock, G. W., Zmud, R. W., Kim, Y. G., & Lee, J. N. (2005). Behavioral intention formation in knowledge sharing: Examining the roles of extrinsic motivators, social-psychological forces, and organizational climate. *MIS Quarterly*, *29*(1), 87-111.

Bower, G. H. (1981). Mood and memory. *The American Psychologist*, *36*(2), 129-148.

Cabrera, A., & Cabrera, E. F. (2002). Knowledge-sharing dilemmas. *Organization Studies*, *23*, 687-710.

Calvo, R., & D'Mello, S. (2010). Affect detection: An interdisciplinary review of models, methods, and their applications. *IEEE Transactions on Affective Computing*, 1(1), 18-37.

Chin, W. W. (1998). Commentary: Issues and opinion on structural equation modeling. *MIS Quarterly*, *22*(1), vii-xvii.

Chin, W. W., Marcolin, B. L., & Newsted, P. R. (2003). A partial least squares latent variable modeling approach for measuring interaction effects: Results from a Monte Carlo simulation study and an electronic-mail emotion/adoption study. *Information Systems Research*, *14*(2), 189-217.

Cohen, J. D. (2005). The vulcanization of the human brain: A neural perspective on interactions between cognition and emotion. *The Journal of Economic Perspectives*, *19*(4), 3-24.

Constant, D., Kiesler, S. & Sproull, L. (1994). What's mine is ours, or is it? A study of attitudes about information sharing. *Information Systems Research*, *5*(4), 400-421.

Cootes, T. F., & Taylor, C. J. (2004). *Statistical models of appearance for computer vision*. Manchester, UK: University of Manchester.

Cowie, R., Douglas-Cowie, E., Tsapatsoulis, N., Votsis, G., Kollias, S., Fellenz, W., & Taylor, J. G. (2001). Emotion recognition in human-computer interaction. *IEEE Signal Processing Magazine, 18*(1), 32-80.

Croson, R., & Gneezy, U. (2009). Gender differences in preferences. *Journal of Economic Literature*, *47*(2), 448-474.

D'Arcey, J. T. (2013). *Assessing the validity of FaceReader using facial EMG (*doctoral dissertation). California State University.

Darwin, C. (1872). The expression of the emotions in man and animals. *Darwin Online*. Retrieved from http://darwin-online.org.uk/content/frameset?pageseq=1&itemID=F1142&viewtype=text

Dawes, R. M. (1980). Social dilemmas. *Annual Review of Psychology*, *31*(1), 169-193.

Diener, E., Sandvik, E., & Larsen, R. J. (1985). Age and sex effects for emotional intensity. *Developmental Psychology*, *21*(3), 542-546.

Dimoka, A, Banker, R. D., Benbasat, I., Davis, F. D., Dennis, A. R., Gefen, D., Gupta, A., Ischebeck, A., Kenning, P. H., Pavlou, P. A., Muller-Putz, G., Riedl, R., vom Brocke, J., Weber, B. (2012). On the use of neuropyhsiological tools in IS research: Developing a research agenda for neuroIS. *MIS Quarterly, 36*(3), 679-702.

Durcikova, A., & Fadel, K. J. (Forthcoming). Knowledge sourcing from repositories: The role of system characteristics and psychological climate. *Information & Management*.

Edwards, J. R., & Lambert, L. S. (2007). Methods for integrating moderation and mediation: A general analytical framework using moderated path analysis. *Psychological Methods*, *12*(1), 1-22.

Ekman, P. (1970). Universal facial expressions of emotion. *California Mental Health Research Digest*, *8*, 151-158.

Fiedler, K. (2000). Towards an integrative account of affect and cognition phenomena. In J. P. Forgas (Ed.), *Feeling and thinking: The role of affect in social cognition* (pp. 223-252). New York: Cambridge University Press.

Forgas, J. (1995). Mood and judgment: The affect infusion model (AIM). *Psychological Bulletin*, *117*(1), 39–66.

Forgas, J. (1998). On being happy and mistaken: Mood effects on the fundamental attribution error. *Journal of Personality and Social Psychology*, *75*(2), 318-331.

Forgas, J., & Eich, E. (2013). Affective influences on cognition: Mood congruence, mood dependence, and mood effects on processing strategies. A. F. Healy & R. W. Proctor (Eds.), *Handbook of psychology* (pp. 61–82). New York: Wiley.

Forgas, J., & George, J. (2001). Affective influences on judgments and behavior in organizations: An information processing perspective. *Organizational Behavior and Human Decision Processes*, *86*(1), 3-34.

Fridlund, A. J. (1991). Evolution and facial action in reflex, social motive, and paralanguage. *Biological Psychology*, *32*(1), 3-100.

Fridlund, A. J. (1994). *Human facial expression: An evolutionary view*. San Diego: Academic Press.

Furl, N., Gallagher, S., & Averbeck, B. B. 2012. A selective emotional decision-making bias elicited by facial expressions, *PLoS ONE*, *7*(3), 1-7.

Gefen, D., & Straub, D. W. (1997). Gender differences in the perception and use of e-mail: An extension to the technology acceptance model. *MIS Quarterly*, *21*(4), 389-400.

Goldberg, J. H. (2014). Measuring software screen complexity: Relating eye tracking, emotional valence, and subjective ratings. *International Journal of Human-Computer Interaction*, *30*(7), 518-532.

Gregor, S., Lin, A. C. H., Gedeon, T., Riaz, A. & Zhu, D. (2014). Neuroscience and a nomological network for the understanding and assessment of emotions in information systems research. *Journal of Management Information Systems*, *30*(4), 13-48.

Grossman, M., & Wood, W. (1993). Sex differences in intensity of emotional experience: A social role interpretation. *Journal of Personality and Social Psychology*, *65*(5), 1010-1022.

Hahn, J., & Subramani, M. R. (2000). A framework of knowledge management systems: Issues and challenges for theory and practice. In *Proceedings of 21st International Conference on Information Systems* (pp. 302-312).

Haas, M. R., & Hansen, M. T. (2007). Different knowledge, different benefits: Toward a productivity perspective on knowledge sharing in organizations. *Strategic Management Journal*, *28*(11), 1133-1153.

Hatfield, E., Cacioppo, J. T., & Rapson, R. L. (1994). *Emotional contagion.* Cambridge, UK: Cambridge University Press.

He, W., Boesveldt, S., de Graaf, C., & de Wijk, R. A. (2014). Dynamics of autonomic nervous system responses and facial expressions to odors. *Frontiers in Psychology*, *5*, 1-8.

Hislop, D. (2002). Mission impossible? Communicating and sharing knowledge via information technology. *Journal of Information Technology*, *17*(3), 165-177.

Hole, G., & Bourne, V. (2010). *Face processing: Psychological, neuropsychological, and applied perspectives*. Oxford, UK: Oxford University Press.

Horstmann, G. (2003). What do facial expressions convey: Feeling states, behavioural intentions, or action requests? *Emotion*, *3*(2), 150-166.

James, W. (1884). What is an emotion? *Mind*, *9*, 188-205.

Kahn, A., Hottes, J., & Davis, W. L. (1971). Cooperation and optimal responding in the Prisoner's Dilemma game: Effects of sex and physical attractiveness. *Journal of Personality and Social Psychology*, *17*(3), 267.

Kalling, T., & Styhre, A. (2003). *Knowledge sharing in organizations*. Liber: The Hague.

Kankanhalli, A., Tan, B. C., & Wei, K. K. (2005). Contributing knowledge to electronic knowledge repositories: an empirical investigation. *MIS Quarterly*, *29*(1), 113-143.

Keil, M., Tan, B. C., Wei, K. K., Saarinen, T., Tuunainen, V., & Wassenaar, A. (2000). A cross-cultural study on escalation of commitment behavior in software projects. *MIS Quarterly*, *24*(2), 299-325.

Kurzweil, R. (2005). *The singularity is near: When humans transcend biology*. Vikin: New York (NY).

Langner, O., Dotsch, R, Bijlstra, G., Wigboldus, D. H. J, Hawk, S T., & van Knippenberg, A. (2010). Presentation and validation of the Radboud Faces Database. *Cognition and Emotion*, *24*(9), 1377-1388.

Larsen, R. J., & Diener, E. (1987). Affect intensity as an individual difference characteristic: A review. *Journal of Research in Personality*, *21*(1), 1-39.

Lazarus, R. S. (1991). Cognition and motivation in emotion. *American Psychologist*, *46*(4), 352-367.

Lewinski, P., den Uyl, T. M., & Butler, C. (2014). Automated facial coding: Validation of basic emotions and FACS AUs in FaceReader. *Journal of Neuroscience, Psychology, and Economics*, *7*(4), 227-236.

Lewinski, P., Tan, E. S., Fransen, M. L., Czarna, K., & Butler, C. (2016). Hindering facial mimicry in ad viewing: effects on consumers' emotions, attitudes and purchase intentions. In P. Verlegh, H. Voorveld, & M. Eisend (Eds.), *Advances in advertising research* (vol. VI, pp. 281-288). Berlin: Springer.

Lin, C. P. (2008). Clarifying the relationship between organizational citizenship behaviors, gender, and knowledge sharing in workplace organizations in Taiwan. *Journal of Business and Psychology*, *22*(3), 241-250.

Loijens, L., & Krips, O. (2014). *FaceReader methodology* (white paper). Noldus Information Technology.

Manstead, A. S. (1992). Gender differences in emotion. In A. Gale & M. W. Eysenck (Eds.), *Handbook of individual differences: Biological perspectives* (pp. 355-387). Oxford, England: John Wiley & Sons.

Marsden, J. R., Pakath, R., & Wibowo, K. (2006). Decision making under time pressure with different information sources and performance-based financial incentives: Part 3. *Decision Support Systems*, *42*(1), 186-203.

Miller, D. L., & Karakowsky, L. (2005). Gender influences as an impediment to knowledge sharing: When men and women fail to seek peer feedback. *The Journal of Psychology*, *139*(2), 101-118.

Mussel, P., Goeritz, A. S., Hewig, J. (2013). The value of a smile: Facial expression affects ultimatum-game responses. *Judgment and Decision* Making, *8*(3), 381-385.

Pavlou, P. (2010). Explaining the adoption of anthropomorphic online product recommendation agents: A functional neuroimaging study. *Journal of Management Information Systems*, *25*(4), 145-182.

Preacher, K. J., & Leonardelli, G. J. (2001). *Calculation for the Sobel test: An interactive calculation tool for mediation tests* (computer software). Retrieved from http://www.people.ku.edu/preacher/sobel/sobel.htm

Pugh, S. D. (2001). Service with a smile: Emotional contagion in the service encounter. *Academy of Management Journal*, *44*(5), 1018-1027.

Riedl, R., Banker, R. D., Benbasat, I., Davis, F. D., Dennis, A. R., Dimoka, A., Gefen, D., Gupta, A., Ischebeck, A., Kenning, P., Müller-Putz, G., Pavlou, P. A., Straub, D. W., vom Brocke, J., and Weber, B. (2010a). On the foundations of NEUROIS: Reflections on the Gmunden Retreat 2009. *Communications of the Association for Information Systems*, *27*, 243-264.

Riedl, R., Davis, F. D., & Hevner, A. R. (2014a). Towards a neuroIS research methodology: Intensifying the discussion on methods, tools, and measurement. *Journal of the Association for Information Systems*, *15*(10), i-xxxv.

Riedl, R., Hubert, M., & Kenning, P. (2010b). Are there neural gender differences in online trust? An fMRI study on the perceived trustworthiness of eBay offers. *MIS Quarterly*, *34*(2), 397-428

Riedl, R., Mohr, P. N. C., Kenning, P. H., Davis, F. D., Heekeren, H. R. (2014b). Trusting humans and avatars: A brain imaging study based on evolution theory. *Journal of Management Information Systems*, *30*(4), 83-114.

Rigdon, E. E., Schumacker, R. E., & Wothke, W. (1998). A comparative review of interaction and nonlinear modeling. In G. A. Marcoulides & R. E. Schumacker (Eds.), *Interaction and nonlinear effects in structural equation modeling* (pp. 1-16). Mahwah, NJ: Erlbaum.

Rizzolatti, G., Craighero, L. (2004). The mirror-neuron system. *Annual Review of Neuroscience*, *27*, 169-92.

Russell, J. A. (1994). Is there universal recognition of emotion from facial expressions? A review of the cross-cultural studies. *Psychological Bulletin*, *115*(1), 102-141.

Sarma, R. N., Subramani, M., & Aldrich, A. (2001). Situated learning and the situated knowledge web: Exploring the ground beneath knowledge management. *Journal of Management Information Systems*, *18*(1), 115-150.

Seidel, E. M., Habel, U., Kirschner, M., Gut, R. C., & Derntl, B. (2010). The impact of facial emotional expressions on behavioural tendencies in women and men. *Journal of Experimental Psychology*: *Human Perception and Performance*, *36*(2), 500-507.

Spender, J. C. (1996). Making knowledge the basis of a dynamic theory of the firm*. Strategic Management Journal*, *17*(2), 45-62.

Sproull, L., Subramani, M., Kiesler, S., Walker, J. H., & Waters, K. (1996). When the interface is a face. *Human-Computer Interaction*, *11*(2), 97-124.

Sweeney, J. W. (1973). An experimental investigation of the free-rider problem. *Social Science Research*, 2(3), 277-292.

Tobii Technology AB. (2012). *User manual—Tobii Studio Version 3.2*. Retrieved from tobii.com

van Kuilenburg, H., Wiering, M., & den Uyl, M. (2005). A model-based method for facial expression recognition. In J. Gama, R. Camacho, P. Brazdil, A. Jorge, & L. Torgo (Eds.), *Machine learning* (LNCS 3720, pp. 194-205). Berlin: Springer-Verlag.

Van Den Hooff, B., Schouten, A. P., & Simonovski, S. (2012). What one feels and what one knows: the influence of emotions on attitudes and intentions towards knowledge sharing. *Journal of Knowledge Management*, *16*(1), 148-158.

Venkatesh, V., & Morris, M. G. (2000). Why don't men ever stop to ask for directions? Gender, social influence, and their role in technology acceptance and usage behavior. *MIS Quarterly*, *24*(1), 115-139.

Wasko, M. M., & Faraj, S. (2000). It is what one does: Why people participate and help others in electronic communities of practice. *Journal of Strategic Information Systems*, 2000, *9*(2-3), 155-173.

Wegener, D. T., & Fabrigar, L. R. (2000). Analysis and design for nonexperimental data: Addressing causal and noncausal hypotheses. In H. T. Reis & C. M. Judd (Eds.), *Handbook of research methods in social and personality psychology* (pp. 412-450). New York: Cambridge University Press.

Weiner, B. (1992). *Human motivation: Metaphors, theories, and research*. Thousand Oaks, CA: Sage.

Whelan, E. (2007). Exploring knowledge exchange in electronic networks of practice. *Journal of Information Technology*, *22*, 5-12.

Wild, B., Erb, M., & Bartels, M. (2001). Are emotions contagious? Evoked emotions while viewing emotionally expressive faces: Quality, quantity, time course and gender differences. *Psychiatry Research*, *102*(2), 109-124.

Zhao, W., Chellappa, R., Phillips, P. J., & Rosenfeld, A. (2003). Face recognition: A literature survey. *ACM Computing Surveys*, *35*(4), 399-458.

About the Authors

Dennis D. Fehrenbacher is a Senior Lecturer at the Department of Accounting, Monash Business School, Monash University, Melbourne, Australia. He received his PhD from Stuttgart University, Germany. He gained professional experience in Germany, Ireland, and the United States; in the manufacturing industry, financial-services industry and in advisory; in small and medium-sized companies as well as multinationals. He conducts research in information systems and managerial control examining professional decision making. He has published in domestic and international journals.