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DESIGNING FOR KNOWLEDGE-BASED FAMILIARITY, TRUST, AND ACCEPTANCE: THE CASE OF AFFECTIVE TECHNOLOGY

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Research in Progress

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Abstract

With the ability to recognize human emotions, so-called affective technology has the potential to provide highly adaptive service to its user in many different areas such as learning, health care, or manufacturing. However, there are specific barriers for the acceptance of affective technology because most people are unfamiliar with the affective components of such technologies and, hence, do not trust them. Assuming that increasing the knowledge-based familiarity with an affective technology is essential for accepting it, so far, only little is known about appropriate design concepts to increase the familiarity and, as a consequence, the acceptance of affective technology. To close this gap, we follow a Design Science approach laying out an explanatory design theory for knowledge-based familiarity and acceptance of affective technology. We argue that familiarity with a technology is built by gaining knowledge about the emotional state the system has recognized and the subsequent behavior of the system and such knowledge will be gained by providing suitable feedback. We develop different designs for feedback systems of an affective technology and propose corresponding design hypotheses. This research-in-progress concludes with the planned experimental approach varying feedback content and feedback explanation.

Keywords: Affective Technology, Trust-based Acceptance, Knowledge-based Familiarity, Feedback, Design Theory, Experiment

1 Introduction

With the ability to recognize human emotions, affective technology has the potential to provide situationally and individually highly appropriate service to its user. Since Picard's ground-breaking book (Picard, 1997), the field of "affective computing" has established itself dealing with the research and development of different affective technology applications, such as in education, security, health care, entertainment, marketing, and many more (D'Mello and Calvo, 2013; Afzal and Robinson, 2015). For instance, affect-aware learning technologies can detect boredom, confusion, frustration, or engagement of the learner based on conversational cues, body language, and facial features and respond adequately to improve the learning experience and to increase the learning effect (D'Mello and Graesser, 2013). In accordance with the definition of affective computing by Picard (2015), we define affective technology as technology which can sense and/or generate human emotions such as happiness, anger, or fear. The acceptance of affective technology, that is the intention to use an affective technology application, is a key condition to make use of the service that such a technology can provide. Nevertheless, so far, research on the acceptance of affective technologies is rather fragmentary. In a qualitative study, Heger et al. (2016) have found that trust, knowledge-based familiarity, and emotional self-reflexivity are key conditions for the acceptance of affective technology. Although there exist many studies on the design of affective technology within the affective computing community (e.g. D'Mello and Graesser, 2013), to the best of our knowledge, only little is known about how to design such technology to explicitly foster its acceptance and, in doing so, the trust and familiarity of its users. Options to increase familiarity of a technology are provided by the field of 'feedback systems'. Since familiarity with a technical system relies on knowledge about it, appropriate feedback could provide suitable information to support the user in gaining knowledge. How technology can be designed to increase acceptance is a question for design science research and explanatory design theories in Information Systems.

Assuming that trust as an antecedent of acceptance and knowledge-based familiarity as an antecedent of trust are essential for the intention to use affective technology (Heger et al., 2016), our aim is to gain insights into how to develop appropriate design concepts to increase the acceptance of affective technology. We therefore identify a missing design theory for the acceptance of affective technology as a research gap. Hence, the research in progress paper at hand has two research objectives:

RO1: We develop and present a design theory for trust-based acceptance of affective technology.

RO2: We outline the research method with which we will test the proposed design theory.

To achieve our research objectives, we develop an explanatory design theory (Gregor, 2009; Baskerville and Pries-Heje, 2010; Niehaves and Ortbach, 2016) comprising the constructs of behavioral intention, trust, knowledge-based familiarity, emotional self-reflexivity, and feedback.

2 Related Work

2.1 Acceptance of Affective Technology: Theory Background

In a qualitative study, Heger et al. (2016) identify trust, understanding the behavior of an affective technology (i.e. knowledge-based familiarity), and emotional self-reflexivity as most important for the acceptance of affective technology. Further research studies on affective technologies with regard to acceptance deal with ethical or social issues. Ethical concerns mentioned by Picard (1997, 2003), Reynolds and Picard (2004), and Cowie (2015) refer to the risk that emotion-related data are ultimately private and personal information that can potentially be provided to third parties. In contrast, data protection and considered privacy concerns could support acceptance and rise trust (Picard, 2003). Cowie (2015) summarizes the relationship between ethics and affective technology to the needs of "characteristic imperatives: to increase net positive affect, to avoid deception, to respect autonomy, to ensure that system's competence is understood and to provide morally acceptable portraits of people" (p. 334).

Trust in IT has been examined in several studies (e.g., Gefen, 2000; Gefen et al., 2003; Komiak and Benbasat, 2006; McKnight et al., 2011). Rousseau et al. (1998) define trust as "a psychological state comprising the intention to accept vulnerability based upon positive expectations of the intentions or behavior of another" (p. 395). High social complexity arises when parties do not always behave rationally and predictably and, yet, people seek to understand them. This complexity can be reduced by trust (Luhmann, 1979; Rousseau et al., 1998). In addition, trust depends on the belief on an individual that the other party behaves dependably (Kumar et al., 1995; Kumar, 1996), ethically (Hosmer, 1995), and in a socially appropriate way (Zucker, 1986). In the context of Information Systems, McKnight et al. (2011) state that trust is not only relevant for person-to-firm relations and interpersonal relationships, but that "trust in the information technology itself plays a role in IT-related beliefs and behavior" (p. 1). Complementarily, Lewicki and Bunker (1995) argue that the other party can be an individual or an object. Moreover, Fukuyama (1995) states that trust is an essential and necessary precondition for the acceptance and adoption of unpredictable, uncontrollable, hazardous, and new technologies. Trust arises by being familiar with the who, how, when, and what is happening (Lewicki and Bunker, 1995). Knowledge-based familiarity reduces uncertainty by creating an understanding for what is happening in the present (Luhmann, 1979; Gefen et al., 2003). Gefen (2000) defines familiarity as a "specific activity-based cognizance based on previous experience or learning of how to use the particular interface" (p.727). In addition, Doney et al. (1998) state that trust arises from a prediction process based on knowledge and information as well as the anticipation of the other's party behavior.

2.2 Design of Feedback Systems of Affective Technologies

Feedback has fundamental influence in a broad variety of settings, such as in learning, working, or training environments. Feedback is an information delivery mechanism used to evaluate the extent to which prior behavior of an individual meets their internal goal standard (Martocchio and Webster, 1992). In the context of training, feedback is meant to improve the employees' performance and to implement procedures (van de Ridder et al., 2015). The benefits of feedback, for instance, in learning environments has been examined in different experimental settings (Graesser et al., 2005), and in a variety of studies (Kulhavy and Stock, 1989; Arnold et al., 2006; Smits et al., 2008; Butler et al., 2013). Graesser et al. (2005) differentiate between positive, neutral, and negative feedback, which can be delivered from the system through prompting the user to fill missing information – through hints for how to go further, corrections if the input is wrong, and assertions as well as summarizations if information is missing or need to be shorten (Graesser et al., 2005). The main goal of feedback here is to deliver the possibility of adjusting actions towards the desired outcome. One crucial element for the design of contextual feedback is the information content (Butler et al., 2013).

Within the affective technology literature, there are many examples for designing feedback for emotional states recognized by the system. Video feedback is used in healthcare systems (Stratou et al., 2015), visual robots in the e-learning context (Wenhui et al., 2009), and visual emotional avatars in social learning environments for people with schizophrenia (Bekele et al., 2016), or in gaming settings (Sourina and Liu, 2013). Kummer et al. (2012) present an approach that reflects emotions of conversational partners by playing music. The studies of Landowska (2013) and Hupont et al. (2013) examine multi-methodical approaches. The first one uses text, audio, and video for tutoring systems while the latter uses smileys, emotional saccade (paths) maps, heat maps, and dashboards for reflecting affective states. In addition, Katmada et al. (2015) use graphs including a timeline in a serious gaming context. Carvalhaes et al. (2013) present a real robot called MollyPet which recognizes emotions of autistic children for therapy purposes. Moreover, Kerr and Bornfreund (2005) develop the virtual and emotional "BuddyBot" to generate consumer trust on a website.

Although substantial research exists in the area of technology acceptance as well as feedback design, to the best of our knowledge, no investigation yet has studied the relation between the design of feedback and the construct of knowledge-based familiarity with a technology.

3 Research Model and Hypothesis Development

In this section, we derive hypotheses to develop an explanatory design theory (Gregor, 2009; Baskerville and Pries-Heje, 2010; Kuechler and Vaishnavi, 2012; Niehaves and Ortbach, 2016). In contrast to design practice theories in which theory development is aimed at informing practice how to design artifacts, explanatory design theories are aimed at "analysing, describing and predicting what happens as artifacts exist and are used in their external environment" (exterior mode; Gregor, 2009, p. 7). For explanatory design theories, this aim can be achieved through setting up hypotheses that can be tested empirically (Gregor, 2009; Niehaves and Ortbach, 2016).

Acceptance of affective technology depends on trust in affective technology due to the fact that affective technologies are unknown to most people, are less controllable than common technologies, and operate with highly sensitive data (Heger et al., 2016). The studies from, for instance, Gefen et al. (2003), Gefen (2000), and McKnight (2011) show that trust is especially important in situations with high uncertainty, which is the case when using affective technology. Technology acceptance has been widely investigated in Information Systems Research, also in a relation with trust and trust antecedents (e.g. (Davis, 1989; Davis et al., 1989; Pavlou et al., 2005; Chen and Barnes, 2007; Ponte et al., 2015; Wang et al., 2015;

Venkatesh et al., 2016). Moreover, Gefen (2000) argues that familiarity has a direct influence on behavioral intention for the reason that people who are overwhelmed by the complexity of an interface are more likely to give up using it. Figure 1 represents the research model.

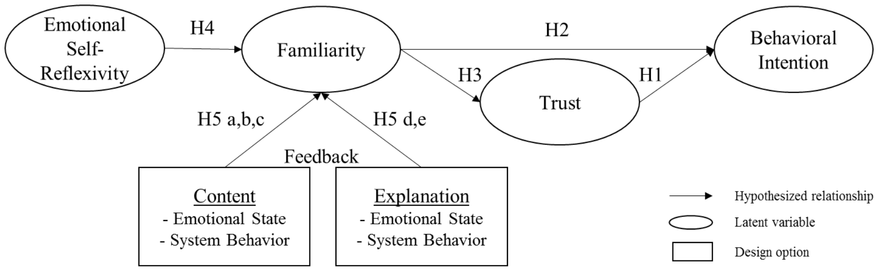

Figure 1. Research Model

H1: Trust in affective technology positively relates to the behavioral intention to use affective technology.

H2: Knowledge-based familiarity with affective technology positively relates to the behavioral intention to use affective technology.

Recent research shows that knowledge-based familiarity is an antecedent of trust (Gefen, 2000; Gefen et al., 2003). In the context of affective technology, understanding an affective technology is significantly important for trust, since the fear of arbitrary behavior by the system will decrease if the behavior of the system is comprehensible, predictable, and can be anticipated (Luhmann, 1979; Lewicki and Bunker, 1995).

H3: Knowledge-based familiarity with affective technology positively relates to trust in affective technology.

Current literature describes "understanding affective technology depends on the capability to reflect and to be aware of one's own emotions", because "only by comparing the technology's behavior with their own perception, a user can develop an understanding of how and why an affective technology behaves in a certain way" (Heger et al., 2016, p. 8). The concept of emotional self-reflexivity overlaps with studies and concepts from psychology, such as "emotional intelligence" (Dulewicz and Higgs, (2000), "self-awareness" (Steiner, (1997), and "emotional competence" (Bar-On and Parker, 2000; Boyatzis et al., 2000; Ciarrochi and Deane, 2001). The sub-constructs "comprehension", "clarity", and "awareness" of emotional competence developed by Goleman (1998) are said to highly overlap with emotional self-reflexivity. We add the category of "sensations" as an affective technology recognizes emotions through physical measurements.

H4: Emotional self-reflexivity positively relates to knowledge-based familiarity with an affective technology.

With the objective to increase a user's familiarity with an affective technology, the integration of a feedback system can be a solution. As the term knowledge-based familiarity indicates, familiarity with a piece of technology relies on knowledge and information about it. Knowledge is built by gaining experience (Gefen et al. 2003). From a technology's perspective, feedback helps a user to gain knowledge about the technology and to reduce confusing interaction by providing appropriate information. Feedback can be designed in different ways. When designing a feedback system for providing appropriate information to increase the user's familiarity with the technology, the designer has to answer the question, which information is useful for this purpose. In the context of affective technology, "the system should constantly make visible to the user on which basis – that is which emotional state of the user the system has detected – the affective technology reacts" (Heger et al. (2016) p. 11), because the behavior of the affective system depends on precisely this. Besides, additional information on the behavior of the system can be useful feedback, since the ability to understand how an affective technology reacts after it has recognized a human emotion is significantly important. Consequently, we hypothesize:

H5a: Feedback from an affective technology which provides information on the emotional state of the user will positively influence their knowledge-based familiarity with the technology.

H5b: Feedback from an affective technology which provides information on the system behavior will positively influence a user's knowledge-based familiarity with the technology.

H5c: Providing information on the emotional state of the user and the system behavior will positively influence a user's knowledge-based familiarity with the technology more than if one of the two pieces of information is left out.

Besides information on the emotional state and system behavior, additional explanatory information on why a certain emotional state has been detected by the system and why the system reacts in a certain way can further help to become familiar with the system. The reason for this assumption is that familiarity relies on the predictability and anticipation of the other's behavior (Lewicki and Bunker, 1995). Familiarity means to develop an understanding of what is happening in the present (Luhmann, 1979). Thus, explaining to a user for which reasons an affective technology functions and behaves in a certain way will help them to anticipate future behavior.

H5d: Feedback from an affective technology which explains why a certain emotional state of the user has been detected will positively influence a user's knowledge-based familiarity with the technology.

H5e: Feedback from an affective technology which explains why it behaves in a certain way will positively influence a user's knowledge-based familiarity with the technology.

4 Method

Design and Participants. To test our hypotheses, we plan to conduct two experiments that are explained below. For the experiments, we choose an affective learning system that teaches the competence of writing a thesis, because many people and students in particular are familiar with e-learning environments and emotions are especially crucial for learning. For the purpose of simplification, we decide to focus the experiment on the recognition of only one emotion. As a low level of confusion is a learning-relevant emotion that, in contrast to frustration or boredom, is potentially beneficial for learning (D'Mello et al., 2014) and therefore should not negatively interfere with the perceived usefulness of the affective technology overall, we select confusion. We do not select engagement as the emotion of interest because, to the best of our knowledge, a reliable induction for this learning-relevant emotion does not exist. We specify the sample size to be 30 participants per group. Thus, we require a sample of 120 participants per experiment. According to power analysis conducted with G*Power (Faul et al., 2007), we need a sample size of 128 participants to obtain a power of 0.8 (assuming a medium effect size of 0.25) for an 2 x 2 ANCOVA with one covariate (emotional self-reflexivity). We plan to recruit students for the experiments because scientific writing is a topic that is actually relevant for students.

Experiment 1: In the first experiment, our objective is to test the effects of different types of feedback content on technology acceptance (H1-4, H5a, H5b, and H5c). Therefore, we want to conduct a 2 (emotion-related feedback vs. control) x 2 (system behavior feedback vs. control) between-subjects design.

Procedure. After the experimenter explains the setting of the study to the participant, the participant is seated at a computer workplace. The experimenter explains that the session is recorded by a camera through which the affects are recognized. On the computer screen, the participant can read a short introduction that summarizes how a thesis should be written and structured. On the next page, we use a confusion induction (adapted from Lehman et al., 2013) to bring participants into a state of confusion which could happen in a normal learning situation. For the confusion induction, two digital agents – a digital tutor (a professor) and a digital student represented with avatars – argue in a chat about the structure of a thesis. In contrast to the previous page, the digital tutor claims that, in the result's section, you should discuss in detail why unexpected results have occurred. The student, on the other hand, argues that the unexpected results should be explained in detail not until the discussion section. After the participant is asked about their opinion, one of the agents still disagrees. Then, the feedback manipulations (see Table 1) are introduced through a pop-up window. Regardless of feedback manipulation, all participants are asked to explain their opinion to the two agents. Finally, participants complete the scales with behavioral intention, familiarity, trust, emotional self-reflexivity, manipulation checks, sociodemographic variables, and control variables on the computer and are debriefed by the experimenter.

Design options. The manipulation of the design options is presented in a pop-up window after the confusion induction is conducted. The design options are realized through different textual statements (see Table 1). In a paragraph under the statement of the feedback manipulation, the following text is presented in all conditions: "Please explain the arguments for your opinion". Thus, the pop-up window in the control condition only differs in the absence of the first paragraph from the other conditions.

Emotion-related feedback	"The system has detected that you are confused."
System behavior feedback	"The system has detected that explaining your opinion is the best learning strategy now."
Emotion-related and system behavior feedback	"The system has detected that you are confused. The system has detected that explaining your opinion is the best learning strategy now."
Control	*No text*

Table 1. Design Options in the different conditions of feedback content.

Manipulation Checks. We will develop three manipulation checks each for emotion-related feedback and system behavior feedback manipulation. The items for emotion-related feedback focus on whether the participants notice that the system tells them about their emotional state. The items for system behavior feedback ask whether they notice that the system told them a change in behavior.

Dependent and control Measures. The dependent and control measures will be measured on a 7-point Likert scale. The dependent measures are presented in the appendix. We adapt additional control measures for perceived ease-of-use und perceived usefulness from Gefen et al. (2003).

Experiment 2: In the second experiment, our objective is to test the effects of different types of feedback explanation on technology acceptance (H1-4, H5d, and H5e). Thus, we will conduct a 2 (emotion-related feedback explanation vs. control) x 2 (system behavior feedback explanation vs. control) between-subjects design.

Procedure. The materials and procedure are mostly identical to the first experiment. In contrast to the first experiment, the design options that are prompted through a pop-up window are different and consist of the textual statements presented in Table 2.

Emotion-related explanation	"The system has detected that you are confused because you frowned. The system has detected that explaining your opinion is the best learning strategy now."
System behavior explanation	"The system has detected that you are confused. The system has detected that explaining your opinion is the best learning strategy now because this reduces your confusion."
Emotion-related and System behavior explanation	"The system has detected that you are confused because you frowned. The system has detected that explaining your opinion is the best learning strategy now because this reduces your confusion."
Control	"The system has detected that you are confused. The system has detected that explaining your opinion is the best learning strategy now."

Table 2. Design Options in the different conditions of feedback explanation.

Manipulation Checks. We will develop three manipulation checks each for emotion-related explanation and system behavior explanation. The items for emotion-related explanation ask whether the participants know how exactly the system identifies the emotions they have. The items for system behavior feedback explanation ask participants whether the system informed them why it reacts the way it reacts.

*Dependent and Control Measures. S*ame as in experiment 1.

Data Analysis: In Experiment 1, we will use two-way ANCOVA to test the main and interaction effects of emotion-related feedback and system-behavior feedback on familiarity, controlling for emotional self-reflexivity as control variable. Likewise, in Experiment 2, we will use two-way ANCOVA to test the main and interaction effects of emotion-related feedback explanation and system-behavior feedback explanation. For additionally testing hypotheses 1-4 in each experiment, we will use Consistent PLS path modeling (Dijkstra and Henseler, 2015; Henseler et al., 2016).

5 Discussion and Outlook

With this study, we contribute to existing literature by building a design theory for the context of affective technology with focus on the relation between feedback and familiarity. Our goal is to identify how an affective feedback system should be developed for increasing acceptance. From theoretical perspective, our experiment could provide useful insights to identify relevant design options for designing affective systems. From practical perspective, the results could lead to higher acceptance by users.

Furthermore, we contribute to design theorizing in providing a methodological approach to test more than two design options of a design theory using a stringent methodological approach. Using two experiments that build upon each other has several advantages. First, as the proposed hypotheses are tested two times with two independent samples, the theory is strengthened when it is not falsified in one or both experiments. Second, when we test the three design options (emotion-related feedback, system behavior feedback, and feedback explanation) in two separate experiments, we maintain a stringent experiment in which we vary as less information as possible in the different conditions. Second, using two separate experiments offers the option of modification in the second experiment if the hypotheses cannot be supported. In this case, the theory can be adjusted for the next experiment without the need to recruit a large sample of participants for one unified experiment.

However, our research approach has limitations. As we want to use a pop-up window to deliver the feedback to the participants, a frequent interruption through pop-ups could be irritating in a real learning setting. Thus, future work could test how the feedback should be presented with regard to interruptions (e.g., testing the continuous presentation of the emotion-related feedback in a small part of the screen or the use of flow over-window or layer-window). Another limitation consists of the uncertainty whether all relevant hypothesized relationships can be supported in experiment 1 which could lead to the necessity of adapting experiment 2.

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Appendix

***Behavioral Intention to Use Affective Technology* (adapted from Gefen et al., 2003 and Gefen, 2000)**
I would use an affective learning system.
I would allow an affective learning system to respond on the basis of my emotions.
When having the choice between the same learning system with or without emotion recognition, I would rather use the one with emotion recognition.
Trust in affective technology (adapted from Gefen, 2000)
I believe that the affective learning system is trustworthy
I trust the affective learning system.
I'd trust the affective learning system to do the job right
Knowledge-based familiarity (adapted from Gefen, 2000 and Gefen et al., 2003)
I am familiar with the behavior of an affective learning system by using it.
I am familiar with how an affective learning system responds.
I can predict how an affective learning system responds.
I understand why an affective learning system responds in the way it responds.
An affective learning system responds in the way I expect.
An affective learning system responds reliably.
Emotional self-reflexivity – clarity (translated from Berking and Znoj, 2008)
Last week I could have stated clearly how I was feeling.
Last week I was clear about what emotions I was experiencing.
Last week I knew well how I was feeling.
Emotional self-reflexivity – comprehension (translated from Berking and Znoj, 2008)
Last week I was aware of why I felt the way I felt.
Last week I understood my emotional reactions.
Last week I knew what my feelings meant.
Emotional self-reflexivity – awareness (translated from Berking and Znoj, 2008)
Last week I paid attention to my feelings
Last week I was aware of my feelings.
Last week I dealt with my feelings.
Emotional self-reflexivity - sensations (translated from Berking and Znoj, 2008)
Last week my physical sensations were a good indication of how I was feeling.
Last week I was physically well aware of my feelings.
Last week I clearly realized when my body reacted noticeably to emotionally meaningful situations.
Manipulation checks – emotion-related feedback (self-developed)
The system told me what I felt.
It was transparent to me which emotions the system recognized.
The system notified me when it recognized a change in my emotions.
Manipulation checks – system behavior feedback (self-developed)
The system told me how it reacted.
It was transparent to me how the system reacted.
The system notified me when it changed the learning strategy.
Manipulation checks – emotional-related feedback explanation (self-developed)
The system told me how it recognized my emotions.
It was transparent to me on which basis the system recognized my emotions.
The system notified me when my bodily reactions changed.
Manipulation checks – system behavior feedback explanation (self-developed)
The system told me why it reacted the way it reacted.
It was transparent to me why the system reacted the way it reacted.
The system notified me why it changed the learning strategy.

Table 3. Measurement items