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Unveiling Emotions: Attitudes Toward Affective Technology

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Completed Research Paper

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Abstract

With its ability to sense and/or generate human emotions, affective computing calls for a new generation of technology. This study brings affective technologies into focus which can sense human emotions. Compared to other types of technology, affective technologies have distinct characteristics—anthropomorphism, uncontrollability, capturing of highly sensitive data, unfamiliarity, and complexity—with fundamental effects on the interaction with humans. These characteristics of affective technology create a feeling of uncertainty about how such a system works. However, the attitudes people exhibit toward the usage, notably trust, such as affective assistance systems has received only scant attention. Hence, we define attitudes toward affective technology and contribute to the literature by proposing a research model that we analyzed using a quantitative methodology with 303 participants. From the theoretical model, we derive implications for theory, practice, and design.

Keywords: Affective Technology, Trust-based Acceptance, Trust, Questionnaire-based Survey

Introduction

Affective technology is increasingly becoming an important type of technology. In 1997, Rosalind Picard published a much-considered book called “Affective Computing” (Picard 1997). Since then, “affective computing” has established itself as a multidisciplinary research field (Picard 2015). It deals with human-computer interaction while focusing on affect or emotion (Braun and Alt 2019). In accordance with the definition of affective computing, affective technologies are systems which can sense and/or generate human emotions (e.g. happiness, anger, fear etc.) (Schwark 2015). Consequently, affective technologies can be subdivided into systems which focus on the feelings of humans and into systems which pretend to generate feelings themselves. For instance, the first case refers to affective technologies that can “understand” what humans feel. Another distinction can be made between affective systems which aim to influence human feelings and supposedly emotion-neutral systems that are able to capture human emotions and respond accordingly without aiming at manipulating the feelings of its users.

Affective technologies can assist humans in several different application fields such as education, security, heath care, entertainment, marketing, and many more (Afzal and Robinson 2015). Affect-aware learning technologies can detect boredom, confusion, or frustration of the learner based on conversational cues, body language, and facial features. They respond with empathetic, encouraging, and motivational dialogue to significantly improve the learning effect (D'Mello and Graesser 2015; Tadayon et al. 2018).

Compared to other types of technology, technologies which can sense emotions have distinct characteristics with fundamental effects on the interaction between humans and technologies. Systems which possess the ability to recognize human emotions—an ability once reserved solely for humans—would be perceived as humanoid. This phenomenon is also known as "anthropomorphism" (Duffy 2008). Moreover, technologies which (primarily) respond to emotional impulses are less controllable. Another characteristic of affective technology is its ability to capture and store emotion-related data of individuals. Such data can be considered as highly sensitive, since feelings belong to the private sphere of humans. Until now, applications of affective technology have been rather unknown to the public and have not yet established a space for themselves in everyday life. They seem to be a very complex piece of technology, whose functioning and behavior cannot be comprehended by an ordinary person. Since these characteristics apply to the category of affective technologies which sense human emotions and respond to them, the focus of this study will lie on this category of affective technology.

Although the distinct characteristics of affective technology have fundamental effects on human-computer interaction, research on attitudes toward affective technology is sparse. So far, the research field of affective computing has focused on theoretical foundations from psychology (Reisenzein 2015), neuroscience (Kemp et al. 2015), or computing (Lisetti and Hudlicka 2015); technical aspects and ways of implementation, for instance, detection (Cohn and La Torre 2015) or generation (Ochs et al. 2015) of affect; specific use cases and application fields (Arkin and Moshkina 2015; D'Mello and Graesser 2015); or ethical issues, and particularly privacy or data protection concerns (Cowie 2015; Picard 2003; Reynolds and Picard 2004a, 2004b; Stahl et al. 2013; Ward and Marsden 2004).

In an empirical study, Karaiskos et al. (2008) examined cognitive and affective antecedents of mobile data service usages. They considered social factors (such as the influence of friends and media), affect (such as being enjoyable or pleasant), and perceived consequences (such as task accomplishment, performance improvement, or effectiveness enhancement) as significantly influencing antecedents of intention. In a similar work, Hoong and Lim (2014) integrated positive and negative affect and technology acceptance constructs (i.e. ease-of-use and usefulness) as antecedents of perception attitude influencing usage and intention to use. Even though affective computing is a striving research field, it remains rather unclear which factors influence the willingness of people to use affective technologies.

In a qualitative study, Heger et al. (2016) showed that trust and familiarity are essential for the acceptance of affective technology. This is due to the characteristics of affective technology. The characteristics mentioned above—anthropomorphism, uncontrollability, capturing of highly sensitive data, unfamiliarity, and complexity—create a feeling of uncertainty about how such a system works and unwanted dependence. According to McKnight et al. (2011), "trust is crucial to almost any type of situation in which either uncertainty exists or undesirable outcomes are possible" (pp. 1–2). Trust is the human strategy to deal with unpredictable situations (Luhmann 1979). Thus, we assume that trust is an essential construct for affective technology acceptance whereby Granatyr et al. (2017) and Braun and Alt (2019) refer to trust and reputation models by means of affective and cognitive paradigms.

In summary, qualitative approaches which deal with attitudes toward affective technology are already available as well as research frameworks which focus on affective trust. However, no research, to the best of our knowledge, exists that shows a generalizable and integrated theoretical approach which includes the mentioned aspects and characteristics of affective technologies (i.e. recognizing and responding to human emotions) related to existing trust-based acceptance theories. Therefore, the next step in the forming of a (holistic) theoretical model that includes acceptance, trust, familiarity, and other relevant factors tested by a quantitative approach is yet to be taken. Consequently, this study is guided the following research question:

> *What attitudes do people exhibit toward affective technology and how do they influence their acceptance of it?*

We use literature on affective computing and trust to identify and define relevant attitudes toward affective technology. We then develop our hypotheses and test the structural equation model. The data bases on telephone interviews with 303 participants. Our results support that trust, familiarity, and structural assurances are major predictors in the willingness to use affective technology. This study contributes to literature by 1) investigating attitudes toward affective technology, 2) by applying a trust-based acceptance theory for affective technology, and 3) by deriving theoretical and practical implications.

Research Background

Affective Technology

In accordance with the definition of affective computing (Picard 2015), an affective technology can be defined as a technology which can sense and/or generate human emotions such as happiness, anger, or fear (Schwark 2015). A large part of the research on affective technologies is restricted to technical solutions to how emotions can be recognized and used by the technology itself (Cowie et al. 2001; Hussain et al. 2015; Mikuckas et al. 2014). For instance, Steephen et al. (2018) focus their work on affective adaption; Wen et al. (2014) investigate multi-variant correlations of physiological signals such as fingertip blood oxygen saturation, galvanic skin response, and heart rate; Cruz et al. (2014) examine vision and attention theory for continuous facial emotion recognition; Xu et al. (2018) research knowledge transfer in video emotion recognition; and Mumenthaler et al. (2018) study emotion recognition in simulated social contexts and interactions. Recent research which concentrates on other purposes than technical solutions has been conducted in learning or car driving contexts (Wu et al. 2016). Lara et al. (2018) investigate emotional states in educational video games by voice analysis, Braun and Alt (2019) present an affective in-car voice assistant, while D'Mello and Graesser (2015) empirically examine an affect-aware learning system based on a mixed-method approach of body pressure, facial expression, and speech recognition.

In contrast, there is only sparse research, which are notably empirical studies, on the acceptance of these technologies. Recent research on the acceptance of affective technologies has focused on ethical issues (e.g. Cowie 2015), explored aspects which lead to trust and acceptance of affective technologies (Heger et al. 2016), or examined affective trust models and frameworks related to personality, emotions, and mood in decision-making processes (Granatyr et al. 2017). Ethical issues are relevant as long as affective technologies have the ability to recognize and express human emotions (Picard 1997; Reynolds and Picard 2004b). Emotions are ultimately something personal and private, because they are deeply ingrained in a human being. Every user of such a technology takes the risk of providing information from within them to others. Picard (2003) puts this fact in an exaggerated nutshell by taking a devil's advocate perspective: She states that that the detection, recognition, or manipulation of emotions is the "ultimate breach of ethics and will never be accepted by users" (p. 61). If there is no privacy and no data protection, affective technologies will be widely rejected and the use of the technology will lead to distrust (Picard 2003). Furthermore, Cowie (2015) argues that the interplay between ethical issues and emotional systems (i.e. affective technologies) needs "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). Within a qualitative study, Heger et al. (2016) examine facets of and emphasize the relevance of trust in the acceptance of affective technologies. Furthermore, they explore the antecedents of trust by matching their empirical findings with the literature. These antecedents are knowledge-based familiarity, institution-based situational normality, and structural assurances, calculation-based beliefs, and disposition to trust technologies.

Trust as a Key Antecedent in Acceptance Research

Trust-based acceptance theories have been examined in several empirical studies. In the field of IS, research focuses on online environments, particularly in the field of e-commerce (e.g. Chen and Barnes (2007); Gefen (2000); Gefen et al. (2003); Hong and Cha (2013); Kim (2012); McKnight et al. (2011); Roghanizad and Neufeld (2015); Wang et al. (2008); Wu and Chen (2005); Che et al. (2015); Jones and Leonard (2008)). For example, Gefen et al. (2003), Gefen (2000), and Davis (1989) examine the interaction between online vendors and private consumers, while McKnight et al. (2011) investigate the interaction between IT artefacts and users focusing on trust as the key construct. Further studies, such as Chen and Barnes (2007), Wu and Chen (2005), and Kim (2012), examine the formation of initial trust of private online shopping consumers. The former identifies drivers for the development process of initial trust (Chen and Barnes 2007), while Wu and Chen (2005) extend the theoretical model of Gefen et al.

(2003) by an investigation of initial adoption of on-line tax. The latter study investigates an initial trust construct and its impact on consumer beliefs and their intentions to purchase (Kim 2012).

Furthermore, Hong and Cha (2013) study trust as an antecedent of purchase intention and as a consequence of perceived risk. An alternative way of studying trust is adopted by Ponte et al. (2015), and Qureshi et al. (2018). They examine the impact of perceived value, perceived security, privacy, chargeback fraud in cross-border, and social interactions on trust and online purchase intentions. Moreover, Dai and Luo (2011) provide an integrated model to investigate consumer characteristics (e.g. innovativeness) and its impact on consumer's evaluation of services (e.g. trust) and satisfaction. The study by Wang and Benbasat (2005) examines trust in recommendation agents for online purchasing. Komiak and Benbasat (2006) extended the model of Wang and Benbasat (2005) and included the construct perceived personalization of technologies to investigate the impact on trust and usage intentions of recommendation agents. Furthermore, Wang and Benbasat (2008) study trust and its antecedents, such as knowledge-based familiarity and interactive, calculative, and dispositional quotient of recommendation agents or online ads. Schaupp and Carter (2010) conducted another online environment study focusing on E-file adoption. They examined the constructs trust of the E-filer and trust of the internet and their impact on perceived risk and the intention behind using E-filing. Sipior and Ward (2008) performed an experiment to investigate trust in vendors whereby the authors focused their work on spyware presence and its negative impact on trustworthiness or privacy control perceptions. Additionally, studies explore data aspects in their work and examine trust as a strategy against uncertainty (Allen et al. 2000).

Hypotheses Development

This section elaborates the attitudes people hold toward the use of affective technology which can sense emotions and store these highly sensitive personal data. Based on these attitudes we derive hypotheses and present an integrated and extended model (c.f. Figure 1).

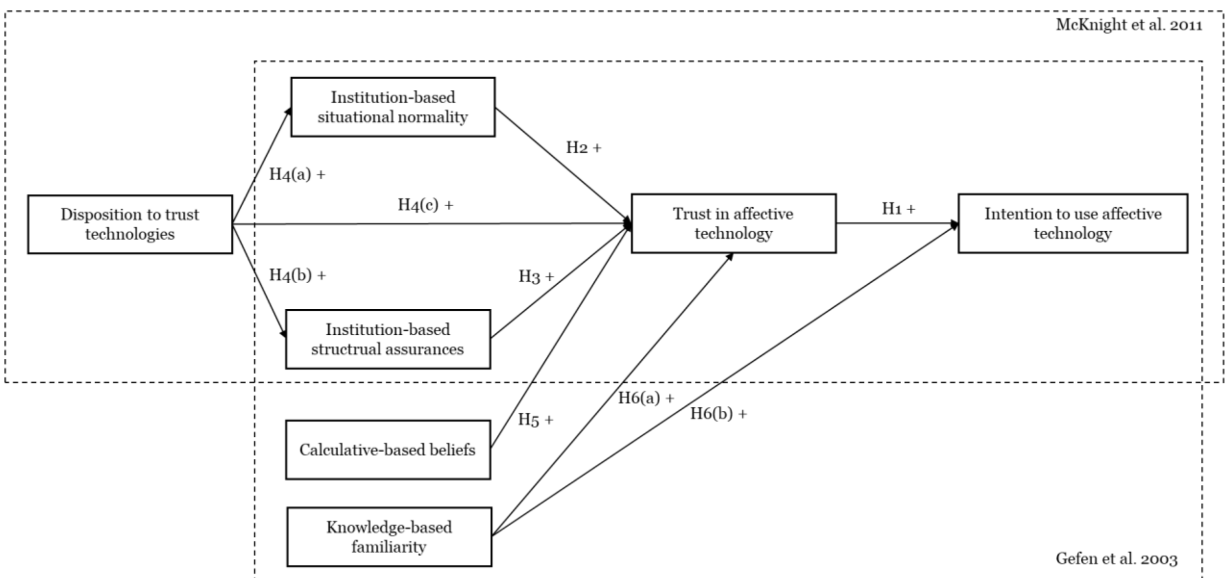

Figure 1. Research Model

Trust in Affective Technology

During social interactions, a high complexity is created by the disharmony between the lack of rational or predictable behavior of the other parties and the need to understand them. To reduce this complexity, humans have developed a strategy, i.e. trust and trusting beliefs in others (Lowry et al. 2014; Luhmann 1979; Rousseau et al. 1998). 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). Therefore, trust is the willingness of people to be exposed to risky situations where they have no control over the others party's (individuals or objects) behavior (Gefen 2000) and is a necessary precondition for the acceptance and adoption of unpredictable, uncontrollable, hazardous, and new technologies (Fukuyama 1995). Thereby, trust or the trusting beliefs of the trustee depends on the attributes and/or characteristics of the other party. Trust is belief in another party, whereby the trustee believes that the other party behaves dependable (Kumar 1996; Kumar et al. 1995), ethical (Hosmer 1995), and in a socially appropriate way (Zucker 1986). These characteristics of trust highlight the complexity of the construct. It is multidimensional (Butler 1991; Zucker 1986) and context-dependent (Luhmann 1979; Rousseau et al. 1998).

Following the idea proposed by McKnight et al. (2011), trust is more than person-to-firm relations and interpersonal relationships. They argue that "trust in the information technology itself plays a role in shaping IT-related beliefs and behavior" (McKnight et al. 2011, p. 1). According to McKnight et a. (2011) and Lewicki and Bunker (1995), the other party can be an individual or an object (such as a technology). Within IS research, for instance, online vendors are unavailable to provide proven guarantees that they do not act opportunistically, such as by "unfair pricing, providing inaccurate information, violations of privacy, unauthorized use of credit card information, and unauthorized tracking of transactions" (Gefen et al. 2003, p. 55); trust is an important construct and worth further investigation. As a consequence of distrust, consumers would avoid such online vendors (Jarvenpaa and Tractinsky 1999; Reicheld and Schefter 2000). Gefen et al. (2003) argue that consumers, which is also true for individuals in general, try to identify and understand the social surroundings of the other's behavior (i.e. the what, when, why, and how the other behaves). A similar condition can be applied to affective technology, which is perceived as complex, less controllable, and creates a feeling of uncertainty (Heger et al. 2016; Jahn et al. 2017). Consequently, affective technology's functioning and behavior is hardly comprehensible (e.g. recognizing and responding to human emotions such as individual user warning while driving (Picard 2000)) and, thus, such a technology will be avoided by potential users. In contrast, if the system behaves in a predictable, dependable, ethical, and socially appropriate manner, individuals tend to trust and accept it.

H1: Trust in affective technologies will positively affect the intention to use affective technologies.

Institution-based Situational Normality of Affective Technologies

McKnight et al. (2011) describe the institution antecedent as the "focus on the belief that success is likely because of supportive situations and structures tied to a specific context of a class of trustees" (p. 8). On the one hand, there exists situational normality. This construct refers to an environment or setting, which is not new to an individual and is well-ordered; thus, trust and trusting beliefs of this individual can be expanded or transferred to a similar but new situation (McKnight et al. 2011). In other words, situational normality is the belief of an individual that the use of a new technology (here the affective technology) is perceived as normal and comfortable in a specific setting (McKnight and Chervany 2001) whereby people "extend greater trust when the nature of interaction is in accordance with what they consider to be typical and, thus, anticipated" (Gefen et al. 2003, p. 64). Hence, the use of an affective technology will be perceived as normal if the capturing of the emotion-related data works similar to the capturing of other personal data such as in-car voice assistance while driving (Braun and Alt 2019).

H2: Institution-based situational normality will positively affect trust in affective technologies.

Institution-based Structural Assurances of Affective Technologies

Moreover, there exist the institution-based structural assurances. An individual's belief is based on the feeling of safety through, for example, regulations, safeguards, or guarantees. Trust arises from the belief of support in a legal, contractual, or physical manner (McKnight and Chervany 2001). Furthermore, this belief strengthens and ensures successful interaction with the other party or use of technology (McKnight et al. 2011). The study by Heger et al. (2016) established the relevance of this construct for affective technologies. The examples mentioned for such structures are the manufacturer's reputation, recommendations by friends, contracts, certificates, studies, regulations, laws, and statements of guarantee. Therefore, higher levels of structural assurances such as guarantees, laws, and regulations on the potential misuse of emotion-related data as well as the positive reputation of the manufacturer and recommendations from third parties will lead to increased trust in affective technology.

H3: Institution-based structural assurances will positively affect trust in affective technologies.

Disposition to Trust Technologies

Researchers in the field of IS have extensively examined the antecedents of trust (e.g. Gefen et al. (2003), Lewicki and Bunker (1995), or Koufaris and Hampton-Sosa (2004)). The disposition to trust is important for the initial formation of trust, whereby the antecedent cognition-based trust refers to the categorization and illusion of control and the antecedent personality-based trust refers to the propensity to trust, further classified into the trusting stance and faith in humanity or technology (McKnight et al. 1998). Furthermore, the propensity to trust refers to a dynamic individual difference and is "neither trustee specific (as are trusting beliefs in a technology), nor situation specific (as are institution-based trusting beliefs)" (McKnight et al. 2011, p. 6). Hence, it is suggestable that disposition to trust is the willingness to depend on a technology across different situations and technologies. Individuals with a higher disposition to trust are assumed to suppose that information technologies are usually reliable, functional, and provide necessary help (McKnight et al. 2011, p. 6). Furthermore, individuals who rely on a technology will gain positive outcomes. The literature on trust proposes that trust constructs have a casual ordering whereby disposition to trust influences institution-based trust and overall trust (McKnight and Chervany 2001). Hence, individuals who tend to trust technology in general believe that positive outcomes are likely because of structures such as regulations, guarantees, laws, or recommendations protect them, and situations are normal or favorable, until their beliefs are altered.

H4 (a): Disposition to trust technologies will positively affect institution-based situational normality.

H4 (b): Disposition to trust technologies will positively affect institution-based structural assurances.

H4 (c): Disposition to trust technologies will positively affect trust in affective technologies.

Calculative-based Beliefs of Affective Technologies

The calculation antecedent contains the idea of economic principles between the trustor and the trustee (Gefen et al. 2003). It is based on the idea of costs and being favorable to the other party to cheat during the interaction. Hence, trusting beliefs arise from a rational assessment that the other party would not benefit by behaving opportunistically (Lewicki and Bunker 1995). Adapted to the field of affective technologies, it means that its user does not believe that the manufacturer of such a technology stands to gain anything by misusing the emotion-related data (e.g. sharing the information with third parties or providing a non-working or malfunctioning technology such as wrong recognitions of human emotions).

H5: Calculative-based beliefs in affective technologies will positively affect trust in affective technologies.

Knowledge-based Familiarity with Affective Technologies

Gefen et al. (2003), Gefen (2000), and Lewicki and Bunker (1995) argue that the knowledge-based familiarity antecedent is based on the idea that trust emerges from being familiar with the what, who, how, and when of what is happening. Again, trust reduces social complexity and simplifies interaction behavior between parties, whether between people or people and objects. According to Lewicki and Bunker (1995), knowledge-based familiarity is the knowledge pertaining to others. Therefore, it relies on the predictability and the anticipation of the other's behavior and it is based on the information an individual possesses about the other. Familiarity contributes to a reduction of uncertainty through an understanding of what is happening in the present (Gefen et al. 2003; Hwang and Lee 2012; Luhmann 1979). Knowledge-based familiarity is a "specific activity-based cognizance based on previous experience or learning of how to use the particular interface [here, an information technology]" (Gefen 2000, p. 727). Gefen et al. (2003) describe familiarity as experience and knowledge of past activity, relying on information, whereby the other party, whether a person or a technology, was not or did not behave opportunistically. Trust arises from an individual's prediction process guided by information and the trustor's knowledge of the other party and the prediction and anticipation of their behavior (Doney et al. 1998). In case of affective technologies, knowledge-based familiarity refers to a user's understanding of how emotions are recognized and how the data is used by the system—in short, the user's comprehension of the affective system (Heger et al. 2016; Jahn et al. 2017). Comprehension of the functioning of a system leads to trust in the system amongst users (Braun and Alt 2019) since it helps them to predict or anticipate that the affective technology is not opportunistically motivated (such as transferring or sharing highly sensitive personal data), that it works reliably in recognizing their emotions, or to understand the usage of the system. Moreover, we argue that users are more likely to use a system if they consider the emotional recognition to be reliable and helpful or useful (such as an affect-aware learning system (D'Mello and Grasser 2015)), than in case the system is malfunctioning. Hence, we hypothesize that higher levels of familiarity lead to higher levels of trust and to higher levels of intention to use affective technologies.

H6 (a): Knowledge-based familiarity will positively affect trust in affective technologies.

H6 (b): Knowledge-based familiarity will positively affect the intention to use affective technologies.

Table 1 provides an overview and summarizes the attitudes toward affective technology, which are investigated in this study.

Table 1. Overview of Attitudes toward Affective Technology

Related constructs	General description	Description with regard to affective technology
Intention to use	Intention to use refers to an individual's plan to purchase or make use of a technology.	Intention to use affective technology refers to an individual's plan to allow such a technology to capture their emotions and store the emotion-related data.
Trust	Trust is the willingness of people to be exposed in risky situations (Gefen 2000) and a precondition for the acceptance of unpredictable, uncontrollable, hazardous, and new technologies (Fukuyama 1995). It depends on the attributes and/or characteristics of the other party. The trustee believes that the other party behaves dependable (Kumar et al. 1995; Kumar 1996), ethical (Hosmer 1995), and in a socially appropriate way (Zucker 1986).	Trust in affective technology is the willingness of people to be exposed to affective technology. Affective technology seems to be unpredictable, uncontrollable, and new, which makes trust particularly relevant. The user believes that affective technology responds dependable, ethical, and in an appropriate way.
Institution-based situational normality	Situational normality refers to a setting which is not new to an individual and well-ordered, so trust can be expanded to a similar situation (McKnight et al. 2011). It is the belief that the use of a new technology is perceived as normal and comfortable in a specific setting (McKnight and Chervany 2001).	Situational normality refers to a setting in which the use of an affective technology is similar to the use of other technologies. For instance, this is the case for technologies in which the affective component is only an additional part of a technology the user already knows.
Intuition-based structural assurances	Structural assurances create a feeling of safety through, for example, regulations, safeguards, or guarantees. Trust arises from the belief of support in a legal, contractual, or physical manner.	Structural assurances with regards to affective technology refers to the manufacturer's reputation, recommendations of friends, contracts, certificates, studies, regulations, laws, and statements of guarantees (Heger et al. 2016).
Calculative-based beliefs	Trust arises from rational assessment that the other party would not benefit by behaving opportunistically (Lewicki and Bunker 1995).	The user of affective technology does not believe that the manufacturer of such a technology will benefit by misusing the emotion-related data.
Knowledge-based familiarity	Knowledge-based familiarity is being familiar with the what, who, how, and when of what is happening. Knowledge-based familiarity is the knowledge about others (Lewicki and Bunker	For affective technology, knowledge-based familiarity means the user's understanding of how emotions are recognized and how the data is used by

	1995). It relies on the predictability and the anticipation of the other's behavior. It is based on the information an individual has about the other.	the system—in short, the user's comprehension of the affective system (Heger et al. 2016). Predictability and information about the technology increases knowledge-based familiarity.

Research Method

Survey Measurements

To test our proposed hypotheses, the questionnaire used in this study was developed by considering current empirical studies on trust (Gefen 2000; Gefen et al. 2003; McKnight et al. 2011). Their measurement items were considered and the literature of affective computing technologies were analyzed (Granatyr et al. 2017; Heger et al. 2016) in order to identify characteristics such as drivers and barriers of affective technology. The items influencing the intention to use affective technologies are adapted from Gefen et al. (2003) and Gefen (2000). They contain the idea of allowing a technology to capture and collect emotion-related data.

The trust construct is adapted from Gefen (2000) and refers to the belief that affective technologies are trustworthy and work effectively. The disposition to trust items are adapted from Gefen (2000) and McKnight et al. (2011) and stand for the general trust in technologies. The calculative-based beliefs items contain the idea that a manufacturer of such a technology has nothing to gain by misusing the emotion-related data or sharing those with third parties (adapted from Gefen et al. (2003)). The items of situational normality refer to the idea that the use of affective technologies is similar to the use of other personal data capturing technologies (adapted from Gefen et al. (2003)).

The institution-based structural assurances trust-building items are derived from Gefen et al. (2003) and refer to the manufacturer's reputation, recommendations of friends, contracts, certificates, studies, regulations, laws, or statements of guarantees that assure positive outcomes. The knowledge-based familiarity items are adapted from Gefen (2000) and Gefen et al. (2003) and deal with the user's knowledge of how affective technologies recognize emotions, how to use such a technology, and how such a technology works. All multi-measurement items (at least three per construct) were measured on a 7-point Likert scale from strongly disagree (1) to strongly agree (7). All items are displayed in the Appendix.

The instruments were pretested with a sample of 30 people. The survey data was collected from private households and individuals who are above 18 years old. Since the aim of the study at hand focuses on affective technologies in general, the authors instructed a market research institute to collect a "representative" sample of the German population (older as well as younger subjects and female as well male participants). On average, the survey required 12 minutes for 30 items. To assess the reflective measurement model (Hair et al. 2012; Henseler et al. 2009), the lowest composite reliability is 0.85 (which is higher than 0.6 and shows the internal consistence reliability). The lowest indicator loading is 0.656 (which is at least high enough to show the indicator reliability within the pre-test) while each average extracted variance (AVE) is higher than 0.59, which is greater or equal to 0.5 and indicates the convergent validity. Furthermore, to check the discriminant validity, no cross loading was striking and in accordance with the Fornell-Larcker criterion, the AVE of each latent variable was higher than the squared correlations with all other latent variables. For the main survey some minor changes within the item's and introduction's wording were made to improve the content quality.

Data Collection and Descriptive Statistics

At the beginning of the questionnaire survey, the participants received an introduction to the topic of affective technologies. The functions of affective technologies, i.e. capturing, storing, and responding to emotions was explained to them. Since many people do not possess any prior experience with affective technology, except examples from newspapers and media, examples of affective technologies were provided. In this way, we ensured that all participants understand the function and purposes of affective technology. We provided examples from literature and media such as an emotion recognizing driver assistance system that can sense human emotions (anger, fear, or happiness), stores the personal data, and respond to them by user-specific warnings for reasons of precaution or an affective learning system, which can sense emotions as boredom, frustration, or confusion, for user-adaptive behavior (e.g. supporting the user through recommendations).

The survey was conducted by a market research institute through computer assisted telephone interviews (CATI). Fricker et al. (2005) recommend to use phone interviews (1) to ensure the participants understand the topic of the survey, which was introduced prior to the questions, (2) to get a completed survey interview (answers to (almost) all items), and (3) because phone respondents answer more differentiated in comparison to web surveys because web items are presented in a grid that make their similarity more salient. The market research institute excluded all respondents for whom the examples were incomprehensible. The corresponding dataset consists of 303 complete responses. All reflective constructs used were measured through multi-items (at least three). In total, 160 male and 143 female persons responded to the survey. 25 of the respondents were 18 to 25 years old, 20 were 26 to 35, 118 were 36 to 55, and 140 were above 55 years old. Furthermore, as per the educational background of the respondents, the study comprised of four students, five individuals who had completed the secondary school but without apprenticeship, 136 who had completed secondary school and an apprenticeship, 56 who were high school graduates, and 102 who had a university degree. Descriptive statistics are displayed in Table 2 whereby the replies ranged from 1 (strongly disagree) to 7 (strongly agree).

Table 2. Descriptive Statistics

Construct	Mean (Std.) of Constructs
Intention to use affective technologies	3.17 (2.00)
Trust in affective technologies	3.04 (2.00)
Disposition to trust technologies	4.80 (2.34)
Calculative-based beliefs	3.47 (2.03)
Institution-based situational normality	3.67 (2.02)
Institution-based structural assurances	3.27 (2.03)
Knowledge-based familiarity	3.69 (2.01)

Data Analysis

The structural equation model was tested with SmartPLS (Ringle et al. 2005). PLS was employed because of several advantages, including the analysis of the outer and inner model as well due to the reason that reflective models and their high complexity can be well-analyzed in cases of prediction or verification/falsification of related hypotheses (Hair et al. 2012; Henseler et al. 2009). A two-step process was conducted to check for (1) reliability and validity and (2) variance explanation of endogenous constructs (Henseler et al. 2009). As it was conducted in the pre-test, the indicator reliability is well-suited. All indicator loadings are above 0.7, except calculative-based belief item 3 (0.6989) which is almost 0.7. We decided to retain this item because the loading is almost 0.7. To check the internal consistency, the lowest composite reliability is 0.84 which is much higher than 0.6. The lowest AVE is 0.59 which shows the convergent validity. A discriminant validity check was performed by testing the cross loadings whereby no correlation was higher with another latent variable and, furthermore, the Fornell-Larcker criterion showed that each AVE of the latent variable was higher than the squared correlations with all other latent variables.

As recommended by Henseler et al. (2009) and Hair et al. (2012) the analysis of the inner model and the hypotheses paths (β) is shown next. To evaluate the proposed research model, the coefficient of determination (R^2) and the significance levels of each path coefficient is used. The results are displayed in Figure 2. The trust-based antecedents' knowledge-based familiarity (H6(a)), calculative-based beliefs (H5), and institution-based structural assurances (H3) are significant to build trust in affective technology. This also applies for familiarity with the intention to use affective technology (H6(b)). Disposition to trust technology is significant on the mediator variables institution-based situational normality (H4(a)) and structural assurances (H4(b)), but not for trust in affective technologies (H4(c)). Institution-based situational normality has no significant impact on trust (H2). Furthermore, trust has a significant impact on intention to use (H1). The control variables gender, age, and education have no significant effect on the dependent variable. In summary, hypotheses H1, H3, H5, H4(a), H4(b), H6(a), and H6(b) are supported while H2 and H4(c) are not significant.

In addition, the proposed research model can explain 48.5% of the variance in intention to use affective technology. The trust antecedents explain 54.8% of the variance of trust in affective technology. Finally, disposition to trust technology explains 6.9% and 8.3% of the variance of situational normality and structural assurances.

To measure the strength of effects of the independent variables, Cohen's f^2 values (Chin 1998; Hair et al. 2012; Henseler et al. 2009) were calculated. Trust in affective technology emerges as the primary influencer of the intention to use affective technology whereas knowledge-based familiarity had no effect. In case of trust in affective technology, knowledge-based familiarity had the strongest effect while institution-based structural assurances had the second strongest. Calculative-based beliefs only had a weak effect while disposition to trust technologies and institution-based familiarity had no effect. To check for control variables, we added age, gender, and education to the model. No further results emerge and the effect sizes on the endogenous variables are not significant.

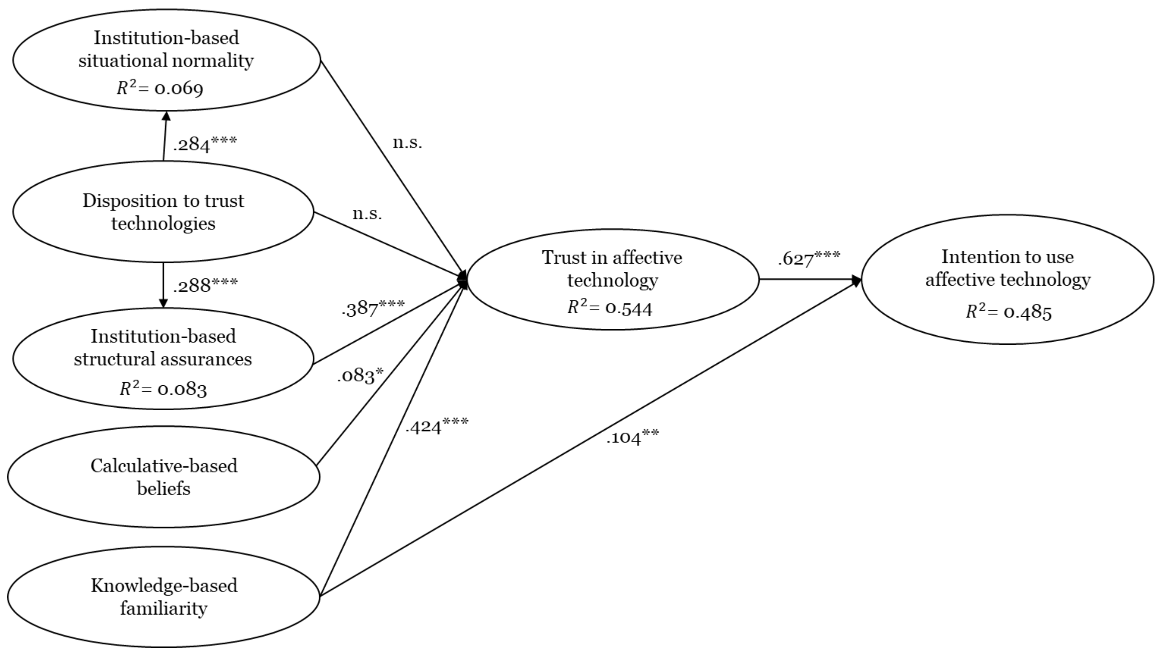

Figure 2. Results of the PLS-PM estimation (β* significant p<.01, β** significant p<.05, β* significant p<.1, n.s. = non-significant)**

Against the background of mediating effects, we conducted a post-hoc analysis and followed existing guidelines on mediation analysis (Aguinis et al. 2016; Baron and Kenny 1986; Zhao et al. 2010). We analyzed institutional-based structural assurances and situational normality as mediating effects of disposition to trust on trust in affective technology. Since our results do not support the hypothesis disposition to trust affects trust (H2(c); β=0.031, p-value=0.473), our mediation analysis indicates a mediation effect and a further indirect effect analysis (Nitzl et al. 2016) supports this emergence of a significant effect (indirect effect β=0.108, p-value=0.000). Additionally, a Sobel-Test (Preacher and Hayes 2004; Sobel 1982, 1986) confirms the result that institution-based structural assurances and situational normality fully mediate disposition to trust. To support these findings, further analysis was conducted to investigate the role of omitted mediators (Zhao et al. 2010). We followed recent guidelines for mediation analysis (Aguinis et al. 2016). We removed mediator variables (i.e. institution-based structural assurances and situational normality) to examine how the relationship between disposition to trust and trust changes. In fact, without both mediator variables, a significant path relationship between disposition to trust and trust remains (β=0.079, p-value=0.05), which is in line with analysis of indirect effects (c.f. above). Hence, we conclude that the institutional-based variables fully mediate the relation between disposition to trust and trust.

Discussion

While several studies investigate trust and trust-based acceptance of information technology, particularly in the context of e-commerce, this paper integrates attitudes people exhibit toward the use of affective technology. We argue that it is important to examine an individual's willingness to use an affective technology because such technologies are expected to have a substantial impact in everyday life and for society (Granatyr et al. 2017; Mikuckas et al. 2014; Picard 2015; Schwark 2015). The premise of this study is that trust and its antecedents are essential for the intention to use applications of affective technology. Additionally, this study examines characteristics and generators (i.e. the antecedents) of trust in affective technologies. Thus, we contribute to literature by investigating and measuring attitudes toward affective technology, by proposing an integrated model of trust-based acceptance for affective technology which can sense, collect, and respond to human emotions, and by empirically testing the model using a quantitative methodology.

In accordance with the existing theories of trust-based acceptance (Gefen et al. 2003; Gefen and Straub 2000), the results show the impact and the importance of trust for the intention to use affective technology ($\beta=0.627$, $p<0.01$). Here, the intention is the willingness to allow a technology to capture, collect, and utilize highly sensitive data, i.e. the emotions of an individual, and is based on the belief that affective technology is trustworthy. The presented study shows antecedents of trust which do exhibit significant effects on trust in affective technology or the intention to use them. One of them refers to the idea that the other party (here the manufacturer of affective technology) has nothing to gain by cheating the user by passing the emotion-related data to third parties or misusing the data (calculative-based beliefs $\beta=0.083$, $p<0.1$). The trust antecedent institution-based structural assurances has the second strongest impact on trust ($\beta=0.387$, $p<0.01$) and indicates that trust emerges from the belief of safety emerging from regulations, safeguards, or guarantees. If users believe, for example, that laws will protect them (e.g. through regulations of how to deal with emotion-related data) or that the manufacturer has a good reputation, trust arises.

Knowledge-based familiarity has the strongest impact on trust ($\beta=0.424$, $p<0.01$), which is also supported by the qualitative study of Heger et al. (2016) who concluded that familiarity is a key construct in explaining trust in affective technology. The construct refers to the user's comprehension of how emotions are recognized, the emotion-related data is captured, and how the data is used by the affective system, i.e. understanding the technology. If an individual can understand the functioning of the technology because its behavior is predictable, then their willingness to trust the technology increases. Moreover, familiarity also has a significant effect on intention to use affective technology ($\beta=0.104$, $p<0.05$). We argue that if users can understand the functioning and recognize an affective technology as reliable and useful, they are more willed to use the technology. In turn, a malfunctioning system would be avoided.

Two constructs, namely institution-based situational normality and disposition to trust technologies, have no significant impact on trust of affective technology. First, institution-based situational normality is based on the idea that a user is confronted with an environment or setting which is familiar to them and is well-ordered. Thus, trust can be transferred to a similar but new situation. One reason why institution-based situational normality has no significant impact on trust could be that some users would trust affective technology although using a technology which recognizes and responds to their emotions is unknown to them. Maybe, it is highly unimaginable to use a technology which can sense, collect, and respond to emotions and, hence, they cannot compare the use to similar technologies which capture and collect personal data.

Secondly, disposition to trust technologies has no significant effect on trust in affective technologies. Disposition to trust technologies is the individual's willingness to depend on a technology across different situations and technologies and refers to the idea that information technology in general is useable, reliable, and provides necessary help (McKnight et al. 2011). One possible reason behind this could be that, similar to situational normality, affective technology is too new and unknown due to which potential users do not relate "common" technologies to affective technologies. Another reason could lie in the data. Here, it is an antecedent of institution-based situation normality and structural assurances (McKnight et al. 2011). A mediation analysis has shown that both institution-based constructs fully mediate disposition to trust technologies (which is also evident by the high indirect effect 0.108, $p<0.01$).

Implications for Theory and Practice

The study contributes to literature by proposing several implications for theory and practice. This research is an approach to show attitudes people exhibit toward the usage of an affective technology. Therefore, we provide characteristics of affective technologies, we determine theoretical constructs which explain interdependencies between acceptance antecedents (notable trust and its predictors), and we propose an integrated model of trust-based acceptance of affective technologies. As identified in the qualitative study conducted by Heger et al. (2016) and the conceptual study by Granatyr et al. (2017), trust is crucial for the use of affective technologies. Our study investigated this construct in this specific context and examined the antecedents that have an essential impact on establishing trust. First, trust in the context of affective technology deals with an individual's willingness to depend on a technology that can recognize highly sensitive private data, i.e. emotions. Such individuals take the risk of sharing such intimate information with others. Our results show that trust in an information technology, and by extension, in an affective technology itself, influences the formation of IT-related beliefs and behavior (Allen et al. 2000; Granatyr et al. 2017; Lowry et al. 2014; McKnight et al. 2011; McKnight and Chervany 2001). Similar to the conclusions reached by Gefen et al. (2003) and Gefen (2000) in the context of e-commerce, users of affective technology try to understand the social surroundings impacting other's behavior and focusing on the what, when, why, and how others behave.

Second, the construct institution-based structural assurances is important for the formation of trust in affective technologies. Due to the specific characteristics and the novelty of such technologies, it is necessary that a user is provided some external safety structures (e.g. regulations, laws, reputation etc.) whereof trust can emerge. Literature has shown that structural safeguards support the user in the process of trust formation while using technology (Gefen et al. 2003; McKnight et al. 2011). If a legislator adopts laws to protect users by regulating the use of emotion-related data or the manufacturer states guarantees that the emotion-related data is not stored or misused by passing them to third parties, trust emerges.

Third, the construct knowledge-based familiarity, i.e. the comprehension of an information system (in our case an affective system), is important for the formation of trust (Gefen 2000; Hwang and Lee, 2012). If a user can understand how emotions are recognized and how the data is used, whether it is an affective driver assistance system or an affective learning system, trust in an affective technology arises. As suggested by Heger et al. (2016) and Granatyr et al. (2017), a high system transparency could support the understanding of the system and, in this way, lead to the formation of trust. A manufacturer, as suggested by Wang and Hsu (2014), should provide adequate information to the user on, for instance, how the emotions are recognized, whether by a camera system, a body pressure system through a chair, or a physiological body recognition system (e.g. EEG, fMRI, EDA etc.).

Fourth, the institution-based situational normality construct has no significant effect on trust. In turn, we assume that in the future, once affective technologies are more available and well-known, as shown in the existing literature (Gefen et al. 2003; McKnight et al. 2011), it will contribute to the formation of trust. Manufacturers of affective technologies could promote affective systems by providing adequate product information and by relating their function and purpose to other better-known information technologies.

Conclusion

The proposed study has several limitations. First, since not all people we questioned had an affective technology at hand, their understanding of the given introduction regarding the functioning and purpose of affective technology was restricted. The study focused on the description of emotion recognition by technology and its purposes. The latent constructs were represented by appropriate items and we ensured that the people we questioned during the phone interviews understood the content and context of the survey. However, the items should be revised for specific examples, particularly with regard to an actual use of an affective technology, in an experimental examination, or in a qualitative study such as a case study. Second, the study at hand focuses on affective technologies that sense, capture, and store human emotions. An issue that was not addressed in this study was the way the results would change if the study also considered affective technologies which pretend to have feelings themselves such as a robot that can imitate human feelings or which aim to influence human feelings such as manipulating human feelings (as suggested by Schwark 2015). Third, the study works under the assumption of a functional affective technology and the reliability of the corresponding recognition of emotions. Until now, affective technology has not penetrated the consumer market and is mostly used for research purposes (Picard 2015; Schwark 2015; Wu et al. 2016). Furthermore, these affective technologies face challenges, although the reliability of certain technologies increases (e.g. D'Mello and Graesser 2015; Mikuckas et al. 2014; Mumenthaler et al. 2018.; Picard 2015; Steephen et al. 2018). In conclusion, future research should consider certain technologies such as an affective driver assistance system or an affective learning system in order to examine the impact of usage in case of privacy and data concerns. For instance, experimental research could reveal direct impacts on humans from revealing their emotions, one of their most intimate parts, to a technology. Furthermore, it would be necessary to develop certain designs to examine which design concepts affect trust in affective technologies and the intention to use them. These could help to understand the IT-related drivers and barriers to the formation of trust in affective technology.

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Appendix: Measurement Items and Loadings

Item	Wording	Loading
	Intention to use affective technologies	
Intention-1	I allow an affective technology to capture my emotions.	0.91555
Intention-2	I allow an affective technology to collect information about me.	0.91671
Intention-3	I accept my emotions to be captured by technology.	0.93373
	Calculative-based beliefs	
Calculative-1	The manufacturer of an affective technology has nothing to gain by passing on my emotion-related data to third parties.	0.90807
Calculative-2	The manufacturer of an affective technology has nothing to gain by using my emotion-related data for other purposes than the one intended.	0.94659
Calculative-3	The manufacturer of an affective technology has nothing to gain by bringing a malfunctioning system to market.	0.69890
	Disposition to trust technologies	
Disposition-1	I generally trust technologies.	0.91406
Disposition-2	I generally have faith in technologies.	0.93537
Disposition-3	I generally trust technologies unless they give me reason not to.	0.90971
	Knowledge-based familiarity	
Familiarity-1	I understand how an affective technology recognizes my emotions.	0.82267
Familiarity-2	I understand how to use an affective technology.	0.74802
Familiarity-3	I understand how an affective technology makes use of my emotion-related data.	0.73788
Familiarity-4	I understand how an affective technology works.	0.76074
Familiarity-5	An affective technology works as I expected.	0.79066
Familiarity-6	An affective technology s works reliable.	0.76322
	Institution-based situational normality	
Situational-1	The captured emotion-related data is as safe as other personal data.	0.81156
Situational-2	The capturing of emotion-related data is similar to the capturing of other personal data.	0.728103
Situational-3	The capturing of emotion-related data works as reliable as the capturing of other personal data.	0.87591
	Institution-based structural assurances	
Structural-1	When capturing and making use of my emotions, I feel safe because laws will protect me.	0.87647
Structural-2	When capturing and making use of my emotions, I feel safe if I can turn to the manufacturer of the technology when required.	0.8270
Structural-3	When capturing and making use of my emotions, I feel safe if the manufacturer contractually guarantees that my emotion-related data will not be passed on to third parties.	0.88517
Structural-4	When capturing and making use of my emotions, I feel safe if the manufacturer of the affective technology has a good reputation.	0.92682
Structural-5	When capturing and making use of my emotions, I feel safe if media such as newspapers, magazines, or news portals reports positively about the technology.	0.83808
Structural-6	When capturing and making use of my emotions, I feel safe if friends recommended the technology to me.	0.85267
	Trust in affective technologies	
Trust-1	An affective technology is trustworthy.	0.91400
Trust-2	I trust that an affective technology derives the correct emotional statements.	0.88341
Trust-3	I trust an affective technology.	0.9407