Design Knowledge on Mobile Stress Assessment

Completed Research Paper

Introduction

Digitalization affects all domains of life including our work and private lives. Emerging technologies such as autonomous driving, smart home, advanced user assistance systems, and eHealth increasingly permeate our lives (Maedche et al., 2016). This digitalization of everything brings many advantages to individuals, organizations, and society as a whole. However, information technology also exhibits a dark side at the individual level, which is well documented in information systems (IS) literature (Pirkkalainen and Salo, 2016). Information overload and technostress – that is, stress directly resulting from technology use – are two examples, in which technology overstrains people. But there are other sources of stress like work overload, role ambiguity, personal conflict, and adverse environmental or health conditions. IS literature on stress commonly focuses on the role of information technology (IT) artifacts in creating technostress. Unlike that, we investigate the role of IT artifacts in managing stress from whatever source. We suppose that increasing pervasiveness of digital technologies and advances in affective computing afford not only lessening negative technostress (techno distress (Tarafdar et al., 2017)) but also positively contribute to stress management at large. Several IS papers have recently made explicit calls for the development of neuro-adaptive information systems – that is, systems that recognize the neurophysiological state of the user and positively adapt to it (Riedl, 2012; Vom Brocke et al., 2013). Researchers responded to this call, e.g., by proposing a design blueprint for stress-sensitive adaptive enterprise systems (Adam et al., 2017).

Recent IS literature discusses the problem and suggests various solutions for ambulatory stress prevention (Adam et al., 2017; Jimenez and Bregenzer, 2018; Friemel et al., 2018). A broad stream of research specifically focusses on assessing individual stress (either related or unrelated to IT) as a prerequisite for IT-enabled targeted stress management. However, the primary challenge in building such IS lies in the reliable assessment of the user's stress. Various approaches for stress assessment exist, for instance, established survey scales like the Perceived Stress Scale (Cohen et al., 1983). Further, physiological measurements such as skin conductance (Riedl, 2013) or cortisol levels (Riedl, 2012) can help to determine stress from a biological point of view. The sensing capabilities of modern mobile devices enable another approach: the mobile stress assessment (MSA) using sensor data on the user, their environment, and the user-environment interaction. Various instantiations have already demonstrated the feasibility of MSA for different application scenarios (Lane et al., 2011; Lu et al., 2012; Wang et al., 2014; Gimpel et al., 2015). However, a common ground on essential design elements and knowledge of MSA across scenarios is yet missing.

In this work, we aim to investigate design-related differences and commonalities of systems that assess stress using mobile devices, present common architectural components in MSA system design, elaborate design elements to communicate MSA design, and identify archetypes of extant MSA systems. In their combination, this condenses the current design knowledge base on MSA and constitutes a first step towards a design theory on MSA. Our research leverages a literature-based approach inspired by the taxonomy development process from Nickerson et al. (2013) to collect, analyze, and cluster examples of MSA systems. In this process, we investigate the following three research questions (RQ):

RQ 1: What design components do MSA systems typically have in common?

RQ 2: What design elements need to be considered when designing an MSA system?

RQ 3: What archetypes of MSA systems exist and how can they be distinguished?

The paper includes justificatory knowledge from various fields of research: it complies with diverse stress models from psychological stress literature, considers common knowledge on affective computing, and provides an extensive review of research on MSA. Specifically, we identify 112 descriptions of MSA in academic literature and summarize their design knowledge. Our findings feature the *Purpose and Scope*, *Constructs*, *Principle of Form and Function*, and *Justificatory Knowledge* components of an IS design theory (Gregor and Jones 2007) and inform further research building on this. The design knowledge presented here may also support practitioners working on stress management systems in building more effective IS.

The paper employs a structure similar to the publication schema suggested by Gregor and Hevner (2013): in the next section, we shed light on the theoretical background on stress and affective computing theories. Building on existing publications on MSA instantiations, we develop a taxonomy for dimensions that need to be considered when designing MSA. Furthermore, we identify typical types of MSA in literature and elaborate a simple design blueprint consisting of general components of an MSA system. Finally, we discuss the implications of our research and conclude with a description of the current work's limitations as well as an outlook on ongoing and future research.

Theoretical Background

Justificatory knowledge related to the research questions originates from research on stress theory and affective computing. Stress is the targeted area of application. Affective computing provides the fundament for the design of human-centered information systems like MSA.

The concept of stress has been extensively researched in psychology and biology for many decades. This has brought up a large number of slightly different definitions. While some of them describe stress from a purely response-based view (Aamodt, 2012), others explain stress as an independent variable, which causes a reaction in people (Earnshaw and Cooper, 2000). Lazarus and Folkman (1984) conceptualize stress as a two-way process that involves the production of and response to stressors. The human mind is permanently challenged by stressors, which are internal or external stimuli with a specific influence on our mental or physiological resources (Varvogli and Darviri, 2011). These stressors can be either physical (e.g., temperature, noise) or psychological (e.g., social problems) (Lu et al., 2012; Riedl and Javor, 2012) and their relevance is evaluated within a complex psychological and biological process. Various sensors in the human body transmit the information about the perception of a stressor to the brain. A psychological process called primary appraisal classifies incoming stressors into three categories: positive, irrelevant, and danger. When the stressor is classified as 'danger', the sympathetic division of the autonomic nervous system (ANS) releases adrenaline and noradrenaline into the bloodstream and induces a state of arousal (e.g., increased heart rate, pupil dilation, increased skin conductance, brain activity, muscle activity, respiratory response, or facial expression) as preparation for the "fight-or-flight" response (Riedl, 2012). In a secondary appraisal, mind and body evaluate for each 'danger' stressor, if enough resources are available to cope with the demand (Lazarus and Folkman, 1984). This step activates the parasympathetic division of the ANS and results in the release of the hormone cortisol, which mediates physiological and behavioral stress response, for example by raising the blood sugar and pausing some biological processes like digestion with positive effects on perception and cognition. This shows that not all 'danger' stressors are harmful but can also represent a challenge. Literature distinguishes eustress – that is, a challenge that can be coped with – and distress – that is, a stressful situation the individual lacks resources to deal with (Lazarus and Folkman, 1984; Selye, 1976). Reactions to stress are commonly referred to as strains. Cassidy et al. (2003) distinguish three different types: physical, emotional, and behavioral strains. Possible physical reactions include the release of the stress hormone cortisol (Riedl, 2013), increased heart rate (Trimmel et al., 2003), and elevated blood pressure (Boucsein, 2009). Emotional and behavioral strains affect the human psyche; a lack of resources may lead to poor judgment (Smith et al., 2014) or moodiness (The American Institute of Stress, 2014). To manage strain, different response strategies can be applied. This process is called coping. Gentry (1984) distinguishes two different types: problem-focused coping and emotion-focused coping. In problem-focused coping, the strained person attempts to change or influence the stressful situation. Potential strategies include requesting assistance and social support (Thoits, 1995) or removing the stressor, for example by turning down loud music. In contrast, emotion-focused coping attempts to influence the emotional arousal caused by stressors, for example by building up mental boundaries (Köffer et al., 2015).

With the increasing ubiquity of information technology, information systems play a growing role in supporting and assisting the user (Maedche et al., 2016). Researchers have understood this need for user centricity in information systems. Recent IS literature suggests first solutions for ambulatory stress prevention (Adam et al., 2017; Jimenez and Bregenzer, 2018; Friemel et al., 2018). Context-aware systems are designed to react to a user's location or nearby people (Marreiros et al., 2010; Schilit et al., 1995). Today's capabilities of information technology like smartphones or social media allow to go one step further: affective systems take personal aspects such as emotions and affective states into account (Marreiros et al., 2010). This can lead to fundamental changes in user interface design, health diagnostics, and stress adaptivity (Adam et al., 2014; Albu et al., 2008; Hockey et al., 1998). The research area of affective computing is committed to building information systems that are capable of detecting and responding to their user's affective state (Picard 2003). The term "affective state" can refer to various psychophysiological constructs that influence the user's behavior. These constructs can generally be divided into three categories: arousal, valence, and motivational intensity (Mehu and Scherer, 2015). Arousal is directly tied to the ANS and can be measured via physiological sensors. Here it is important to note that arousal can have different reasons, of which stress, anger, and physical exercise is only a small selection. Valence rates an affect as positive, negative, or neutral. Motivational intensity requires both physiological and psychological information on the individual's current situation. The literature on affective computing has a strong focus on the determination of emotions (joy, anger, surprise, disgust, sadness, and fear), but also considers other affects such as frustration and stress. With the rapid and ubiquitous acceptance of new technologies, algorithms can measure the affective state and behavior of individuals based on data. Affective computing systems use data acquired from different sensors and sources (e.g., smartphones, wearables, but also data from social media platforms) to create "affect models" and statistical models that are capable of interpreting the user's feelings and psychological states. They further involve the tasks of "affect information capture and modeling, affect understanding and expression" (Tao and Tan, 2005, p. 982).

The combination of stress and affective computing may result in systems that are capable of assessing a user's stress and adapting itself. This might become an indispensable factor in personal life management and work productivity (Sarikaya, 2017). However, the development of such systems is not trivial and requires the continuous and reliable assessment of stress. To do so, assessment systems need to "minimize retrospective biases while gathering ecologically valid data, including self-reports, physiological or biological data, and observed behavior, e.g., from daily life experiences" (Trull and Ebner-Priemer, 2013, p. 1), e.g., by means of mobile hardware. Stress assessment, and in particular MSA, has recently received significant attention due to its potential and complexity. Several literature reviews have been published over the last years, which aggregate the current state of the art of identifying stress or stress-related concepts using mobile data: Þórarinsdóttir et al. (2017) published a comprehensive review of the literature on smartphone-based stress assessment. Aigrain (2016) analyzed the topic of stress and discusses different assessment strategies for stress detection. Greene et al. (2016) published a survey on affective computing for stress detection. Liew et al. (2015) further analyzed the capability of mining personal data acquired by smartphones and wearable devices. Glenn and Monteith (2014) researched medical and commercial projects on pervasive healthcare enabling remote disease monitoring. These literature reviews demonstrate that a multitude of MSA prototypes and systems already exists and the field of research is growing.

Design Knowledge Base

Despite the increasing attention towards MSA, design knowledge on MSA has not yet been consolidated. We argue that a common ground for the design of MSA systems could enhance transparency in this interdisciplinary field, which is low on theoretical insights in designing such systems and foster sophisticated systems for stress assessment and stress adaptation in both research and practice. Inspired by the taxonomy development process by Nickerson et al. (2013), we collect and analyze literature in multiple iterations to identify commonalities and differences in MSA systems' designs. In doing so, we construct a design knowledge base for MSA that, in line with the research questions, consists of three integral parts: (I) an abstract architectural blueprint of MSA systems comprising design components that are common in all MSA systems, (II) a morphological box of design elements that shape and specify the design of an MSA system depending on its application scenario, encompassing relevant dimensions of design elements as well as their specific characteristics, and (III) a description of MSA system archetypes prevailing in current literature. While (I) and (II) result directly from the iterative literature analysis, (III) involves an additional cluster analysis that groups all MSA systems from literature according to their design element manifestations.

The defined ending conditions for the iterative procedure are met when (1) all identified studies on MSA are analyzed and classified, (2) each characteristic is unique within its dimension, (3) each dimension is unique within the morphological box, and (4) at least one study represents each characteristic for all dimensions. The first iteration of our literature analysis starts with the basket of extant literature reviews in the context of MSA introduced in the previous section. These reviews contain aggregated descriptive knowledge on MSA systems and, thus, provide a good foundation to identify common architectural components of MSA system design (I) and essential dimensions and characteristics of design elements, whose manifestation highly depends on the MSA system's application scenario (II). The preliminary results are refined in a second iteration, in which we analyze the 55 individual studies referenced in the literature reviews in detail. The search for properties that all MSA systems have in common (I) already converges in this iteration and reveals typical design components. However, we still find new dimensions and characteristics of design elements depending on the application scenario (II) in the second iteration. As they are particularly interesting for understanding the variety of MSA systems and designs, we complement our list of studies in a third iteration by searching in the AIS Senior Scholars Journal Basket (MISQ, ISR, JAIS, JMIS, EJIS, ISJ, JSIS, JIT) and all outlets of the IEEE Xplore. We limit our search to research articles on the assessment, detection, determination, or recognition of stress using mobile or smartphone-based information systems or technology in the context of humans, people, users, or individuals. We consider only studies from 2010 and later because stress detection gained substantial attention only since then and exclude all studies that refer to stationary medical devices or are designed to work only in a certain location. This search resulted in an additional list of 57 studies discussing MSA. We classify each of them into our schema of design elements. In this third iteration, only marginal rewording but no significant changes to the dimensions or characteristics of design elements were necessary. Complying with our ending conditions, we stop the process after the third iteration. For the complete coding, please see https://www.dropbox.com/s/99zdxfqia2yksly/MSA_Literature_Review.pdf?dl=0.

The iterative process revealed insights into several facets of MSA design knowledge. The findings regarding architectural commonalities (I) detail two anatomical parts of a design theory (Gregor and Jones, 2007): on the one hand, it describes the essential components of MSA systems as *Constructs* of their design, on the other hand, the interrelations between these components enable to understand MSA's *Principle of Form and Function*. Dimensions and characteristics of design elements further specify the operating principles of MSA systems and provide details on the design of MSA for different application scenarios. The following sections describe these contributions.

(I) Design Components

The literature analysis yielded general architectural components of MSA that are common in MSA instantiations and form a simple blueprint, which interrelates these components. Even though they are neither new in literature nor overly surprising to practitioners, we describe each component to ensure a common understanding, which is essential when it comes to different application scenarios for MSA.

The prevailing insight gained from the literature analysis is that the components of MSA do not form a purely technical system, but a sociotechnical system. Five major components are present in all studies: (A) the user and its environment, (B) data collection, (C) data storage, (D) data transformation, and (E) stress prediction. Figure 1 illustrates their interrelations. There are two transitions between the technical and the social part of the system: First, sensors digitalize information on the user and its environment into computer-processible data. Second, the stress assessment and its implications loop back to the user and its environment using stress feedback, emotion-focused or situation-focused coping suggestions.

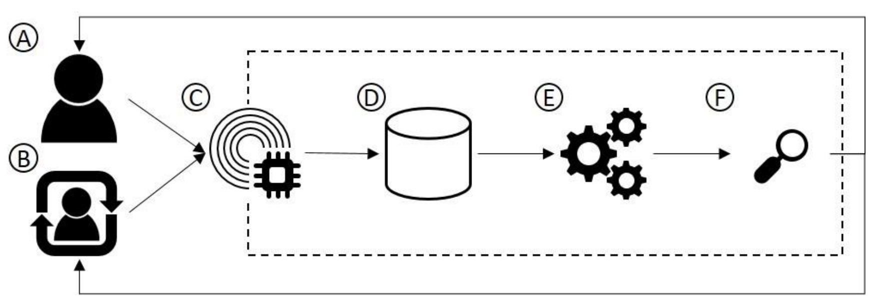

Figure 1. Illustration of the architectural components forming a simple blueprint

(A) User and environment: As described in the theoretical background, human physiology (Singh et al., 2011; Cho, 2017), human behavior (Lawanont and Inoue, 2018; Liao et al., 2005), human perception (Rodrigues et al., 2015; Gaggioli et al., 2013), and environmental conditions (Lane et al., 2011; Garcia-Ceja

et al., 2016) can provide valuable input to stress assessment of individuals (Cohen et al., 1983; Traina et al., 2011; Weisman et al., 2016). This enables a comprehensive view on stress-related factors, which is vital for MSA and gives an indication for both stressors and strains. While we found in our literature analysis that all systems view the user or the environment as an important informer of their system, not all systems include both the user and its environment. Besides sensing, some systems incorporate a second interaction point with the user and apply the processed data to provide behavioral or environmental feedback to the user. Although MSA systems could also benefit from direct interaction with the environment to correct stressing environmental conditions like noise pollution or stroboscopic light, currently no system incorporates actuation on the environmental level due to technological boundaries. However, the increasing pervasiveness of smart home technologies could help to overcome difficulties with automatic environmental adjustments to reduce people's stress.

(B) Data Collection: In MSA, data is the foundation for all analytical activities that allow for the assessment of stress. According to the principle "Garbage in – garbage out", sound data is a vital determinant of MSA performance. Thus, significant thought should be put into the specification of what data to collect and how to collect it. In our literature analysis, we found that a multitude of different approaches to data collection exists in the context of mobile stress assessment. These approaches range from self-reported data manually provided by the user to sophisticated sensor fusion models that automatically combine data from different sensors using machine learning techniques in order to create new variables (Gimpel et al., 2015). Approaches based on self-reported data include, for example, periodic questionnaires or the manual input of stress-relevant data (Rodrigues et al., 2015). While these approaches are rather easy to implement, they also demand for strong user engagement. Consequently, we found that the focal point in current research lies on sensor-based approaches, which use sensors to automatically collect information on the user and its environment. Instead of having to rely on the user's steadiness, the performance of sensor-based approaches highly depends on the adequate choice of sensors (Greene et al., 2016). In our terminology, 'sensor' refers to every single data source that automatically gathers relevant information for MSA. Hardware sensors (e.g., microphone (Arkhangelsky et al., 2018) or accelerometer (Garcia-Ceja et al., 2016)) often provide powerful capabilities on sensing environmental information (Zhao et al., 2013; Ollander et al., 2016) or human physiology (Adnane et al., 2011), but only occasionally allow to draw direct conclusions on the user's behavior (Bauer and Lukowicz, 2012; Gjoreski et al., 2015). Although the term 'sensor' is commonly associated with hardware, there are also software sensors that capture data on the application level. Software sensors have easier access to behavioral data, for example, in the number of incoming text messages (Bogomolov et al., 2014) or the degree of social interaction based on nearby Bluetooth devices (Lu et al., 2012). Both types of sensors can be attached to a single device (e.g., a smartphone (Ciman et al., 2015)), distributed over multiple devices (e.g., a smartphone and a wearable (Zenonos et al., 2016)), or integrate information from other IS (e.g., online social networks (Lee et al., 2012)). Further, sensors can be triggered either by time (e.g., continuously, every 5 minutes, once) or by event (e.g., incoming text message, significant change of location) (Pioggia et al., 2010). With all these possibilities, the appropriate design of the data collection part of an MSA system is vital. While data with high resolution allows deeper analyses and can result in higher stress assessment accuracy, this performance boost often comes at the cost of battery life, data transmission volume, and, consequently, user acceptance. If sensors are distributed across different devices, additional factors like time synchronization may need to be considered as the clocks of two devices generally slightly differ. Time-triggered sensors that are distributed across these devices, should be synchronized to ensure comparability over time and between sensors (Adams et al., 2014).

(C) Storage: The data collected in *(B)* needs to be stored to enable data analysis. This can be performed locally on the device that captures sensor data (Bauer and Lukowicz, 2012; Massot et al., 2012), on an external storage attached to the system via a wired or wireless connection (Mohino-Herranz et al., 2015; Zhang et al., 2012), or on a cloud platform (Gaggioli et al., 2013; Berndt et al., 2011), which is particularly relevant, when sensors are distributed across multiple devices as described in *(B)*.

(D) Transformation: As stress assessment requires a set of sensor observations, raw sensor data does usually not directly qualify for the model generation but needs to be pre-processed. In doing so, the systems must aggregate sensor data over time and apply various transformations, which need to be defined before the model generation and stress assessment (Ben-Hur and Weston, 2010; Bakker et al., 2011). The design choices relevant for this component include the selection of an appropriate approach to data aggregation, the definition of how to deal with missing values, or the decision on a method for removing outliers in variables (Fernandez and Picard, 2003).

(E) Stress Assessment: Finally, statistical model building allows for the assessment of stress based on the acquired and transformed data points (Picard, 2003). In this step, the selection of statistical models appropriate for the application scenario at hand is of vital importance (Salai et al., 2016), especially when it comes to sophisticated scenarios that require a rapid, near real-time assessment of stress and involve calculation- and resource-intense tasks like updating the model with new observations (Zubair et al., 2015). Sensor fusion – i.e., the generation of new variables by combining data from different sensors – can improve robustness and confidence, and reduce ambiguity and uncertainty of the model (Xiong and Svensson, 2002) by providing a more valid representation of the user (Chen et al., 2014), their environment (Lu et al., 2012; Huh et al., 2014), and the user-environment interaction (Zenk et al., 2014). In a final step, the results of this stress assessment component can be communicated to the user to foster stress coping and management.

(II) Design Elements

As indicated in the descriptions of common architectural components, a deeper look on the specific systems also reveals that there is a large variety of differences in MSA system design. In the following, we present an overview of the dimensions and characteristics of relevant MSA design elements as a result of the iterative literature analysis (Table 1). While the first two dimensions describe *WHAT* should be assessed and gathered, dimensions three to six describe *HOW* the assessment is performed. Dimensions seven to nine consider relevant *BOUNDARIES* in the design of MSA systems. The number next to each characteristic indicates how many of the identified systems exhibit the given characteristic.

	Dimension	**Characteristics** (mutually exclusive, collectively exhaustive)				
WHAT	Subject of Investigation	Biological Stress (4)	Perceived Stress (24)	Stress Indicators (84)		
WHAT	Stress Determinants	Environment (0)	Introspection (2)	Biological Symptoms (50)	Behavioral Symptoms (21)	Mixed (39)
HOW	Visibility for the User	Obtrusive (43)	Unobtrusive (62)	Life-integrated (7)		
HOW	Assessment Frequency	Regular Intervals (33)	Continually (42)	Continuously (37)		
HOW	Assessment Scale	Binary (61)	Ordinal (42)	Metric (9)		
HOW	IT Ecosystem	Single Device (18)	Multiple Devices using Local Communication (70)	Multi-Platform-System (24)		
BOUNDARIES	User Privacy	Non-Personal Data (4)	Non-Personal and Aggregated Personal Data (71)	Non-Personal and Raw Personal Data (37)		
BOUNDARIES	IT Resource Requirements	Substantial Resources (86)	Limited Resources (26)			
BOUNDARIES	Robustness	Normal Fault Tolerance (94)	Low Fault Tolerance (18)			

Table 1. Morphological box of the dimensions and characteristics of design elements (numbers refer to n = 112 MSA instantiations)

WHAT

Naturally, an IS incorporating stress assessment should be able to assess the user's stress. However, as outlined in the theoretical background, different definitions of stress exist and they substantially affect the input needed, depending on the actual *subject of investigation*. While some MSA instantiations focus on the assessment of *perceived stress* as stress based on self-perception, feelings and emotions (Ayzenberg et al., 2012; Zenk et al., 2014), e.g., by using the Perceived Stress Scale (Cohen et al., 1983), other systems assess *biological stress* using evidence or indication of biological and neurological reactions such as an increased cortisol level or decreased heart rate variability (Berndt et al., 2011; Cho, 2017). Traditionally, biological stress parameters are measured by means of medical equipment such as electrocardiogram or electroencephalogram that are hard to apply in a mobile context, but today, emerging technologies such as wearables or NeuroIS devices also enable the mobile sensing of some biological markers (Riedl et al., 2010). We further find a third category of instantiations that targets the assessment of stress with the help of theoretically grounded *stress indicators*, in particular stressful situations induced by putting the participants into a stressful task. These studies aim to distinguish normal and stressed time periods based on differences they observe in sensor data (Liao et al., 2005; Bauer and Lukowicz, 2012; Bogomolov et al., 2014), but do not target assessing stress itself.

Stress assessment can draw information from various sources as *determinants for stress*. As outlined in the section Design Components both the user and its environment are valuable sources for sensor data. While we do not find any systems that use exclusively *environmental* data such as weather information or ambient noise to infer external stressors affecting the individual, many systems include environmental information to improve assessment performance (Plarre et al., 2011; Mayya et al., 2015). On the user side, various facets are relevant for stress assessment. Although quite scarce, some systems use methods of *introspection* and ask the user to provide input on their stress perception or feelings at certain points in time. Typical application scenarios for systems using introspective methods typically stress diaries following the idea of quantified self or analyzing differences in stress over time (Aigrain, 2016; Wang et al., 2014). Again, the number of systems relying only on introspective methods is low (only two studies), but eight more instantiations use introspection in combination with other stress determinants. Especially in the last years, many systems make use of smartphone and wearable sensors to conclude an individual's symptoms of stress. These symptoms can manifest either biologically or in changed behavior. *Biological symptoms* of stress include all bodily changes associated with automatic, mostly unconscious, biological processes such as heart rate, blood pressure, sweating, or pupil dilation. Many wearables come with sensors that allow to sense one or multiple biological factors related to stress. Still their application for stress assessment is not trivial due to reduced accuracy compared to expensive medical equipment and their application in an uncontrolled environment. Therefore, a large part of MSA systems aims to demonstrate that stress assessment based on wearable sensor data is feasible. Fifty systems use only data on biological symptoms; another 32 systems combine biological data with other data sources, e.g., Rodrigues et al. (2015) or Pioggia et al. (2010). A common additive is data on *behavioral symptoms* such as reduced typing accuracy (Gimpel et al., 2015), characteristic gestures (Lefter et al., 2016), or voice modulation (Ferreira et al., 2009). Systems in this category often apply software sensors that provide valuable information on behavioral patterns by analyzing how the user interacts with the mobile device. Studies classified into the *Mixed* category apply various stress determinants together. The most frequent combinations are *Biological* and *Behavioral Symptoms* (e.g. Liao et al. (2005), Ayzenberg et al. (2012)) as well as the both symptom types plus data on the *Environment* (e.g. Kocielnik et al. (2013), Picard and Sano (2013)).

HOW

Conventional methods of stress assessment involve the subject to undergo medical tests (e.g., measurement of cortisol levels in the saliva), think about their perception (e.g., questionnaires), or be mentally aware (e.g., due to wearing unaccustomed devices like custom-made heart trackers). MSA has the potential to achieve a high degree of independence of location, attention, and thought, if this is a requirement for the application scenario (Gimpel et al., 2015). Therefore, we find systems in our literature analysis that have different levels of *visibility for the user*, which we define as the degree to which an MSA system is integrated into an individual's life. In its highest stage, the MSA system is not interfering with an individual's perceived routine constraints, which means that the individual does not have to adapt his habitual routines for MSA. Contrary, an *obtrusive* way to MSA requires the attention of users (but – speaking of 'mobile' stress assessment –

does not demand a specific location). Typical methods in this level are questionnaires (Ferdous et al., 2015) that are used in combination with smartphones to trigger ecological momentary assessments (Chang et al., 2011; LiKamWa et al., 2013). More sophisticated MSA systems do not require any user attention at all. These *unobtrusive* systems employ long-range devices to assess the stress level, e.g., video cameras as an indicator for the heartbeat (Elgharib et al., 2015) or additional devices like wearables developed specifically for this purpose, e.g., heart rate tracker (Chang et al., 2011; Lu et al., 2012). However, they still might interfere with the user's perceived routine constraint by requiring the user to adapt their habitual routines (e.g., by wearing additional devices). Exemplary approaches assess stress based on a voice analysis involving two smartphones to distinguish speakers (Chang et al., 2011; Lu et al., 2012) or use wearables to assess skin conductance or activities (Lane et al., 2011; Picard and Sano, 2013; Wang et al., 2014). Less obtrusive approaches employ only the smartphone to assess stress but can require additional knowledge on the user's location (Lane et al., 2011) or connectivity to the internet (Lee et al., 2012). These *life-integrated* systems refrain from altering the user's daily routines and integrate themselves into their daily routines without interference (e.g., by doing all work on the user's smartphone). While this type of assessment is the most natural way to determine stress, it is also the most difficult and potentially yields more noise in the assessment compared to the other characteristics of the *visibility for the user* dimension.

From a time perspective, there are two different types of stress: chronic stress (referring to a long-lasting endurance of stress) and acute stress (short-term stress). While chronic stress constantly exposes people to a certain level of stress, for most people the level of acute stress varies over time depending on the individual's availability of resources and the load induced by environmental stressors. This difference makes also an impact on the *assessment frequency* of MSA. If the application scenario targets a long-range assessment of stress (Fehrenbacher, 2017; Unsoo et al., 2015) or involves the analysis of treatment effects in lab studies (Costin et al., 2012), an elicitation of stress in *regular intervals* of weeks or months is sufficient. To evaluate the effects of stress interventions targeting chronic stress or investigate extended episodes of acute stress (Wang et al., 2014), stress assessment is required to *continually* (e.g., daily) retrieve reliable values for the current level of stress. Complex scenarios, which perform just-in-time interventions (Nahum-Shani et al., 2015), like stress-sensitive adaptive enterprise systems (Adam et al., 2017) pose even higher requirements and demand for the *continuous* assessment of stress to obtain real-time stress levels.

Stress levels can be reported in different levels of granularity. The dimension *assessment scale* specifies what requirements are made towards the level of detail of the assessment results. In the most basic way, stress can be modeled as a *binary* variable that differentiates 'stress' or 'no stress' (Bogomolov et al., 2014; Chen et al., 2014; Hovsepian et al., 2015). While this distinction might be sufficient for many application scenarios, other MSA use cases require more details on the level of stress intensity. This can be achieved using an *ordinal* scale with three or more increments (Garcia-Ceja et al., 2016). *Metric* scales enable an even more granular differentiation of stress levels (Gao et al., 2014; Zhang et al., 2012). The 4-item Perceived Stress Scale (Cohen et al., 1983), for example, assesses stress on a scale ranging from 0 to 16 and allows for the recognition of subtle changes in the user's stress. However, the *assessment scale* should be aligned with the application scenario as assessment accuracy generally decreases with an increased level of detail (Lawanont and Inoue, 2018; Mohino-Herranz et al., 2015).

As discussed in the section on design components, MSA systems consist of several components responsible for the acquisition of sensor data, the storing of gathered data, and the processing to qualify data for the assessment of stress. While these components muse have the possibility to communicate with each other, they do not necessarily have to operate on a *single device*. While several MSA systems target such an all-in-one solution (Bauer and Lukowicz, 2012; Lane et al., 2011) on a single device, the majority of instantiations distributed these components across multiple mobile devices. These systems generally exhibit a distributed system architecture that connects *multiple devices using local communication* protocols like Bluetooth or NFC (Liao et al., 2005; Singh et al., 2011). Some application scenarios require an even more holistic approach that connects devices and components via internet-based protocols (e.g., by using cloud services) to form *Multi-Platform-Systems (Berndt et al., 2011; Ayzenberg et al., 2012)*. Contrary to systems using local communication, these multi-platform systems enable, e.g., the integration of location-dependent sensors in the smart home or the dynamic incorporation of omnipresent powerful sensors.

BOUNDARIES

Aligned with traditional non-functional requirements for medical IS (Meulendijk et al., 2014), we like to emphasize three dimensions of quality factors for MSA systems that constitute central boundaries in the design of MSA. First, stress is highly individual and, thus, its assessment requires collecting information that describes the user. By design, the collection of this data intrudes into users' *privacy*. Therefore, MSA systems must implement security and privacy measures to best possibly eliminate user concerns (Adams et al., 2014; Miyamoto et al., 2016). The specific measures strongly depend on the data gathered by the MSA. If the system collects exclusively *non-personal data* from the environment (Arkhangelsky et al., 2018; Betti et al., 2017), there are no to little privacy concerns that need to be addressed. This changes as soon as the application scenario additionally demands for *aggregated personal data* (e.g. number of incoming and outgoing calls; average duration of a phone call) and complicates even more if the application scenario requires the additional processing of *raw personal data* (e.g., message content (Ayzenberg et al., 2012), video processing (Cho, 2017), or sentiment analysis (Gimpel et al., 2015)).

Second, to gain a high level of user acceptance, the *technical resources* required for stress assessment (e.g., data, storage, time, and energy) should be handled with care. Otherwise, an excessive drain of resources may induce stress itself (Tarafdar et al., 2011). Some scenarios, in particular in a multi-platform ecosystem, can be designed to have *sufficient resources*, e.g., by performing computationally expensive activities such as model training to cloud platforms (Berndt et al., 2011) or gathering data via personal computers (Garcia-Ceja et al., 2016). This enables models that are more complex and opens the doors for complex sensors such as voice analysis. In contrast, if the MSA system has only access to very *limited resources* such as wearable (Muaremi et al., 2013) or smartphone resources (Hovsepian et al., 2015), careful thought is necessary for the design of model building, sensing frequency, and sensing extent.

Third, *robustness* is a vital aspect of stress assessment. The increased complexity of sensing and model building can result in increasing noise in the data and reduced data quality (Bogomolov et al., 2014; Garcia-Ceja et al., 2016). While some MSA systems are for personal use only without any serious influence on a user's health, other MSA heavily rely on sound results. Domains where high robustness is necessary are, for example, traffic (Gao et al., 2014), business (Adam et al., 2014; Adam et al., 2017), or healthcare (Zenonos et al., 2016; Gaggioli et al., 2013). Hence, we distinguish MSA systems with a *normal fault tolerance* (errors are rather uncritical) and such with a *low fault tolerance* (errors can result in severe negative effects).

(III) MSA Archetypes

The literature analysis process revealed valuable insights into the design of MSA by producing both essential design components of all MSA systems and design dimensions as levers that help tailor the system's design to the specific application scenario. To achieve higher-level insights into the current diversity of MSA systems and demonstrate the design elements' utility, we perform a hierarchical cluster analysis that aims to identify MSA archetypes by clustering all 112 MSA studies according to their manifestation of the design elements using divisive clustering. The elbow method (Thorndike, 1953) reveals that four clusters are an appropriate choice of clusters. In the following, we describe them in detail based on information on how strongly the clusters correlate and how clusters developed during clustering.

A first split divides our sample into two clusters. Compared to all subsequent splits, this shows the highest distance and the lowest correlation between the grouped objects. One cluster comprises MSA systems that have a low fault tolerance (n = 10). We call this archetype *Critical Foundation* as it comprises systems that lay the foundation for critical services supporting users in their daily life. They are designed to support car drivers, fire workers, people with diseases (e.g., depression), or people in a working context. Systems of this archetype usually do not aim to assess stress in the first place, but use stress indicators to continuously infer their user's stress level and exhibit an emphasis on biological markers (e.g., heart rate variability) collected via wearables and smartphones. The systems remaining for the other cluster are significantly more tolerant to fault. They involve logging tools for the quantified self or systems aiming to prove the feasibility of MSA in various application scenarios. Further dividing the systems with normal fault tolerance in a second split ejects an archetype of MSA systems that apparently make use of multiple data sources. These *Multimodal Sensing* systems (n = 20) employ sensors to gather information on the user (i.e., changes in behavior and biology) and its environment to infer the user's level of perceived stress. Most of these systems also use perceived stress questionnaires to calibrate the assessment models. Due to their broad data collection, the majority of systems in this archetype processes critical personal data such as message contents or video signals and, thus, has the highest demand for security and privacy measures. This split leaves behind systems that focus on the sensing of biological symptoms and primarily use aggregated personal data. The third split divides these remaining systems into two archetypes. With 61 studies falling into this cluster, the *Visible Tracker* archetype is the biggest cluster. It comprises systems, which gather biological data using sensors that are visible for the user. Their application scenarios do rarely pose complex requirements to the system design and mostly require only a distinction whether a user is in a stressful condition (by consulting different stress indicators) or not. The last archetype, *Resource Consumer* (n = 21), can primarily be found in application scenarios, where the general availability of resources (for gathering data, the analysis of data, etc.) is given. These systems are unobtrusive and use complex sensors with a high acquisition rate to gather a variety of biological markers. Data is analyzed using sophisticated algorithms (e.g., neural networks, random decision trees) to infer the general availability of stress indicators on a continual basis.

Table 2 presents the footprints of each archetypes within the design elements classification. This footprint shows the prevailing characteristic (occurring with a frequency of at least 50%) within each archetype. Each archetypes' specifics are highlighted in blue.

		Archetypes			
		Critical Foundation	Multimodal Sensing	Visible Tracker	Resource Consumer
	Number of Studies	10	20	61	21
WHAT	Subject of Investigation	Stress Indicators	Perceived Stress	Stress Indicators	Stress Indicators
WHAT	Stress Determinants	Biological Symptoms	Mixed	Biological Symptoms	Biological Symptoms
HOW	Visibility for the User	Unobtrusive	Unobtrusive	Obtrusive	Unobtrusive
HOW	Assessment Frequency	Continuously	Continually	-	Continually
HOW	Assessment Scale	Ordinal	Ordinal	Binary	Binary
HOW	IT Ecosystem	Multiple Devices	Multi-Platform-System	Multiple Devices	-
BOUNDARIES	User Privacy	Non-Personal and Aggregated Personal Data	Non-Personal and Raw Personal Data	Non-Personal and Aggregated Personal Data	Non-Personal and Aggregated Personal Data
BOUNDARIES	IT Resource Requirements	Limited Resources	Limited Resources	Limited Resources	Substantial Resources
BOUNDARIES	Robustness	Low Fault Tolerance	Normal Fault Tolerance	Normal Fault Tolerance	Normal Fault Tolerance
	Examples	(Singh et al., 2011; Mohino-Herranz et al., 2015; Lefter et al., 2016; Gao et al., 2014)	(Picard and Sano, 2013; Wang et al., 2014; Gimpel et al., 2015; Ayzenberg et al., 2012)	(Liao et al., 2005; Lawanont and Inoue, 2018; Bauer and Lukowicz, 2012; Massot et al., 2012)	(Zubair et al., 2015; Ciman et al., 2015; Sanches et al., 2010; LiKamWa et al., 2013)

Table 2. Archetypes of MSA systems

Overall, we observe that most MSA systems do not assess stress directly, but aim to identify situations or contexts that are typically stressful and differentiate between more and less stressful phases, e.g., in games, in artificial tasks, or in school. Furthermore, the broad availability of cheap commodity devices (wearables) facilitates gathering data on biological markers and, thereby, fosters the development of MSA systems that investigate biological symptoms. Therefore, most systems incorporate biological features either exclusively or in combination with other stress determinants. Only few systems focus on neither biological nor behavioral symptoms. However, enabled by today's omnipresence of powerful sensors, e.g. in smartphones or smart things, recently published MSA systems use multiple rich sensing capabilities to unobtrusively and continuously collect data on an individual and a situation. Finally, it is surprising to note that although there are already many systems demonstrating the feasibility of MSA, only few application scenarios incorporate MSA components to form new and individual systems and services.

Conclusion

In this paper, we performed an iterative literature analysis inspired by Nickerson et al. (2013) to establish a common ground for the design of mobile stress assessment systems. We follow the call for the development of neuro-adaptive information systems (Riedl, 2012; Vom Brocke et al., 2013) and analyze design-related commonalities and differences in 112 individual MSA studies. We find that the basic architecture is similar across MSA instantiations, but different application scenarios of MSA make specific requirements on the system design with observable emphases on the assessment of stress indicators, the sensing of biological symptoms, and binary or ordinal valuation of stress.

In this iterative literature analysis, we construct a design knowledge base, which introduces an abstract architectural blueprint comprising design components common in all MSA systems, proposes a set of design elements that shape and specify the design of an MSA system depending on its application scenario, and describes archetypes of MSA systems prevailing in current literature. Our work makes a first step towards a design theory (Gregor and Jones, 2007) on MSA by presenting its *Purpose and Scope* (design of MSA systems in general), *Justificatory Knowledge* (the theoretical background on stress theory and affective computing), the *Constructs* of interest (the design components), and the *Principle of Form and Function* (the architectural blueprint and design elements) of existing MSA systems.

A subsequent cluster analysis groups all MSA studies included in the literature analysis according to their manifestation of design elements and reveals four archetypes of MSA systems prevailing in current literature. These archetypes range from obtrusive MSA over systems with high demands on accuracy or high resource availability to multimodal systems exploiting all available data sources. For communication, we describe each archetype by means of the dimensions and characteristics of design elements and, thereby, demonstrate the utility of our work for communicating differences in the design of MSA systems.

Future research could extend our work to a comprehensive design theory on MSA that features all elements of a design theory proposed by Gregor and Jones (2007) and includes best practices as prescriptive knowledge on MSA system design. Although 112 studies is already a substantial amount, we did not yet search in all outlets of IS and adjacent disciplines. Our literature analysis only considered papers published in 2010 or later, but might have neglected very early works on MSA. The design knowledge presented in this work could be further refined by incorporating studies, which were published before 2010 or in outlets that were not in our scope. While the MSA archetypes provide an overview which types of MSA systems and application scenarios exist, they do not yet indicate where research gaps exist that might be worth exploring.

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