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mHealth approaches addressing stress-induced eating via mobile smartphone applications

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Abstract

The increasing number of diet-related diseases presents a major public health concern. Within the developed countries this is especially caused by the intake of unhealthy foods. The food selection is a complex process which can be affected by various factors. An important factor is stress. Stress can influence the quantity as well as the quality of the food intake. The ongoing development of mobile health applications (mHealth apps) provides the opportunity to address this topic and support healthier dietary patterns in stressful situations. The aim of the present thesis was to investigate characteristics of the potential user group and to identify requirements for the development of a digital advisor focused on stress-induced dietary behavior.

The online survey on 1,222 participants (31.5 ± 12.8 years) revealed, that about 46 % of the participants show a hypophagic reaction to stress (eat less) and 42 % show a hyperphagic reaction to stress (eat more). The remaining 12 % are insensitive to the influence of stress. The vulnerability to stress-induced changes of the dietary behavior was associated with sex, body mass index (BMI), eating motives and personality facets. The app analysis indicated that nutritional values and intake recommendations estimated by currently available apps deviated from the values of the national nutrition databases and recommendations of the nutrition societies. The apps' content gets generated based on the data obtained. Missing or imprecise data affect the apps' quality. The results of the quality assessment showed that especially the quality domains skill development and aesthetic require to be improved. Regarding stress related aspects, the literature overview revealed twelve non-invasive stress indicators. The indicators can be assigned to the categories physiology, behavior and subjective perception. Smart devices like smart watches or wristbands can be used to capture these indicators. The highest stress detection rate of 89 % was achieved by the combination of various stress indicators.

For the development of a stress-focused digital dietary advisors, the precise collection of nutritional and stress data is fundamental. The integration of features like barcode scans or the combination of diverse sensor data simplifies the collection process. A target group orientated development approach can improve the apps' usability. Considering all aspects mentioned, an effective digital dietary advisor to support healthy dietary patterns in stress situations can be developed and implemented.

Zusammenfassung

Die steigende Anzahl an ernährungsbezogenen Krankheiten gehört zu den größten Public Health Problemen weltweit. Ursache hierfür ist innerhalb der Industrieländer besonders der Verzehr von ungesunden Lebensmitteln. Die Auswahl von Lebensmitteln ist ein komplexer Vorgang, welcher durch eine Vielzahl von Faktoren beeinflusst wird. Ein wichtiger Faktor ist Stress. Der Einfluss von Stress kann sowohl die Quantität wie auch Qualität der konsumierten Lebensmittel verändern. Die fortschreitende Entwicklung von Gesundheits-Applikationen für mobile Endgeräte (mHealth Apps) bietet die Möglichkeit diese Thematik zu adressieren und gesunde Ernährungsweisen in Stresssituationen zu unterstützen. Das Ziel dieser vorliegenden Arbeit war es, Merkmale der potenziellen Nutzergruppe zu erforschen und Anforderungen für die Entwicklung eines digitalen Ernährungsberaters mit dem Fokus auf stressbedingtes Ernährungsverhalten zu identifizieren.

Die Online-Umfrage mit 1.222 Teilnehmern (31,5 ± 12,8 Jahre) hat gezeigt, dass 46 % der Teilnehmer eine hypophage (essen weniger) und 42 % eine hyperphage (essen mehr) Reaktion auf Stress zeigten. Die restlichen 12 % zeigten sich unempfindlich gegenüber dem Einfluss von Stress. Die Vulnerabilität für stressbezogene Veränderungen des Ernährungsverhaltens war mit Geschlecht, Body Mass Index (BMI), Essmotiven und Persönlichkeitsfacetten assoziiert. Die Analyse aktueller Ernährungsapps hat ergeben, dass die mittels Apps erfassten Nährstoffdaten und Zufuhrempfehlungen von den Werten nationaler Nährstoffdatenbanken und Ernährungsgesellschaften abwichen. Basierend auf den erhobenen Daten wird der Inhalt der Ernährungsapps generiert. Fehlende oder ungenaue Daten beeinflussen die Qualität der Apps. Die Ergebnisse der Qualitätsbewertung zeigten, dass besonders in den Bereichen Fähigkeitsentwicklung und Ästhetik Verbesserungsbedarf besteht. Für die Integration stressbezogener Aspekte wurden mittels Literaturüberblick zwölf nicht-invasive Stressindikatoren identifiziert. Die Indikatoren der Kategorien Physiologie, Verhalten und subjektives Empfinden können mittels smarter Geräte, z.B. Smartwatches oder smarter Armbänder, erfasst werden. Die höchste Stresserkennungsrate von 89 % wurde durch die Kombination verschiedener Indikatoren erzielt.

Für die Entwicklung eines stressbezogenen digitalen Ernährungsberaters ist die exakte Erhebung von Ernährungs- und Stressdaten grundlegend. Diese wird durch den Einsatz von Features wie Barcode-Scan oder durch die Kombination von Daten verschiedener Sensoren erleichtert. Durch ein zielgruppenorientiertes Entwicklungsdesign kann die Benutzerfreundlichkeit verbessert werden. Unter Berücksichtigung aller genannten Aspekte kann ein effektiver digitaler Ernährungsberater zur Unterstützung gesunder Ernährungsweisen in Stresssituationen entwickelt und implementiert werden.

Abbreviations

24 HR	24-hour recalls
AS	Average Score
BCT	Behavior Change Technique
BFI-10	Big Five Inventory
BLS	German Nutrient Database (Bundeslebensmittelschlüssel)
BMI	Body Mass Index
BSI	Federal Office for Information Security (Bundesamt für Sicherheit in der Informationstechnik)
BP	Blood Pressure
BVP	Blood Volume Pulse
CRH	Corticotropin-Releasing Hormone
DACH	Germany, Austria and Switzerland (Deutschland, Österreich, Schweiz)
DBCI	Digital Behavior Change Interventions
DGE	German Nutrition Society (Deutsche Gesellschaft für Ernährung e.V.)
DiGA	Digital Health Applications (Digitale Gesundheitsanwendungen)
DiGAV	Digital Health Appliance Ordinance (Digitale Gesundheitsanwendungen-Verordnung)
DSI	Daily Stress Inventory
DVG	Digital Healthcare Act (Digitale-Versorgung-Gesetz)
DALY	Disability-Adjusted Life Years
EDA	Electrodermal Activity
eHealth	Electronic Health
FFQ	Food Frequency Questionnaire
FR	Food Record
SGB V	German Social Code Book V (Fünftes Buch Sozialgesetzbuch)
GPS	Global Positioning System
HPA	Hypothalamic-Pituitary-Adrenal axis
HRV	Heart Rate Variability
HR	Heart Rate
ICT	Information and Communication Technology
mHealth	Mobile Health
NCD	Noncommunicable Diseases
ISO	International Organization for Standardization
PSQ	Perceived Stress Questionnaire
PSS	Perceived Stress Scale

RCT	Randomized Controlled Trial
SSES	Salzburg Stress Eating Scale
SCI	Stress Coping Inventory
SAM[1]	Stress Appraisal Measure
SAM[2]	Sympathetic-Adrenal-Medullary System
TEMS	The Eating Motivation Survey
USDA	United States Department of Agriculture
WHO	World Health Organization

Tables and Figures

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1 Introduction

1.1 Dietary risk factors

Unhealthy diets are still a main risk factor for the development of noncommunicable diseases (NCDs) like diabetes, cancer and heart diseases [1]. In 2019, unhealthy dietary behavior accounted for 3.48 million deaths in women and 4.47 million deaths in men as well as for 105 million disability-adjusted life years (DALYs) in central and eastern Europe, central Asia and most of China [2]. The main dietary risks comprise low intakes of fruits, vegetables, whole grains, nuts, milk, fiber and seafood omega-3-fatty-acids and high intakes of red or processed meat, sugar, trans fatty acids and sodium [2, 3].

Intake recommendations for these food groups and nutrients are provided by the national nutrition societies to facilitate healthy dietary behavior. Recommendations for Germany are released by the German Nutrition Society (Deutsche Gesellschaft für Ernährung e.V. - DGE) in form of ten rules for a wholesome diet (e.g., five portions of fruit and vegetables per day, reduction of salt and sugar intakes) [3]. In Germany, dietary recommendations for daily fruit consumption are met by 55.6 % of women and 38.7 % of men on average, whereas recommendations for daily vegetable consumption are met by only 42.5 % of women and 25.3 % of men [4].

Non-wholesome diets and overage caloric intake combined with low physical activity lead to an increase of the body mass index (BMI) [2]. Reference values for energy intake for an adult population range from 1700 kcal/day (female person, older than 50 years, low physical activity level) to 3100 kcal/day (male person, aged between 19 and 25 years, high physical activity level) [5]. Between 1975 and 2014 the global mean BMI raised by 2.5 kg/m² in men (21.7 kg/m² to 24.2 kg/m²) and 2.3 kg/m² in women (22.1 kg/m² to 24.4 kg/m²), accompanied by an increased prevalence of obesity by 7.6 percentage points in men (3.2 % to 10.8 %) and 8.5 percentage points in women (6.4 % to 14.9 %) [6].

The World Health Organization (WHO) highlights the importance of a healthy diet to reduce the risk of NCDs [7]. To achieve a healthy diet, energy intake and energy expenditure need to be well-balanced and food choices should be diversified to ensure a sufficient supply with essential nutrients [1]. An important influential factor of the maintenance of a healthy dietary behavior is stress. It can trigger changes in the food intake behavior reflected by e.g., an increase of the overall energy intake, which can contribute to a higher risk for the development of diet-related NCDs [8].

1.2 Stress

1.2.1 Stress – Definition

A variety for definitions of stress exists. Seyle (1976, p. 137) defined stress as “the nonspecific response of the body to any demand made upon it” [9]. Stress is also correlated with a person’s capability “to meet, mitigate, or alter these demands” (Lazarus et al., 1985, p.770) [10].Stress is triggered by demands of endogenous as well as exogenous stressors [11]. Stressors can occur in different types of daily life hassles (e.g., financial stressors, health stressors, work overload or interpersonal tensions) [12]. The presence of any stressor threatens the homeostasis of the organism and prepares the body for a “fight or flight” reaction [13]. As a response to the perceived threat, a cascade of changes is started. For the stress reaction process the sensory system of the brain, the hypothalamic-pituitary-adrenal (HPA) axis and the sympathetic adrenomedullary system (SAM[2]), are activated [14]. If the stimulus is classified as potential stressor, relevant stress hormones are released, which further provoke an increased cardiac output and blood pressure to support the blood flow from skin and gut into the skeletal muscles [14]. Energy provisioning is centered towards the brain and skeletal muscles [15]. As a result, stress-related biomarkers increase (e.g., serotonin in blood, dopamine in urine, cortisol in salivary and blood) [16]. Additionally, various physiological and behavioral stress responses like increased heart rate (HR) or heart rate variability (HRV), elevated blood pressure, electrodermal activity (EDA), decreased sleep quality and variation in voice locals can be measured [17, 18]. Repeated or continues activation of these acute stress responses can be maladaptive [19]. As a result, consequences on health like sustained increased blood pressure or vascular hypertrophy can occur [20].

Seyle (1976) further described stress as “the spice of life” referring to its contrasting effect [9]. Stress can be typified as eustress or distressed. Eustress is associated with positive feelings, a good health status and agreeable effects (e.g., increased physical performance as achievement of physical exercise). Contrary, distress is related with negative feelings, bad health status and pathological effects [9]. The impact of stress on health can be a risk factor for the development of several diseases. Consequences occur in the area of mental health, especially stress-induced mental overload, burnout, depression and sleep disturbances are widespread [21]. Physiological responses to stress, like increased heart rate and blood pressure, can manifest and cause long-term cardiovascular diseases [22].

The procedure of the stress response is subject to individual differences regarding the intensity or severity as well as controllability of a stressor and response stereotypes [15]. The intensity of the perceived stress is related to the coping behavior. Coping describes the process of managing “demands that are appraised as taxing or exceeding the resources of the person” (Lazarus & Folkmann, 1984, p. 141) [23]. The coping process can include social, religious, emotion regulation and positive emotional aspects. Adequate coping can mitigate the stress impact [24]. Besides, different types of personality perceive stress dissimilar. Increased stress exposure is attributed to neuroticism personality, whereas a reduced stress perception is associated with the personality type conscientiousness [25].

1.2.2 Stress – Consequences on eating behavior

In the context of nutritional behavior, maladaptive stress responses can cause serious illnesses. In the moment of stress, all processes of the organism are focused on a fight or flight reaction, accompanied with a suppression of hunger, induced by the corticotropin-releasing hormone (CRH) [26, 27]. After the stressful event is overcome the release of glucocorticoids (e.g., cortisol) restimulates the appetite [28, 29]. Thus, changes in the eating behavior and food choice can occur. Stress is associated with an increased snacking behavior and decreased consumption of other meal types [30, 31]. Additionally, the reward system is triggered in the context of stress. The desire for “mood-enhancing foods” is reinforced and so-called “comfort-foods” are consumed to satisfy that desire [32]. Especially stress-related preferences for unhealthy high palatable foods, which are low in nutrients, were determined [33]. Comfort foods are characterized by high levels of fat and sugar and low nutrient density [34]. Highly preferred comfort foods are potato chips, ice cream and cookies [35]. In the cause of a stressful event the food choice basis is shifted from nutritional to emotional needs [36]. Conscious, healthy nutritional claims are neglected and unhealthy habitual food choices become predominant [37].

Individual differences effect the nutritional response to stress. About 80 % of the population change their eating behavior in relation to stress [30]. 38 % are classified as stress-induced overeaters (people with hyperphagia) and 42 % are classified as stress-induced undereaters (people with hypophagia) [30].

The influence of stress on the dietary behavior is mediated by various factors. Women tend to be more vulnerable to stress-induced eating, leading to greater numbers of calories consumed after a stressful event [28]. There is also a mediating effect of age and gender on the preference for certain comfort foods, indicating that women as well as people of younger age favor snack-like comfort foods over hearty meals [38]. Women were found to be more sensitive to stress-induced eating than men [39]. Additionally, adequate coping mitigate the effect of stress-induced eating behavior and serves as buffering effect for the perception of stress in general [40, 41]. Furthermore, the dieting status mediates the influence of stress on the dietary behavior. Dieting or restrained eating behavior were found to be associated with unhealthy stress-induced eating patterns [39, 42].

The stress-induced consumption of unhealthy foods and the tendency to overeat (intake exceeds metabolic needs) contribute to weight gain and obesity [26, 43]. Furthermore, stress-induced eating constitutes a risk factor for the development of prediabetes and diabetes [43]. Besides, symptoms of eating disorders have been reported, as a response to stress [44].

Unhealthy stress-induced dietary patterns and their (long-term) health consequences affect a great proportion of the population and contribute to serious health issues. Actions to address this health problem need to be undertaken. In the era of digitalization, information and communication technologies (ICTs) are used to provide health information and are implemented to empower individual health promotion [45]. They offer the potential to reach a broad range of the population and provide stress-eating focused health interventions via technical everyday life companions.

1.3 mHealth

1.3.1 mHealth – Definitions

The health care sector enhances with the progress in digitalization, contributing to the emergence of the field of electronic health (eHealth). eHealth is defined as “cost-effective and secure use of information and communication technologies in support of health and health-related fields, including health-care services, health surveillance, health literature, and health education, knowledge and research” (WHO, 2021) [46]. A special field of eHealth is mobile health (mHealth), comprising digital health services supported by smart mobile devices (e.g., mobile phones, wearables) [47]. The main characteristics of smart devices are the features, which enable context-awareness through sensor-based environmental data (e.g., microphone, accelerometer) and connectivity with other (smart) devices or networks [48]. mHealth provides the opportunity to address a broad range of target groups and contexts to deliver services that aim to improve the health access, knowledge and behavior of the users [49]. Primary used functions to improve health aspects are tracking and clinical feedback data as well as reminders and alerts for the system-user relationship [50].

1.3.2 mHealth – Functions

The main purpose of mHealth technologies is to capture, process and communicate health-related data [51]. Thereby, the accurate data collection is essential for further data procession and output generation. To capture relevant health data, features for active or passive self-tracking of physiological as well as behavioral parameters are implemented [51]. Active tracking requires the user to engage with the device and manually input relevant information [52]. For passive tracking data gets generated via smart devices worn on the body or integrated within a smartphone, to process the data a synchronization with other devices can be necessary [53]. Smart wearables have been developed to collect time and place specific data [54]. Tracking devices can be applied at all parts of the human body to enable health monitoring (e.g. heart rate, blood pressure), chronic disease management, diagnosis and treatment (e.g. diabetes, depression) as well as support rehabilitation (e.g. stroke) [55]. The devices' sensing areas can be divided into physiology, activity and environment [56]. The most widespread physiological sensors record heart rate and body temperature. Furthermore, blood pressure and oxygen saturation as well as blood sugar and blood volume pulse can be captured (**Figure 1**). The field of activity is dominated by motion and gestures as well as proximity detection, additionally body acceleration can be assessed. Location sensors are most frequently used devices to capture environmental information like air temperature, altitude, light and sound can be recorded [56].

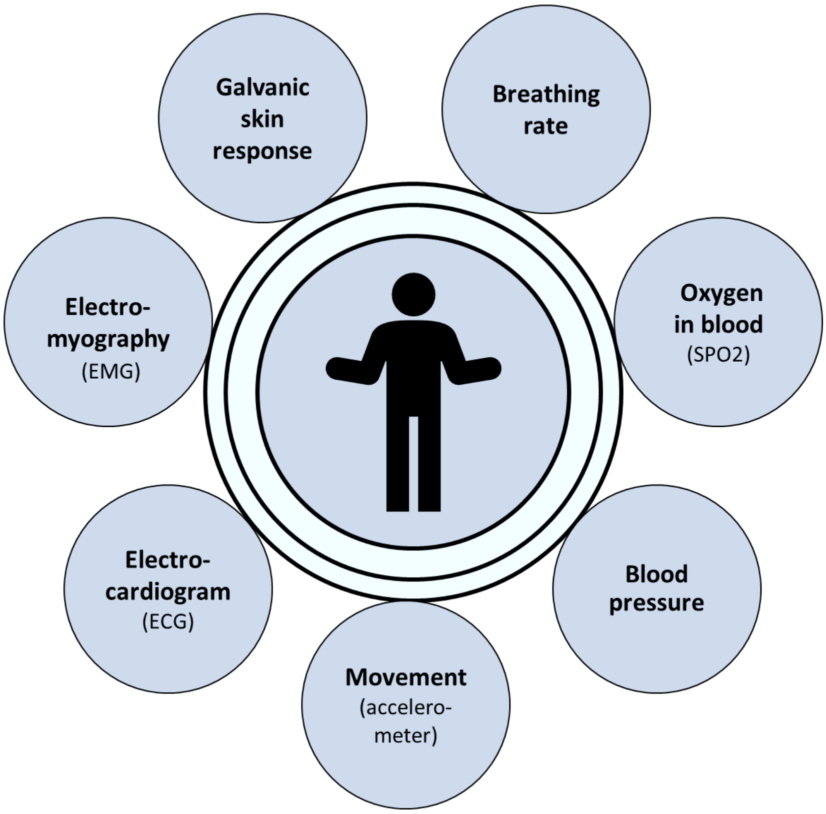


Figure 1: Sensor-based monitoring of physiological signals. Adopted from Rodrigues et al.(2018) [57].

1.3.3 mHealth – Behavior Change Techniques

The collected (sensor-based) data gets further processed by the smart device itself or specific accompanied software [58]. The generated system output of mHealth applications (apps) provides an overview of measured health parameters and can additionally include features to support sustainable changes to the individual's behavior [59]. Therefore, many health-related apps already integrate effective behavior change techniques (BCT) [54]. Most common physical activity, dietary behavior or disease specific (e.g., HIV) outcomes are addressed by digital behavior change interventions (DBCI) [60]. **Table 1** presents most frequently integrated categories of BCT within mHealth apps and a description on how these are used within DBCIs.

Table 1: Most frequently used BCTs within mHealth.

BCT taxonomy	**Description of usage within DBCI**
Goals and planning	Specific health outcomes defined as goal (e.g., weight loss), grocery list for healthy shopping or (increased physical activity, workout plan)
Feedback and monitoring	Visual display of self-monitoring health parameter (e.g., chart of weight measurements or nutrient intakes) feedback whether recommendations are met
Reminders and alerts	Push-notifications as reminders to record food intake or drinking
Social support	Forums or online community
Shaping knowledge	Information on health behavior (e.g., benefits of specific foods or nutrients for the body)
Comparison of behavior	Competitions or challenges for goal achievements
Reward and threat	Trophies for goal achievements

BCT taxonomies based on Abraham & Michie et al. (2008) [60].
Description of usage within DBCI according to Tham et al. (2020) and Lister et al. (2014) [53, 61].

1.3.4 mHealth – Quality aspect

The rapid progress of digitalization in the health care sector entails a growing number of commercially available health-related apps. In the multitude of available mHealth apps, great variances in terms of quality exists. According to the International Organization for Standardization (ISO, 1994) quality is defined as “the totality of features and characteristics of a product or service that bear on its ability to satisfy stated or implied needs” [62]. To assess these features and characteristics quality classifications are deployed. According to the German Federal Office for Information Security (Bundesamt für Sicherheit in der Informationstechnik - BSI) a demarcation between health apps, medical apps and digital health applications (Digitale Gesundheitsanwendungen – DiGA) is performed [63]. DiGAs are listed in the DiGA directory and its details are legally regulated within the Digital Health Appliance Ordinance (Digitale Gesundheitsanwendungen-Verordnung – DiGAV) [64]. Appropriate DiGAs are medical devices, which are CE-marked. To receive the CE-mark, DiGAs need to fulfill certain requirements (e.g., support recognition, treatment, alleviation of diseases and injuries) defined in Section 33a of the German Social Code Book V (Fünftes Buch Sozialgesetzbuch, SGB V) [65]. Pursuant to the Digital Healthcare Act (Digitale-Versorgungs-Gesetz -DVG) DiGAs can be prescribed by healthcare professionals as “app on prescription”. According to the DVG these “apps on prescription” need to meet requirements regarding quality, data protection and security [66]. Furthermore, the compliance with the international standard for software architecture ISO/IEC/IEEE 42010 promises appropriate levels of security and privacy [67]. Based on a systematic literature review including healthcare professional websites, the following criteria for mHealth standards were detected: usability, privacy, security, appropriateness, suitability, transparency and content, safety, technical support and updates as well as technology [68]. A great number of assessment tools to evaluate the quality of health-related apps has been developed. These tools cover a broad range of quality aspects and are therefore very heterogenous regarding their content, focus, terminology and valuation [69-71].

Evidence on mHealth interventions still needs to be further assessed. Randomized controlled trials (RCTs) on the effectiveness of mHealth interventions demonstrated significant differences between mHealth intervention groups and control groups. For example, mHealth interventions were found to improve mental health parameters (resilience, personal growth, positive relationships and anxiety) [72]. Furthermore, significant positive effects of mHealth interventions on sedentary time and BMI were found in RCTs [73, 74].

1.3.5 mHealth – Current market situation

mHealth content can be disseminated through various mobile devices like smart phones or wearables (e.g., smartwatches, wristbands) [75]. For these ICTs apps are being developed to offer health-related services which are based on user input and provide health-related output. mHealth apps can be accessed via commercial App Stores like Google's Play Store or Apple's App Stores. Within these stores, the health apps are assigned to the categories 'Health & Fitness', 'Lifestyle', 'Food & Drink' and 'Medical'. Across all categories, over 85 % of the health apps are available free of charge or at a low price (less than 1 €) to download [76]. Almost every second smartphone owner uses mHealth apps. Most of all, tracking apps of body and fitness data (e.g., heart rate, steps) are used, followed by informational apps on health, fitness, weight and nutrition and apps which generate motivational and behavioral advice based on tracked data [77]. The increasing use of mHealth apps is reflected in the forecasted mobile health market growth rate of about 36 % from 2020 to 2026 [78].

Most of the downloaded health-related apps can be assigned to the field of prevention (89.6 %), followed by self-management (about 8 %), diagnosis (1 %) and therapy (1 %) [79]. In the context of health prevention, mHealth services address the fields of health promotion by providing services to motivate and support a healthy lifestyle (e.g., health and fitness apps, online-courses) or enable health care communication (e.g., consultation with health professionals, self-help panels) [80]. Likewise, mHealth apps can be used to provide individual or disease specific treatment plans from therapists and physicians [80]. mHealth apps can be further distinguished into the following types: remote monitoring apps (e.g., real-time tracking of heart rate, blood pressure, blood glucose level), clinical and diagnostic apps (e.g., lab results, electronic health records), healthy living apps (e.g., sleep, exercise), clinical reference app (e.g., ICD-9 and -10 reference documents) and productivity apps (e.g., mobile charting, healthcare scheduling) [81].

1.3.6 mHealth – Nutrition

In the field of mHealth app-based prevention, nutrition is one of the most frequently downloaded usage contexts (28 %), followed by women health (15 %) and relaxation (13 %). Only the field of physical activity obtains higher download numbers (39 %) [79]. 34 % of mHealth app users apply health or fitness apps for motivation to eat and drink healthier and 29 % use these technologies to lose weight [82]. Recently most used concepts of nutrition-related apps are dietary intake counters, restaurant finders and recipe apps [83].

1.3.6.1 mHealth – Nutrition – Dietary intake

Accurate data collection is the basis for digital tools to process and communicate health-related data [51]. In the context of nutrition, the dietary behavior and related parameters (e.g., physical activity level interrelated with energy expenditure) are captured via mobile devices [84]. Existing dietary intake assessments have been enhanced from their original paper-pen-based versions into digitalized tools [85]. Most frequently used dietary intake assessment methods are food frequency questionnaires (FFQs), 24-h recalls (24 HRs) and food records (FRs) [86]. All these tools are subject to specific bias and can be tiresome for the participants to complete. For example, FFQs can record the food intake of the previous month and are therefore prone to recall bias, additionally extensive food lists prolong the completion time [86]. The integration within mHealth devices makes these assessments ubiquitous and therefore more time- and cost-effective [85].

Physical activity parameters are already captured automatically through integrated step counting features based on accelerometer or global positioning system (GPS) data [87]. Whereas nutritional assessments mainly rely on self-reports, which need further user effort for completion. The majority of nutrition apps provide input features like manual text entry fields or preselected item shortlists [88]. The effort to collect data can be reduced by integrating semi-automatic functions like barcode-scanning or voice-recordings within these apps. To fully automatically capture the dietary intake, sensors recording and analyzing eating gesture, chewing or swallowing sounds and motions are used [89]. The usage of sensors placed on the body (e.g., wristbands) aims to further reduce reporting biases and therefore improve the continued dietary monitoring [90]. In general, the use of digital approaches to assess dietary behavior enables real-time food recording, which not only improves the accuracy of captured data, but also represents a cost- and time-effective alternative to paper-pen methods with decreased user effort and increased user acceptance [85].

Additionally, to the way the data is recorded, various characteristics of intake data like food groups and eating occasion need to be considered. As stated by the DGE some food groups (e.g., fruits and vegetables) are the basis for the daily diet, whereas the intake of other food groups (e.g., meat or sweets) should be limited [3]. Furthermore, the tracking of at least two eating occasions a day has been found to be positively associated with primary nutritional outcomes (weight loss) [91].

1.3.6.2 mHealth – Nutrition – System output

The collected data are further processed by the nutrition apps. The objective of most dietary apps is to analyze the dietary intake and eating behavior to provide feedback to the user. Feedback commonly includes estimates of caloric intake (53 %), followed by details on macronutrient (44 %) and micronutrient estimations (14 %) [92]. Therefore, energy and nutrient values as well as information on the portion size and contextual data need to be appraised to estimate the individual's food intake [92]. On the basis of age and gender, intake reference values for macro- and micronutrients vary [93]. Integrated databases are used to calculate the individual energy and nutrient intakes [94]. Food composition data for the German population are compromised within the Bundeslebensmittelschlüssel (BLS) which is provided by the Federal Ministry of Food and Agriculture (Bundesministerium für Ernährung und Landwirtschaft) [95]. App analyses revealed that between 65 % and 75 % of the analyzed apps integrated food databases to calculate energy intakes [88, 96].

Apps are also capable to calculate the daily energy turnover of users and provide feedback on the energy intake in relation to the individual energy expenditure To estimate the individual energy expenditure, information on parameters influencing the basal metabolic rate (e.g., age, sex, body height, weight, muscle mass) and on physical activity is needed [97]. Therefore, most of the diet apps gather specific user data to calculate the individual's energy expenditure [98].

As a final step, the processed nutrition related data are communicated to the user. Communicated content can provide meal suggestions, information on caloric status, healthier alternatives or warnings (e.g., salt warnings linked to blood pressure monitoring) [99]. The provided output is related to the objective of the regarded nutrition app. A multitude of diet-related apps are focused on weight loss and caloric counting, other apps center on healthy eating or disease-related specificities [87]. Consequently, especially energy intake and expenditure as well as nutritional status are displayed by the majority of the nutrition-related apps. This is also reflected in the users' intention for dietary app usage, where the achievement of dietary goals is a key factor concerning usage intention [100, 101]. To meet users' expectations, nutrition apps target to change the users' dietary behaviors. Therefore, effective BCTs (e.g., goal setting, monitoring and feedback, education) are already integrated within a various nutrition apps [102, 103].Users BCT engagement was found to be positive associated with mHealth intervention outcomes [104]. Still not all nutrition related apps utilize BCT techniques [105].

Intake calculations and the effectiveness of mHealth interventions on nutrition-related outcomes were appraised for the quality assessment of the system output. For the validation against standardized reference methods weighted food records (WFR) or 24 h recalls and doubly-labelled water (DLW) are applied and assessed based on national food composition data bases. Results reveal correlations between national food composition databases and nutrition tracking apps between 0.73 and 0.96 for total carbohydrates, protein and fat and between 0.57 and 0.93 for sodium, total sugars, fiber cholesterol and saturated fatty acids [106]. Furthermore, investigated diet apps differ from reference methods between 8.4 % and 23.1 % regarding energy content [88, 107]. Considering the effects on nutritional outcomes, nutrition-based mHealth groups showed greater reduction in energy and nutrient intake (fat, sugar, salt) and greater increases in fruit and vegetable consumption compared to groups using traditional paper-based dietary record methods [98, 108, 109]. Furthermore, significant positive changes in primary outcomes (weight loss, waist circumference, behavior change) as well as in secondary outcomes (acceptability, blood pressure) were achieved using mHealth apps [110].

1.3.7 mHealth – Stress

As mentioned above, stress is an influential factor of the dietary behavior. Therefore, the current state of stress-related mHealth apps should be further investigated. Stress is one of the main indications for DiGAs regarding prevention and health promotion [80]. On the one side, stress-related mHealth approaches comprise the recording of stress responses. A multitude of commercially available smart devices include features to capture stress-related biomarkers [111]. Sensors integrated into smart wearables (e.g., wrist band, smart watch, chest strap) for example measure changes in heart rate (HR) variability (HRV), blood volume pulse (BVP), blood pressure (BP) and electrodermal activity (EDA) [111]. Additionally, behavioral patterns like facial expression, body posture or keyboard striking are captured via smart sensors to assess stress exposure [111].

On the other side, stress-related mHealth systems also focus on the management of stress. In general, common ways to treat stress are pharmacological approaches, relaxation and meditation techniques, neuromuscular relaxation and biofeedback treatments as well as respiration control exercises [112]. Most frequently used stress management techniques within commercial stress-focused apps are music and sounds (20 % to 30 %) as well as breathing and meditation/mindfulness (15 % to 27 %), only few apps include bio signals (e.g., heart rate control) [113, 114].

Just like for nutrition apps, the validity of the stress assessment itself is evaluated against a standard reference method and the effect of applied interventions on stress parameters is investigated. In the context of mHealth, stress is most commonly assessed via self-reporting items (e.g., 5-point-likert scale or Yes/No- decision question) and compared against validated stress assessment measures like the perceived stress scale (PSS) [115, 116]. Changes in HRV and EDA are recorded by smart wearables and used to accurately detect stress [117]. Accelerometer data as well as verbal data were also found to detect stress with an accuracy of up to 71 % [118-120].

The usage of stress-management apps can reduce the stress level (measured by validated stress assessment scales and objective bio signal parameters) as well as improve the overall well-being [121, 122]. Furthermore, unhealthy eating patterns in the context of stress can be reduced and healthy food choices improved through the use of these apps [123].

2 Aim

Unhealthy dietary patterns in the context of stress and their resulting health consequences are concerning a great proportion of the population. The emerging field of mHealth offers a solution to address this target group via techniques of our everyday life and deliver preventive strategies for the topic of stress eating. This approach could be implemented in form of a digital dietary advisor focused on stress-eating. Therefore, the primary aim of this work was to identify the characteristics of the potential user group of stress-induced overeaters. The second objective was to assess the quality of currently available nutrition apps and define necessary elements in this field. The third objective was to assess existing options of stress measurement in the context of mHealth. Finally, requirements for the development of a digital dietary advisor should be derived from the results. On that account the following research steps were undertaken:

- Step 1 – Characterization of the potential user group of a stress-focused digital dietary advisor

  A digital dietary advisor focusing on eating occasions in the context of stress might be especially helpful to people who increase their dietary intake due to stressful events. The aim was to identify relevant characteristics of this “stress-eater” target group to better understand the potential users and to consider these characteristics for the development of a digital stress dietary advisor approach.

- Step 2 – Identification of relevant mHealth quality aspects

  Currently a great variety of mHealth services in the field of nutrition exists. The selection of effective approaches can be overwhelming and needs standardized guidelines. In this context, the aim was to identify validated quality assessments for mHealth solutions and highlight aspects for an overarching quality appraisal.

- Step 3 – Exploration of mHealth based stress indicators and measurement aspects

  The possibilities to detect stress via mHealth-related smart measurement enhance. Therefore, the aim was to identify stress indicators and explore the smart solutions to measure the selected indicators.

3 Methods

3.1 Survey on characterization of stress-induced hyperphagia

3.1.1 Survey – Development, revision and design

The aim of the survey was to investigate stress-eating behavior in a sample of German citizens. It was developed by an interdisciplinary team of researchers of public health nutrition science, nutritional science and computer science. As an online-survey, it offers a time-saving and low cost way to reach a broad population and achieve greater statistical power [124]. The formation process was iterative. To improve the completion process for the participants, surveys need to be structured into main sections [125]. This survey was subdivided into introductory, main and final part. Within the introductory part, information about the research project, protection of privacy and voluntary participation were provided and digital consent (checkbox) was queried. The main survey part compromised aspects of nutrition behavior, stress, stress-eating, technical parameters, personality, sociodemographic and anthropometric data. The final part displayed the acknowledgements and an opportunity for participants' feedback. Most survey items were issued as short and easy to understand questions with closed, open, single or multiple-choice answering options. Filter questions were integrated if appropriate to simplify the completion of the survey [126]. SoSciSurvey platform (V 3.1.06) [127] was used to create the online version of the survey.

A pre-test was performed to check the comprehensibility and appropriateness of the survey items [126]. Ten project-independent persons (aged 35.8 ± 9.9 years) pre-tested and evaluated the preliminary version of the survey between October and November 2020. Based on the evaluation results and the participants' feedback some survey items were rephrased and the total survey length was shortened.

3.1.2 Survey – Final Questionnaire

The final questionnaire consisted of 38 items (**Appendix**), the distribution of survey items across the different survey topics is displayed in **Table 2**.

This work focused on the identification of possible associations with stress-overeating characteristics, accordingly non-relevant items (e.g., technical parameters) were neglected. The present investigation comprised 13 survey items, including five psychometrical tools (nutrition: The Eating Motivation Survey -TEMS [128]; stress: Perceived Stress Scale - PSS [115]), Stress Coping Inventory -SCI [129]; stress-eating: Salzburg Stress Eating Scale -SSES [130]; personality: Big Five Inventory – BFI-10 [131]).

Table 2: Survey items - overview final survey and extraction for publication.

Survey topics	**Final survey** Number of items	**Extraction for publication** Number of items
Nutrition	1	1
Stress	4	3
Stress-eating	17	3
Technical aspects	6	-
Personality	1	1
Sociodemographic and anthropometric data	9	5

Changes of the nutritional behavior in response to stressful events were appraised using the Salzburg Stress Eating Scale (SSES) [130]. Based on the SSES scores (mean score range 1- 5), participants can be allocated into three different response types: ‘eats less when stressed’ (score < 3), ‘eats the same amount as usual’ (score = 3) and ‘eats more when stressed’ (score > 3) [130]. Besides the validated assessment, participants were asked to subjectively evaluate their response to stress and categorize themselves as stress-overeater or non stress-overeater. A literature search was performed to identify comfort foods (and beverages), which are preferably consumed in stressful situations. The 13 preselected comfort foods are chocolate & confectionery, sweets, ice cream, cake, cookies, chips & crackers, salted nuts, fries, fast foods (burger, curry sausages or pizza), alcohol, sugar sweet beverages, energy drinks and coffee [132-134] and were presented within a closed-list. Participants were asked to indicate the frequency of their individual selection of each presented comfort food.

The Perceived Stress Scale (PSS) [115] was applied to assess participants’ stress. The PSS captures the frequency of specific stress-related feelings and thoughts within the previous month. Sum scores of the ten items (single item score range 0-4) are calculated. Higher sum scores are associated with a higher amount of perceived stress.

The Stress and Coping Inventory (SCI) [129] was used to determine individual strategies of coping. The SCI comprises ‘Positive Thinking’, ‘Active Stress Coping’, ‘Social Support’, ‘Keeping Faith’ and ‘Increased Alcohol and Cigarette Consumption’. Sum scores are calculated for each strategy, based on item score ranges between 1 and 4. Higher scores indicate greater relevance of the respective strategy within the individual coping process [129]. Additionally, own items were integrated into the survey to capture the stress frequency and potential stressors.

The participants eating motives were investigated to address their nutritional behavior. The eating motives were assessed using The Eating Motivation Survey (TEMS) [128]. The TEMS comprises the following 15 eating motives: ‘Liking’, ‘Habits’, ‘Need & Hunger’, ‘Health’, ‘Convenience’, ‘Pleasure’, ‘Traditional Eating’, ‘Natural Concerns’, ‘Sociability’, ‘Price’, ‘Visual Appeal’, ‘Weight Control’, ‘Affect Regulation’, ‘Social Norms’ and ‘Social Image’. The output, mean scores between 1 and 7, reveals the relative importance of the motives. Higher mean scores indicate greater relative importance of the respective motive [128].

The *Big Five Inventory* (BFI-10) was used to assess the participants' personality [131]. The BFI-10 scores determine the importance of the five dimensions 'Openness', 'Conscientiousness', 'Extraversion', 'Agreeableness' and 'Neuroticism', regarding the individual personality. For evaluation mean scores for each dimension (two items per dimension) are calculated (range 1-5). Higher mean scores indicate greater contribution of the respective dimension to the individual's personality [131].

3.1.3 Survey – Recruitment and Performance

The survey was registered in the German Register of Clinical Studies (Registration number: DRKS00023984) and approved by the Ethical Committee of the Technical University of Munich (ethical vote: 729/20 S). Potential participants were recruited digitally using homepages, mailing lists and social media accounts of the involved institutes and further corporations to display study information. Online recruitment offers the chance for a vast reach within the population, but neglects people not internet versed [124]. The sampling was performed in a convenient way, allowing people to participate based on the interest on the survey topic [135]. Participants needed to fulfill the following inclusion criteria: full of age (18+ years), able to read and write in German, present digital approval to declaration of consent and protection of privacy. Appropriate participants were provided with an online link to the digital survey questionnaire. The survey data were checked for integrity and plausibility. Respondents with missing or seemingly invalid data (e.g., BMI < 17 kg/m² or > 50 kg/m²) were excluded from the analysis. Commonly, people who change their eating behavior due to stressful situations are defined as stress eaters [136]. Within this manuscript, respondents are categorized according to the SSES evaluation and only participants who 'eat more' when stressed, are hereinafter referred to as stress-overeaters, while the remaining participants are summarized as non stress-overeaters (stress-undereaters and stress-insensitive eaters). The open online survey was conducted between January and April 2021. Participant flow is presented in **Figure 2**.

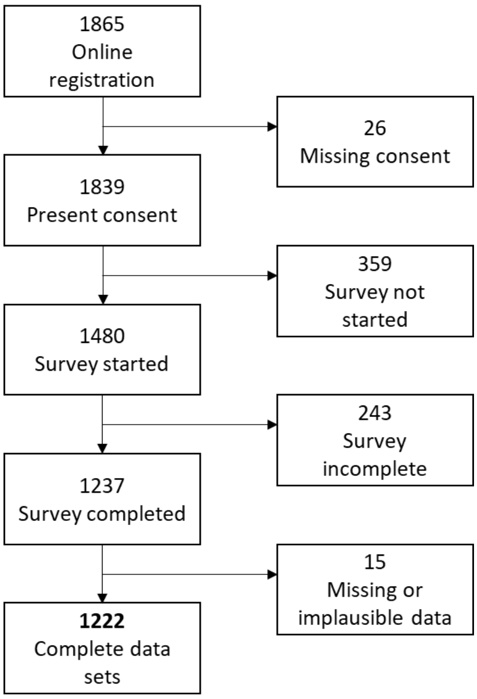


Figure 2: Participant flow chart.

3.2 Overview stress indicators and smart measurements

3.2.1 Stress overview

The review was conducted to identify and evaluate stress indicators and related smart measurements. Firstly, a literature review was performed to determine appropriate stress indicators. Secondly, ways to measure selected stress indicators were contemplated.

3.2.2 Literature search

Scientific literature was searched to compile a broad overview of the available literature on stress indicators and their smart measurement techniques. Within the research process not all criteria for a systematic literature review, specified by the PRISMA statement [137], were applied. Instead, a comprehensive literature search was performed. The search was conducted between December 2018 and February 2019. For the first step of the literature research, fundamental scientific works were identified [138]. Reviews on the measurement of acute distress were searched within the scientific data bases PubMed and Web of Science as well as in Google Scholar. The search terms “stress”, “measure”, “monitor”, “detect”, “track”, “assess” and “review” were used and Boolean operators [139] were applied to best concatenate the search terms. In a second step, the literature search was expanded and an additional in-depth search was performed based on further data base keyword search and evaluation of the bibliography of relevant identified articles [138]. The acquired literature was then scanned according to predefined in- and exclusion criteria:

- study population of healthy adults,
- study setting within laboratory or field trial,
- focus on distress or acute stress, provoked by general stressors (e.g., validated stress tasks, everyday life),
- use of non-invasive measurement techniques,
- publication date between 2000 and 2019.

The publication date was specified between the years 2000 and 2019. The smart measurement technologies addressed in this paper rely on the wireless interoperation between devices. The establishment of standards for the implementation of Bluetooth can therefore be considered as a precondition. The development of Bluetooth is dated around the turn of the millennium [140], which is why only papers published after 2000 have been considered for this review paper.

Besides ascertained reviews, single original papers cited in those reviews were selected for further analysis. After appropriate stress indicators were extracted, a further investigation on the suitability to measure the selected indicators with smart devices was performed. The indicators were categorized and narratively summarized. Within main categories indicators were grouped into different subcategory areas (e.g., organs or behaviors) and associated (smart) measurement tools were listed.

3.3 Quality assessment of nutrition apps

3.3.1 App quality analysis

The app quality analysis was conducted to assess the quality of prime example apps to illustrate current nutrition app quality standards and identify communalities and limitations of existing quality assessment tools. Therefore, nutrition apps first needed to be ranked based on their star rating and the number of installations and then a quality rating was performed. Commercially available nutrition apps state January 2020 were considered. The quality assessment was carried out by two independent nutrition experts after familiarization and thorough app testing.

3.3.2 App ranking

The German version of the Google Play Store was used to select potential apps for the analysis. On January 30th, 2020, all apps identified by the keyword “nutrition” were extracted, including their number of installations, user star-rating, number of reviews and additional information (e.g., date of last update, provider, developer). Apps with specific target populations (e.g., pregnant women, cancer patients) were excluded. The remaining apps were ranked according to their number of installations, their 5-star user rating in descending order and their number of reviews. To cover a broad range of currently offerings, apps of different levels of user ratings were selected. For the final analysis four apps of high user rating (number of installs > 1.000.000, user rating > 4-star), four apps of medium user rating (number of installs > 50.000, user rating = 2 to 4-star) and two apps of low user rating (number of installs < 50.000, user rating < 3-star) were included. For all apps the (free) basic version was used for the in-depth analysis. Additionally, the app ranking positions were compared to the researchers extracted list of the previous year with the state of January 10th, 2019 (**Table 3**).

Table 3: Top 10 of keyword search "nutrition" in German Google Play Store (2019 vs. 2020).

App name	Rank 2019	Rank 2020
Calorie Counter – MyFitnessPal (MyFitnessPal Inc.)	1	2
8fit Workouts & Meal Planner (Urbanite Inc.)	2	6
Calorie Counter by FatSecret (FatSecret)	3	3
Lifesum – Diet Plan, Macro Calculator & Food Diary (Lifesum)	4	7
Noom: Health & Weight (Noom Inc.)	5	9
Lose Weight in 30 Days (Veev Apps)	6	X
Fabulous – Motivierend! (TheFabulous)	7	12
YAZIO Caloric Counter, Nutrition Diary & Diet Plan (Yazio)	8	8
Weight Loss Tracker & BMI – akti BMI (aktiWir GmbH)	9	X
Barcoo – QR Scanner (Offerista Group GmbH)	10	x

Hits were sorted in descending order according to the number of app downloads, user's average star ratings and number of ratings. X= apps that were not listed in 2020.

3.3.3 Quality rating

The quality of the selected apps was assessed using validated and previously published quality assessment tools for (health) apps. A preceding literature search revealed three assessment tools commonly used in the context of mHealth apps:

1.) the App Quality Evaluation (AQEL) instrument, a checklist to evaluate an app's educational quality and technical functionality [141]

2.) the Mobile App Rating Scale (MARS), a questionnaire to classify the quality of mobile health apps [142]

3.) the ENLIGHT score, a comprehensive quality and therapeutic potential evaluation tool for mobile and web-based eHealth interventions [143].

All assessment tools consisted of different quality categories. The AQEL score includes the categories: behavior change potential, support of knowledge acquisition, skills development, app functions, app purpose, appropriateness for target audience and appropriateness to satisfy users' expectations. Answers are converted to a 10-point scale and mean scores are estimated. Higher scores indicate a higher quality (scores ≥ 8 equate high quality). The MARS estimates an overall score containing engagement, functionality, aesthetics and information. Scores are rated on a 5-point scale (1 = inadequate and 5 = excellent) and mean scores for each MARS categories are calculated. The AQEL and MARS tools were used to their full extent.

The AQEL assessment was applied via an online survey [144] coded in Qualtrics (version 2017, Provo, UT). ENLIGHT provides subscales which can be applied independently. To best address the aim of this work, checklist items focusing on general app quality (credibility, privacy explanation, basic security) were extracted and subscales based on therapeutic aspects were disregarded. Credibility mean scores range between 1 and 10 (1= 'can't be accounted for' and ≥ 8 'excellent'). User privacy scale ranges between 0 and 8 points and security scale between 0 and 4 points. For both scales, lower scores indicate greater data protection or security.

For all assessment tools, scores were calculated according to their manuals. Then intra-app variability was addressed comparing the results of the three assessment tools of the same app. Afterwards, inter-app variability was determined comparing the results of the same assessment tool between all ten selected apps.

Besides general app quality aspects, the nutritional-related content of the apps was evaluated. In detail, the nutritional information provided by the apps and intake recommendations were analyzed. Since not all apps provide the same amount of nutritional information, the evaluation was focused on the "Big 5" (content of energy, fat, carbohydrates, protein, sodium), provided by all apps examined. Five food items of different categories available in Germany were preselected (cornflakes, wild rice cooked, potato bread, gumdrops, raspberries) (**Table 4**).

Table 4: Nutrient values for selected food items based on the German Nutrient Data Base (BLS).

Food item, BLS code	Calories (kcal)	Fat (g)	Carbo-hydrates (g)	Protein (g)	Sodium (mg)
Cornflakes, C515000	360.0	0.6	79.7	7.7	960
Wildreis gekocht (wild rice, cooked), C353132	134.0	0.4	26.9	5.3	2.0
Kartoffelbrot (bread, potato), B710400	243.0	1.3	48.8	8.0	330.0
Gummibonbons (gumdrops), S360000	348.0	0	78.6	6.6	62.0
Himbeere roh (raspberries), F302100	34.0	0.3	4.8	1.3	1.0

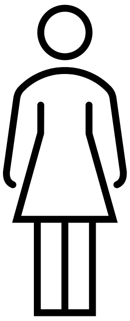
To compare the results, the same amount of each food item was entered into each of the selected apps. The generated nutritional information was then compared against the German Nutrient Database (Bundeslebensmittelschlüssel; BLS) [95], on the basis of the DACH reference values for nutrient intakes (DACH = Germany, Austria and Switzerland) (**Table 5**) [93].

Table 5: Intake recommendations by the German Nutrition Society (DGE) for selected nutrients.

"Big5"-nutrient	**Energy (kcal/day)**	**Fat (g/day)**	**Carbohydrates (g/day)**	**Proteins (g/day)**	**Sodium (mg/day)**
Recommendations German Nutrition Society	1800	45-80	225-275	48	1500

Recommendations are related to a female person, 38 years, 165 cm in size, 70 kg in weight and low level of physical activity (PAL value=1.4)

Additionally, a standardized user profile based on data of an average German women [145] (female, 38 years old, 165 cm in size, 70 kg in weight and with a low level of physical activity, PAL value=1.4) was created (**Figure 3**) to obtain intake recommendations for the "Big 5". These were then contrasted with the DGE guidelines [93].



Miss App-Test

- Sex: female
- Age: 38 years
- Height: 165 cm
- Weight: 70 kg
- Activity level: low (PAL = 1.4)

F**igure 3**: Female use case for content analysis of selected nutrition apps.

3.4 Statistical Analysis

The consumption frequencies of preselected comfort foods were generated based on a 5-point Likert scale ranging from 0=never to 4=very often. Answers 'often' and 'very often' (3 and 4) were considered as positive value and answers 'sometimes', 'seldom' and 'never' were considered as negative value for the consumption of the comfort food. Positive values were dummy coded with 1 and negative values received the dummy coding 0. Descriptive statistics (frequencies and percentages), non-parametric tests for subgroup analysis (Kruskal–Wallis test and Wilcoxon signed-rank test) and inferential statistics (linear regression, z-standardized) and responding effect sizes (eta squared, Cramer's V) [146] were estimated using Microsoft Excel 2016 (Microsoft Corp) and R 3.6.0 (R Foundation). P-values of $p \leq 0.05$ were considered as indicating statistical significance [147].

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4 Results

4.1 Publication 1: Stress-induced hyperphagia: empirical characterization of stress-overeaters

Stress-induced overeating affects a great part of our population, still little is known about individual characteristics (e.g., stress perception, coping, eating motives, comfort foods, personality types) having an impact on stress hyperphagia. This online survey aimed to identify associations between relevant individual characteristics and stress-induced overeating of adults in Germany.

Overall, 1,222 adults (female 80.8 %, 31.5 ± 12.8 years, BMI 23.4 ± 4.3 kg/m²) across Germany participated in the online survey. 42.1 % were categorized as stress-overeaters and 57.9 % as non stress-overeaters (78.9 % stress-undereaters, 21.1 % stress-insensitive eaters) according to their SSES scores. Female participants had a significant higher SSES mean score (m = 3.1 ± 0.8) than males (m = 2.9 ± 0.6); $p < 0.0005$). BMI was found to be positively correlated with SSES score r (1220) = 0.28, $p < 0.005$. The association between age and SSES was not significant ($p = 0.60$). SSES score classification was positively associated with subjective classification (stress-overeater and non stress-overeating), X^2 (1, 1222) = 488.05, $p < 0.005$ and frequencies of stressful events (daily, few times a week, few times a month, seldom, never) X^2 (6, 1222) = 53.98, $p < 0.005$, V = 0.149. There was no significant difference between stress-eating subgroups with respect to stress coping (SCI). Eating motives (TEMS) 'habits' (b = 0.105, t = 4.263, $p > 0.005$), 'health' (b = 0.072, t = 2.727, $p = 0.006$), 'weight control' (b = 0.056, t = 2.149, $p = 0.032$) and 'affect regulation' (b = 0.448, t = 0.026, $p < 0.005$) were found to positively predict SSES scores and 'hunger' (b = -0.065, t = -2.596, $p = 0.010$), 'traditional eating' (b = -0.065, t = -2.616, $p = 0.009$), as well as an 'agreeableness' personality (BigFive) (b = -0.051, t = -2.113, $p = 0.035$) were found to negatively predict SSES scores, $R^2 = 0.3048$, F(8,1213) = 67.92, $p < 0.005$. Scores for 'neuroticism' personality (BigFive) were significantly higher for stress-overeaters compared to stress-insensitive eaters (Δ = 0.2, $p = 0.01$, $n^2 = 0.006$). Across the total sample, top three most preferred comfort foods were 'chocolate & confectionery' [stress-overeaters 70.9 %, stress-undereaters 33.0 %, stress-insensitive eaters 30.2 %, X^2 (2, 1222) = 177.0, $p < 0.005$, V = 0.380)], 'coffee' [stress-overeaters 52.4 %, stress-undereaters 41.4 %, stress-insensitive eaters 42.3 %, X^2 (2, 1222) = 14.1, $p < 0.005$, V = 0.108)] and 'cookies' [stress-overeaters 36.9 %, stress-undereaters 14.9 %, stress-insensitive eaters 16.1 %, X^2 (2, 1222) = 76.8, $p < 0.005$, V = 0.251)].

These findings emphasizes that stress-induced overeating affects a great proportion of the (surveyed) population. Especially, women and people with a high BMI were found to be vulnerable to stress eating. Additionally, eating motives and personality traits need to be put into focus, when designing stress-eating intervention.

Contribution: The doctoral candidate was in joint charge of the design and development of the survey and had the main lead in data analysis, prepared tables and figures and drafted and revised the manuscript.

Kaiser, B., Gemesi, K., Holzmann, S. L., Wintergerst, M., Lurz, M., Hauner, H., Groh, G., Böhm, M., Krcmar, H., Holzapfel, C., & Gedrich, K. (2022). Stress-induced hyperphagia: empirical characterization of stress-overeaters. *BMC Public Health*, 22(1), 100. https://doi.org/10.1186/s12889-021-12488-9 [148]

4.2 Publication 2: Nutrition Apps on Focus: A Qualitative Assessment

In the digital age the development of apps focusing on the topic of nutrition rapidly progresses. Comparing our hits for the keyword "nutrition" within the Google Play Store it gets obvious that there is a high rate of movement and fluctuation. 40 % of the top 50 apps in 2019 (based on number of installs and user ratings) vanished in 2020 and were replaced by new apps.

Ten apps covering different levels of popularity and user ratings were selected for further analysis. The results of the analysis using the AQEL score showed that eight of out ten apps scored high quality (score ≥ 8) for app purpose [Average Score (AS) = 8.7]. For the category app function an AS of 6.5 was obtained. The categories behavior change potential and support of knowledge acquisition yielded only scores of medium quality (AS = 5.3 and 5.6). The category with most potential for improvement was *skill development* (AS = 2.8).

According to the MARS tool, none of the examined apps achieved an excellent (score = 5) quality rating. MARS scores for investigated apps ranged between 4.5 and 2.4. Putting a focus on the quality domains, the overall AS was best for functionality (4.0) and lowest for aesthetics (3.5).

The ENLIGHT tool showed high scores for credibility, with excellent scores (score ≥ 8) for three apps. In the field of data protection requirements regarding user privacy and data security 20 % of the investigated apps achieved high scores.

Additionally, the apps' nutritional content was further examined. The accordance with the German Nutrient Database (BLS) ranged between 57 % and 20 % agreement across examined apps. All apps provided information on energy but not all displayed further information about the selected nutrients. The same was found for the intake recommendations, only six of ten apps provided intake recommendations for specific nutrients. All apps showed deviations from the intake recommendations of the German Nutrition Society (DGE) in both directions (lower and higher).

The analysis revealed a great variety of the quality of the examined nutrition-related apps. The broad range of different qualities was found regarding app features in general (e.g., function, data protection) as well as specific nutritional content (e.g., nutrient and intake information). Different quality categories and distinct scoring systems inhibit the comparison of the results of the applied quality assessment tools. This indicated that the tools are suitable to assess different parts of quality on a stand-alone basis, but that an overarching quality assessment tool is needed. For the development of a new tool additional app quality indicators should be considered. Especially, the source and credibility of third party-content and related links need to be put into focus. Furthermore, the nutrient database integrated in those apps need to be examined regarding target population (country of origin) and topicality.

Contribution: The doctoral candidate was in charge of the design of the app selection and quality analysis, prepared tables and figures and drafted and revised the manuscript.

Kaiser, B. M., Stelzl, T., & Gedrich, K. (2020). Nutrition Apps on Focus: A Qualitative Assessment. *European Journal of Public Health Studies*, 3(1), 9-33. https://doi.org/http://dx.doi.org/10.46827/ejphs.v3i1.67 [149]

4.3 Publication 3: Nutrition and stress. Overview of selected stress indicators and smart measurement techniques

Stress still remains a risk factor for the development of certain noncommunicable diseases (NCDs) like cardio-vascular diseases. The development of technology-based ways to assess stress proceeds quickly. Within a literature search, seven reviews addressing stress indicators and their smart measurement techniques were extracted. The identified stress indicators covered objective as well as subjective topics. The indicators were assigned to five main categories: biochemistry, physiology, behavior, perception and context.

The preliminary extraction yielded a total of 25 different stress indicators across all categories. They were further differentiated based on the ability to be measured non-invasively using smart devices, especially smartphones and wearables. This led to a final pool of twelve indicators to be further examined. Most selected indicators were categorized as physiological indicators. In this category stress was measured via skin (conductance and temperature), heart activity [heart rate variability (HRV)] and blood volume pulse (BVP)], lung (breathing rate) and voice (voice variances). The main smart technologies used to capture stressful events were chest straps, smartwatches and fitness trackers. The discrimination ranged between 90% accuracy for breathing rate captured by a chest strep and 44 % sensitivity for skin temperature via smart wristband. The measurement accuracy could be further improved by combining different stress indicators and jointly analyzing their results. Regarding behavioral indicators, especially ICT-usage and sleeping behavior were found to be reliable. Smartphone usage behavior could be used to detect stress with an accuracy of 55 %. The sleeping duration, captured via smartphone, was found to have a significant inverse association with stress.

Additionally, subjective stress perception is obtained via validated questionnaires integrated into smart technologies (e.g., smartphone applications). The four main questionnaires used to detect subjective stress within the considered literature are Daily Stress Inventory, (DSI), Perceived Stress Questionnaire (PSQ), Perceived Stress Scale (PSS) and Stress Appraisal Measure (SAM[1]). Furthermore, stress types can be characterized based on various validated questionnaires on stress related eating behavior like the Salzburg Stress Eating Scale (SSES).

This overview distinguished selected physiological and behavioral parameters as best indicators of stress to be measured via smart techniques. Additionally, questionnaires to capture the subjective stress perception are helpful tools to address the effect of stress. Single indicators are already reliable on their own. Nevertheless, best accuracy to discriminate between stress and non-stress situations is achieved via the combination of different stress indicators.

Contribution: The doctoral candidate co-designed and performed the review, managed and analyzed the results, prepared tables and figures and drafted and revised the manuscript.

Kaiser, B., & Holzmann, S. H., H Holzapfel, C Gedrich, K. (2020). Nutrition and stress. Overview of selected stress indicators and smart measurement techniques. Ernahrungs Umschau 67(5), 98-107. https://doi.org/10.4455/eu.2020.017 [150]

5 Discussion

5.1 Characterization of the potential user group of a stress-focused digital dietary advisor

Stress remains an important influential factor for the dietary behavior. Different effects of stress on individuals' eating behaviors have long been on scientific focus. Scientific evidence has shown that the majority of the population changes their eating behaviors in the context of stress, only about 8 % are unaffected by stress exposure, whereas 48 % show a hypophagic reaction and 44 % show a hyperphagic reaction to the experience of stress [151]. This is in line with the findings of Kaiser et al. (2022), estimating 12 % of study participants to be stress-insensitive eaters, 45% to be hypophagic eaters and 42 % to have an hyperphagic reaction in the context of stress [148]. Stress-induced overeating can lead to weight gain and obesity, increasing the health risk for example for diabetes and the metabolic syndrome [152]. Undereating in contrast can lead to malnutrition and further health consequences like nutrient deficits in the long term. As mentioned before, stress not only influences the amount of the foods eaten, but also the diet quality towards unfavorable highly palatable and energy dense food items, increasing the risk of diet related NCDs [153]. Derivatively, health promotion approaches tackling stress-induced unhealthy eating patterns are needed. Regarding the development of a stress-focused digital dietary advisor the potential target group needs to be further analyzed and relevant characteristics identified. It has been shown that the consideration of the target group's interests and specifies within the development process of mHealth apps improves the perceived usability and usage motivation [154].

Research has been performed to identify predictors of the stress-eating behavior. The prevalence of higher stress-induced food intake increases with the level of perceived stress [155]. Results of the cross-sectional study by Vidal et al. (2018) indicate that the association of perceived stress level and the intake of unfavorable foods gets modified by gender [156]. The results of Mikolajczyk et al. (2009) present significant changes on the frequency of food consumption and perceived stress in women but not in men [157]. The results by Kaiser et al. (2022) showed only a very small 4 % difference of SSES scores between men and women ($p < 0.005$) [148]. Contrastingly, the results by Siervo et al. (2018) highlight that men change their eating behavior towards unfavorable foods in the context of stress as well and should therefore not be neglected [158]. In relation to mHealth applications, women show significantly higher interest in health and lifestyle apps than men [159]. Based on the clusters of Sanders et al. (2019) it can be assumed that clusters of younger participants show higher stress scores [160]. The study by Kaiser et al. (2022) yielded divergent results with no significant association of SSES scores and age [148].

As a consequence of increased food intake, the risk of stress-induced weight gain increases [161]. The results of the study by Tomiyama et al. (2011) show that BMI is significantly higher in the group of high stress participants compared to the low stress group [162]. The results by Kaiser et al. (2022) are in agreement with previously described studies, demonstrating a positive correlation between SSES and BMI (r (1220) = 0.28, $p < 0.005$) [148]. This highlights the need for action since a high BMI is associated with the development of diabetes and the metabolic syndrome [163]. The results by Kaiser et al. (2022) show that especially high-caloric sweet foods, including chocolate and cookies, are preferred as stress comfort foods [148]. This is in line with current research, indicating an increased intake of highly palatable energy dense foods, especially high in sugar and fat, due to the perception of stress [164, 165]. In more detail, stress was found to increase appetite, especially for sweet as well as crunchy and salty foods [166].

Besides the mentioned aspects, personality has been shown to be associated with individual stress perception. Especially, people with a neurotic personality seem to have a high vulnerability to stress [167]. Furthermore, high scores in neuroticism were found to be related with disordered eating [168]. Research focusing especially on personality domains and stress-induced eating patterns could not be identified. However, the results by Kaiser et al. (2022) demonstrate that hyperphagic participants achieved higher scores within the personality domain of neuroticism [148]. Ervasti et al. (2019) applied an online questionnaire to investigate the relationship between personality types and the interest to use stress management apps [169]. The results revealed a significant positive correlation between the interest in stress management app usage and neuroticism [169]. Neuroticism was also found to be a positive predictor for the checking frequency of the smartphone [170].

A stress-focused digital dietary advisor has the potential to operate context aware and reach people, who are vulnerable to over-eating in situations of high stress (e.g., work, home). As mentioned above, a neurotic personality as well as a female sex were found to be predictive for stress-eating. Both groups have already been shown to be interested in mHealth apps, which makes these groups more accessible for a digital advisor. However, other factors like BMI, which were found to be harder to approach, need to be considered to tailor the digital advisor to a broad range of potential users.

5.2 Quality requirements for mHealth solutions addressing stress and nutritional behavior

The number of mHealth apps, also in the context of nutrition, has been skyrocketing within the last years. Still concerns of the quality and effectiveness of these mHealth apps exist [75] and numbers of DiGAs listed within the DiGA directory are still low (n = 28, dated 20.01.2022) [171].

From a scientific point of view, many attempts have been undertaken to evaluate mHealth apps and develop standardized quality assessment tools. Muro-Culebras et al. (2021) conducted a systematic review of evaluation tools for mHealth apps [70]. Reviewed tools focused on usability, engagement, aesthetics and functionality as well as reliability, validity, responsiveness and interpretability [70]. The frequently used Mobile App Rating Scale (MARS) for example includes engagement and aesthetic [142], whereas the App Quality Evaluation (AQEL) instrument puts behavior change potential and app purpose on focus [141]. Still quality evaluation tools need to be refined and further quality aspects (e.g., user-centered approach, validation, focus on mobile apps) should be included [70]. The results by Kaiser et al. (2020a) support this conclusion, suggesting additional quality parameters regarding the trustworthiness and appropriateness of topic specific content as well as of third party-content [149].

Nonetheless, existing quality assessment tools can be used to evaluate various quality aspects in current mHealth apps. McKay et al. (2019) performed a rating of health and well-being apps [172]. Out of the 344 analyzed apps 23 were assigned to the topic of healthy eating promotion. The results present an average overall MARS score of 2.7 out of 5 and the highest domain score for accuracy of description (in app store) of 3.8 and the lowest MARS score of 2.1 for quantity of information [172]. Bardus et al. (2016) performed a content analysis on 23 popular health and fitness apps [173]. An average overall quality score (MARS) of 3.2 was estimated with functionality as highest domain (4.0) and information quality as lowest domain score (2.0) [173]. McAleese & Papadaki investigated the quality of apps including the Mediterranean diet [174]. The average overall quality (MARS) score of the 93 apps analyzed was 3.0 ± 0.46 with highest scores for functionality (4.0 ± 0.45) and lowest scores for engagement (2.4 ± 0.62) [174]. This is in line with the results of the app quality assessment by Kaiser et al. (2020a), presenting the highest MARS scores in the domain of functionality (4.0). However, the lowest app quality scores were estimated for the domain of aesthetics (3.5) [149]. Ahmed et al. (2021) conducted a content analysis on apps comprising a dietary approach low in Fermentable Oligo-, Di-, Monosaccharides and Polyols (FODMAPs) [175]. The content analysis was focused on nine eligible apps out of 1304 screened apps. Analyzed apps yielded a high overall app quality MARS score (3.6 out of 5) and highest AQEL average score for app purpose (7.4 out of 10) and lowest AQEL average score for skills development (2.4) [175]. These results are reflected within the analysis by Kaiser et al. (2020a), estimating the highest AQEL quality score for app purpose (8.7) and the lowest for skill development (2.8) [149].

For a stress-focused digital dietary advisor, especially quality domains, which achieve low quality scores so far, should be put into focus. Skill development should be focused on nutritional knowledge acquisition including information on dietary guidelines and diet-related health consequences [176]. The results by Samoggia & Riedel indicate that the usage of a nutrition-information app increases the subjective as well as objective nutrition knowledge

[177]. Improvements on app aesthetics include layout, interactivity, presentation and graphics [178].

5.3 Current state of mHealth services addressing nutritional behavior

Evidence on the effectiveness of digital dietary apps to improve eating behavior is mounting. Research has shown significant changes in primary nutritional outcomes as results of digital dietary interventions. Digital dietary tools were found to be associated with greater weight loss and increased intake of healthy foods (e.g., fruits and vegetables) as well as decreased intake of unfavorable foods and nutrients (e.g., chocolate snacks and saturated fat) compared to traditional self-monitoring tools [179-181]. Furthermore, it has been shown that the usage of mHealth apps results in a decrease in energy intake in a sample of obese and overweight individuals [182]. Nevertheless, evaluations of mHealth apps revealed a great need for quality improvement regarding the content of those apps (e.g., inaccurate food composition databases) [183].

In the context of mHealth dietary tools, food intake parameters need to be presented in adherence to public guidelines and recommendations. About 30 % of smartphone-based dietary assessment tools used within scientific studies integrate food databases to estimate the users' food intakes [184]. Ferrara et al. (2019) reviewed the top seven diet-tracking apps based on user ratings and installation numbers and compared the energy and nutrient intake estimations with the food composition database of the United States Department of Agriculture (USDA) [185]. The analysis of a 3-day diet revealed an overestimation for protein (average difference 10 %), energy (average difference 1 %) and carbohydrates (average difference 1 %) and an underestimation for fat (average difference -7 %) [185]. The analysis of MyFitnessPal, one of the most popular apps within the 'health & fitness' category, displayed an underestimation of the mean energy intake by 1863 kJ/d (sd = 2952 kJ/d, $p < 0.005$) [186]. On the contrary, Ambrosini et al. (2018) found no significant difference between energy intake estimations of 50 adults comparing a commercial smartphone app with 24 h recalls [187]. The majority of the participants (83 %) even preferred using the app over completing the 24 h recalls obtained via telephone interviews [187]. The results of the study by Kaiser et al. (2020a) show a great discrepancy regarding nutritional estimates of the investigated apps and the accordance to the BLS, showing an accordance of less than 20 % for the majority of the apps [149]. Based on the available data, overestimation (positive deviation between 18 % and 50 %) as well as underestimation (negative deviation between -13 % and – 50 %) was found across all apps. Nutrient values could not be estimated for all apps, because of missing information about included references or food composition information [149]. Maringer et al. (2019) confirm these results by highlighting great variances in the number of provided nutrient values across various apps [188]. Incomplete intake data might cause imprecise nutrient estimations. Divergent values could be generated due to different underlying country-specific food composition databases or user-specific customization of the integrated food lists [189]. Another reason for varying estimations could be the applied intake features, leading to differences in the volume estimation. Whereas manual data input and barcode scan are commonly used within dietary apps, photo-based intake assessments still face usage difficulties (e.g., detection markers, used plate sizes) [190]. Additionally, reminders and notifications can be used to improve data input and reduce underreporting. Pirolli et al. (2017) showed a positive effect of reminders in the context of achieving behavioral goals and highlight the importance of the right timing to display those reminders [191].

Based on the intake data, the individual’s dietary behavior is estimated and displayed. In the context of unhealthy stress-related dietary patterns, features need to be integrated to achieve long term dietary behavior change. Commonly applied BCT-based features are self-monitoring, feedback, gamification, goal reviews, social support, and educational information [192]. The integration of BCTs within diet-related apps was furthermore found to be positively associated with the app quality [174]. Especially, good user experience and intention (e.g., reaching a health goal) support the long-term engagement of mHealth apps [193]. This needs to be considered for the development of a stress-focused digital dietary advisor. As a start, country specific food data bases adapted to the target group need to be integrated. These data bases need to be updated regularly and the completeness of the information needs to be checked. Additionally, the input burden for the user can be reduced by using precise (semi) automated techniques (e.g., barcode scan). BCT features like goal setting can further improve the engagement of a digital advisor and improve its long-term effectiveness.

5.4 Current state of mHealth services addressing stress

As mentioned before, stress is a context factor that can influence the individual’s dietary behavior and trigger unhealthy eating patterns. Therefore, stress-related aspects of mHealth tools need to be put into focus, including aspects of stress detection as well as stress management.

The in-time stress interventions rely on accurate stress detection. In this context, relevant stress indicators measurable by smart devices need to be identified. Considering the potential of smart devices to continuously capture user data, relevant indicators need to be narrowed down to unobtrusive measurement ways. Within laboratory settings, novel systems are developed to validly measure participants’ stress levels. However, these systems often consist of various technological modules which need to be connected to special software for data analysis, therefore the application outside the laboratory setting is inconvenient. For an appropriate use in everyday life, stress detection and the integration of stress measurement techniques within at hand devices is necessary. The advancement of wearable devices led to a growing number of features and functions to detect vital signs [194], integrated within a variety of smart devices [195]. Up to now, evidence on commercial stress indicator tracking is still scarce and protocols for standard test procedures are missing [196]. Nevertheless, commercial devices already include sensors to capture physiological stress indicators. Thiebaud et al. (2018) investigated the accuracy of heart rate measurements of wrist-worn devices of different brands. The results indicate mean error rates between 1 % and 8 % [197]. In line with that, the results of Can et al. (2019) show high accuracy (85 to 90 %) for heart rate and electrodermal activity measurements of wrist-worn commercial devices [198]. Used for stress classification, a greater accuracy was shown for the combination of HR and EDA data (92 %) compared to the separate consideration of the modalities (86 %) [198]. This gets supported by the results of the overview by Kaiser et al. (2020b), demonstrating an improved detection accuracy for the combination of various stress indicators [150]. Additionally, behavioral indicators were found to be suitable for the detection of stress. In an ICT context especially, smartphone related behavioral indicators need to be put into focus. Ciman et al. (2018) investigated participants smartphone usage gestures and estimated an accuracy for stress detection between 63 % and 88 % [199]. Bogomolov et al. (2014) additionally included weather conditions and personality data into their stress recognition system and achieved an accuracy of about 72 % [200]. These results indicate that physiological and behavioral data captured by wearable devices as well smartphones can already be used to detect stress. Nevertheless, the accuracy of this systems still needs to be improved. Besides software-based enhancements, further adaptions are necessary to reduce missing data due to unsuitable and unfitting wearables [198]. This can also be seen in relation to innovative sensor-equipped clothes and jewelry, which still need further improvement to reliable capture relevant (physiological) signals [195].

Based on accurate stress detection, various apps have been developed to address stress management. Most of the existing apps focus on mindfulness and meditation or breathing control techniques [201]. Based on results of RCT studies, intervention groups using mindfulness focused apps were found to have significantly lower stress levels as well as greater stress reduction [123], compared to the respective control groups. The results of Huberty et al. (2019) demonstrated a significant negative interaction between the usage of their mindfulness meditation app and the perceived stress level [202]. Weber et al. (2019) showed a significant improvement on stress and wellbeing in users of mHealth apps on mental health [203]. Still, the majority of existing apps focused on stress management lack scientific validation. The results of the systematic review by Lau et al. (2020) revealed that only about 2% of investigated apps were examined within original research publications [204]. This gets supported by the results of Peake et al. (2018) finding that only about 5 % of health technologies provide scientific validation [205].

For the development of a stress-focused digital dietary advisor, validated stress detection methods should be integrated and combined with validated stress management techniques.

Strength & Limitations

This work focused on relevant aspects to identify requirements for the development of a digital dietary advisor concentrating on stress-induced unhealthy eating patterns. An online survey was performed to find characteristics of people with stress-induced hyperphagia, which present the potential target group for the planned digital dietary advisor. Although the survey covered a broad spectrum of possible stress-eating predictors, not all relevant aspects (e.g., dieting status) were included. Further research on additional characteristics is needed to better understand the target group. Additionally, the applied cross-sectional study design does not reveal the causality and only allows conclusions on the relationship between investigated parameters. As often observed within nutrition related research, female participants are overrepresented. An additional study with a higher percentage of male participants is needed to enhance insight into the matter.

An app analysis was conducted to address the quality of available nutrition related apps. Investigated apps were selected from all levels of download and rating. Nevertheless, a selection bias cannot be precluded. Further analysis including additional apps would be helpful to sharpen the results.

In the context of stress, a literature overview was performed to identify stress indicators and their smart measurements. It needs to be mentioned that additional indicators (e.g., blood parameters) exist, which were not included within this study. Due to the rapid emerging in the field of smart technologies, the completeness of relevant smart measurements cannot be claimed.

6 Conclusion and Outlook

A great proportion of the population is sensitive to the influence of stress regarding their eating behavior. The survey on the characterization of stress-induced overeaters revealed that the vulnerability to stress-induced dietary changes can be associated with some of the investigated characteristics. Considering the implementation of a stress-focused digital dietary advisor for this target group, a female sex and neurotic personality seem to be more approachable than other characteristics. For the development process a user-centered approach including further identified characteristics (e.g., high BMI, eating motivations, male sex) should be undertaken to address the complete target group. Additionally, the current status of mHealth apps on the topics of nutrition and stress need to be considered. A stress-focused digital dietary advisor needs to firstly record the dietary behavior adequately by using validated input features as well as target group specific nutrition data bases and recommendations. Secondly, the advisor needs to detect stress correctly, which is best enabled by the combination of multitude stress indicators and validated mHealth features. An intervention to support healthy food choices in the context of stress should combine dietary recommendations and features for stress management including BCTs.

At present, the focus of mHealth apps has not yet been put on dietary behavior in the context of stress. Further research is essential to improve current mHealth quality and develop a stress-focused digital dietary advisor.

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Appendix Online Survey

28.4.2021 Druckansicht base (StrEssSurvey) 28.04.2021, 10:06

enable Ernährungsforschung

MRI Klinikum rechts der Isar

TUM Technische Universität München

StrEssSurvey → base 28.04.2021, 10:06

Seite 01

Befragung zu Stress-Essen (StrEss) & digitalen Stress-Interventionen - Der *enable* StrEss-Survey

Sehr geehrte Damen und Herren,

Herzlich willkommen - schön, dass wir Ihr Interesse geweckt haben.

Diese Befragung wird im Rahmen des vom **Bundesministerium für Bildung und Forschung** (BMBF) geförderten ***enable* Kompetenzclusters** (*www.enable-cluster.de*) durchgeführt.

Ziel dieser Umfrage ist es, neue Erkenntnisse zum Zusammenspiel von Ernährung und Stress (**„Stress-Essen"**) zu gewinnen. Zudem soll herausgefunden werden, wie der Einsatz von **digitalen Geräten** und **Anwendungen** (z.B. Smartwatches, Apps) zur Vorbeugung von **Stress-Essen** beitragen kann. Die Teilnahme an der Befragung ist **freiwillig**.

Bitte lesen Sie sich jede Frage **sorgfältig** durch und versuchen Sie **möglichst genaue und ehrliche Angaben** zu machen. Sollten Sie sich bei einer Frage unsicher sein, dann wählen Sie bitte die Antwortmöglichkeit aus, die Ihrer Meinung nach am ehesten auf Sie zutrifft.

Aus Gründen der besseren Lesbarkeit bezieht sich die **männliche Schreibform (z.B. Teilnehmer)** auf beide Geschlechter.

Sollten Sie **Fragen** haben, wenden Sie sich gerne an uns (sophie.holzmann@tum.de).

Vielen Dank für Ihre Unterstützung!

Ihr enable Studienteam

Seite 02

Einwilligungserklärung (Datenschutz)

Ihre **Einwilligung zur Teilnahme** ist Voraussetzung für die Erfassung und Nutzung Ihrer Daten zu Forschungszwecken. Alle Daten werden **streng vertraulich** behandelt. Die Erhebung und Auswertung der Daten erfolgt **anonym** und in aggregierter Form, d.h. es sind keine Rückschlüsse auf Ihre Person möglich.

Bitte achten Sie beim Ausfüllen darauf, dass Sie **in keines der möglichen Felder persönliche Daten (z.B. Mailadresse, Namen) eingeben**, da sonst die Anonymität der Befragung nicht mehr gewährleistet ist.

Erfasste Daten werden **ausschließlich im Rahmen dieser Befragung** verwendet. Die Verantwortung für die Erhebung und Analyse der Daten obliegt der **Technischen Universität München**.

Die Einwilligung zur Verarbeitung Ihrer Daten erfolgt **freiwillig**.

Nutzen: Die Befragung dient allein dem wissenschaftlichen Forschungszweck. Für Sie besteht **kein individueller Nutzen** durch die Teilnahme an der Befragung.

Risiken: Durch die Teilnahme an der Befragung sind Sie **keinen Risiken** ausgesetzt.

Vielen Dank, dass Sie sich die Zeit genommen haben, diese Information zu lesen.

Bitte bestätigen Sie Folgendes:

- ☐ Hiermit bestätige ich, dass ich die Informationen zu Datenschutz und Datensicherheit **gelesen und verstanden** habe und ich bestätige ferner, dass ich **volljährig** bin.
- ☐ Mit dem Klick auf die Checkbox willige ich an der Teilnahme der Befragung ein.

https://www.soscisurvey.de/admin/preview.php?questionnaire=base&mode=print 1/19

Seite 03

Teil 1: Ernährung

In diesem Teil des Fragebogens geht es um Ihre **Ernährungsgewohnheiten** im Alltag.

Seite 04

1. Zur Aussage *„Ich esse das, was ich esse, ...“* finden Sie eine Reihe von Antwortmöglichkeiten. Bitte kreuzen Sie bei jeder Aussage an, wie sehr diese auf Sie zutrifft!

Bitte pro Zeile ein Kästchen ankreuzen!

Ich esse das, was ich esse, . . .	stimme über-haupt nicht zu	stimme nicht zu	stimme eher nicht zu	stimme weder zu noch nicht zu	stimme eher zu	stimme zu	stimme voll und ganz zu
weil ich es gerne mag.	○	○	○	○	○	○	○
weil ich es üblicherweise esse.	○	○	○	○	○	○	○
weil ich Hunger habe.	○	○	○	○	○	○	○
weil es gesund ist.	○	○	○	○	○	○	○
weil es wenig Aufwand bedeutet.	○	○	○	○	○	○	○
weil ich mir etwas gönnen möchte.	○	○	○	○	○	○	○
aufgrund von Traditionen (z. B. Familientradition, Feste).	○	○	○	○	○	○	○
weil es naturbelassen ist (z. B. nicht gentechnisch verändert).	○	○	○	○	○	○	○
weil es gesellig ist.	○	○	○	○	○	○	○
weil es preiswert ist.	○	○	○	○	○	○	○
weil es mich spontan anspricht (z. B. in Augenhöhe platziert, farbliche Gestaltung).	○	○	○	○	○	○	○
weil ich mein Gewicht halten möchte.	○	○	○	○	○	○	○
weil ich frustriert bin.	○	○	○	○	○	○	○
weil es von mir erwartet wird.	○	○	○	○	○	○	○
weil andere es gut finden.	○	○	○	○	○	○	○

Seite 05

Teil 2: Stress

Im Folgenden finden Sie Fragen zum Thema **„Stress im Alltag“**. Bitte denken Sie an Ihren Alltag während des **letzten Monats** und versuchen Sie, die Fragen möglichst **spontan** zu beantworten. Bitte geben Sie an, was am besten auf Sie zutrifft!

Seite 06

2. Wie häufig fühlen Sie sich aktuell gestresst?

Nur eine Antwort ist möglich!

- ○ täglich
- ○ mehrmals pro Woche
- ○ mehrmals pro Monat
- ○ selten
- ○ nie

1 aktive(r) Filter
Filter ST02/F1
Wenn eine der folgenden Antwortoption(en) ausgewählt wurde: **5**
Dann nach dem Klick auf "Weiter" direkt zur Seite **%page%** springen

Seite 07

3. Was stresst Sie aktuell am meisten?

Mehrere Antworten sind möglich!

- ☐ Arbeit
- ☐ Partner(in) / Familie / Freunde
- ☐ Straßenverkehr
- ☐ Haushalt
- ☐ Digitale Geräte (z.B. Smartphone, Smartwatch, Laptop)
- ☐ Finanzielle Sorgen
- ☐ Freizeit
- ☐ Gesundheitliche Sorgen
- ☐ Sonstiges: __________

Seite 08
Umgang

4. Im Folgenden finden Sie Aussagen zum Umgang mit Stress. Bitte geben Sie an, was am besten und aktuell auf Sie zutrifft!
Bitte pro Zeile ein Kästchen ankreuzen!

	trifft gar nicht zu	trifft eher nicht zu	trifft eher zu	trifft genau zu
Ich sage mir, dass Stress und Druck auch ihre guten Seiten haben.				
Egal wie groß der Stress wird, ich würde niemals wegen Stress zu Alkohol oder Zigaretten greifen.				
Ich mache mir schon vorher Gedanken, wie ich Zeitdruck vermeiden kann.				
Wenn ich mich überfordert fühle, gibt es Menschen, die mich wieder aufbauen.				
Ich sehe Stress und Druck als positive Herausforderung an.				
Auch wenn ich sehr unter Druck stehe, verliere ich meinen Humor nicht.				
Ich versuche Stress schon im Vorfeld zu vermeiden.				
Bei Stress und Druck finde ich Halt im Glauben.				
Gebete helfen mir dabei, mit Stress und Bedrohungen umzugehen.				
Egal wie schlimm es wird, ich vertraue auf höhere Mächte.				
Wenn mir alles zu viel wird, greife ich manchmal zur Flasche.				
Ich tue alles, damit Stress erst gar nicht entsteht.				
Wenn ich unter Druck gerate, habe ich Menschen, die mir helfen.				
Bei Stress und Druck entspanne ich mich abends mit einem Glas Wein oder Bier.				
Bei Stress und Druck finde ich Rückhalt bei meinem Partner oder einem guten Freund.				
Bei Stress und Druck konzentriere ich mich einfach auf das Positive.				
Bei Stress und Druck beseitige ich gezielt die Ursachen.				
Bei Stress und Druck erinnere ich mich daran, dass es höhere Werte im Leben gibt.				
Egal wie schlimm es wird, ich habe gute Freunde, auf die ich mich immer verlassen kann.				
Wenn ich zu viel Stress habe, rauche ich eine Zigarette.				

Seite 09

5. Die folgenden Fragen beschäftigen sich mit Ihren Gedanken und Gefühlen während des letzten Monats. Bitte geben Sie für jede Frage an, wie oft Sie in entsprechender Art und Weise gedacht oder gefühlt haben.

Bitte pro Zeile ein Kästchen ankreuzen!

	nie	fast nie	manchmal	ziemlich oft	sehr oft
Wie oft waren Sie im letzten Monat aufgewühlt, weil etwas unerwartet passiert ist?	○	○	○	○	○
Wie oft hatten Sie im letzten Monat das Gefühl, nicht in der Lage zu sein, die wichtigsten Dinge in Ihrem Leben kontrollieren zu können?	○	○	○	○	○
Wie oft hatten Sie sich im letzten Monat nervös und gestresst gefühlt?	○	○	○	○	○
Wie oft waren Sie im letzten Monat zuversichtlich, dass Sie fähig sind, ihre persönlichen Probleme zu bewältigen?	○	○	○	○	○
Wie oft hatten Sie im letzten Monat das Gefühl, dass sich die Dinge zu Ihren Gunsten entwickeln?	○	○	○	○	○
Wie oft hatten Sie im letzten Monat den Eindruck, nicht all Ihren anstehenden Aufgaben gewachsen zu sein?	○	○	○	○	○
Wie oft waren Sie im letzten Monat in der Lage, ärgerliche Situationen in Ihrem Leben zu beeinflussen?	○	○	○	○	○
Wie oft hatten Sie im letzten Monat das Gefühl, alles im Griff zu haben?	○	○	○	○	○
Wie oft haben Sie sich im letzten Monat über Dinge geärgert, über die Sie keine Kontrolle hatten?	○	○	○	○	○
Wie oft hatten Sie im letzten Monat das Gefühl, dass sich so viele Schwierigkeiten angehäuft haben, dass Sie diese nicht überwinden konnten?	○	○	○	○	○

Seite 10

Teil 3: Stress-Essen

Im Folgenden finden Sie eine Reihe von Aussagen und Fragen zum Thema **„Ernährungsverhalten bei Stress"**. Bitte denken Sie an Ihren Alltag während des **letzten Monats** und versuchen Sie, die Fragen möglichst **spontan** zu beantworten.

Seite 11

Wer bei Stress anders als gewöhnlich (nicht unter Stress) isst, gilt als ***„Stress-Esser"***.

6. Denken Sie, dass Sie ein Stress-Esser sind?

○ ja
○ nein

1 aktive(r) Filter

Filter SE02/F1
Wenn eine der folgenden Antwortoption(en) ausgewählt wurde: **2**
Dann nach dem Klick auf "Weiter" direkt zur Seite **%page%** springen

Seite 12

Wenn Ja, was trifft bzgl. Stress-Essen auf Sie zu?
Bitte pro Zeile ein Kästchen ankreuzen!

	nie	selten	manchmal	häufig	sehr häufig
Ich esse mehr.	○	○	○	○	○
Ich esse weniger.	○	○	○	○	○
Ich esse häufiger.	○	○	○	○	○
Ich esse seltener.	○	○	○	○	○
Ich esse schneller.	○	○	○	○	○
Ich esse langsamer.	○	○	○	○	○
Ich esse andere Lebensmittel.	○	○	○	○	○

Seite 13
Salzb

7. Bitte geben Sie an, welche der folgenden Aussagen jeweils am besten auf Sie zutrifft!
Bitte pro Zeile ein Kästchen ankreuzen!

	esse ich **viel weniger** als sonst	esse ich **weniger** als sonst	esse ich **genauso viel** wie sonst	esse ich **mehr** als sonst	esse ich **viel mehr** als sonst
Wenn mich die Dinge, die ich erledigen muss zu erdrücken drohen, ...	○	○	○	○	○
In sehr stressbelasteten Zeiten ...	○	○	○	○	○
Wenn ich das Gefühl habe, dass mir die Dinge über den Kopf wachsen, ...	○	○	○	○	○
An Tagen, an denen alles schiefzugehen scheint, ...	○	○	○	○	○
Wenn ich mich auf eine anstrengende Aufgabe vorbereite, ...	○	○	○	○	○
Wenn ich unter Druck stehe, ...	○	○	○	○	○
Wenn ich mich nervös und gestresst fühle, ...	○	○	○	○	○
Wenn ich das Gefühl habe, wichtige Dinge in meinem Leben nicht beeinflussen zu können, ...	○	○	○	○	○
Wenn ich das Gefühl habe, nichts mehr wirklich im Griff zu haben, ...	○	○	○	○	○
Wenn ich das Gefühl habe, dass sich die Probleme so aufgestaut haben, dass ich sie nicht mehr bewältigen kann, ...	○	○	○	○	○

Seite 14
Comfort

8. Denken Sie bitte an den letzten Monat zurück. Wenn Sie Stress hatten, wie häufig haben Sie die folgenden Lebensmittel gegessen?
Bitte pro Zeile ein Kästchen ankreuzen!

	nie	selten	manchmal	häufig	sehr häufig
Schokolade oder Konfekte	○	○	○	○	○
Bonbons oder Gummibärchen	○	○	○	○	○
Eiscreme	○	○	○	○	○
Kuchen	○	○	○	○	○
Kekse	○	○	○	○	○
Chips oder Cracker	○	○	○	○	○
Gesalzene Nüsse	○	○	○	○	○
„Frittiertes" oder Pommes frites	○	○	○	○	○
Hamburger, Currywurst oder Pizza	○	○	○	○	○
Alkohol	○	○	○	○	○
Zuckerhaltige Getränke	○	○	○	○	○
Energy-Drinks	○	○	○	○	○
Kaffee	○	○	○	○	○

Seite 15
Schoko

PHP-Code

```
if (value('SE07_01')==1){
goToPage('Bon');
}
```

9. Könnten Sie sich vorstellen, in Stresssituationen anstelle von Schokolade oder Konfekte Folgendes zu essen?
Mehrere Antworten sind möglich!

- ☐ Getrocknetes Obst, Beeren
- ☐ Frisches Obst, Beeren
- ☐ Dunkle Schokolade
- ☐ Schokomilch ohne Zuckerzusatz
- ☐ Pudding, Cremespeise
- ☐ Joghurt, Quark ohne Zuckerzusatz
- ☐ Müsliriegel, Fruchtriegel
- ☐ Fruchtkugeln, Energiekugeln
- ☐ Schokofrüchte
- ☐ Sonstiges (bitte angeben): ____

Seite 16
Bon

PHP-Code

```
if (value('SE07_02')==1){
goToPage('Eis');
}
```

10. Könnten Sie sich vorstellen, in Stresssituationen anstelle von Bonbons oder Gummibärchen Folgendes zu essen?

Mehrere Antworten sind möglich!

- ☐ Getrocknetes Obst, Beeren
- ☐ Frisches Obst, Beeren
- ☐ Nuss-Frucht-Mischungen
- ☐ Joghurt, Quark ohne Zuckerzusatz
- ☐ Bonbons, Kaugummi ohne Zuckerzusatz
- ☐ Fruchtkugeln, Energiekugeln
- ☐ Müsliriegel, Fruchtriegel
- ☐ Sonstiges (bitte angeben): ______

Seite 17
Eis

PHP-Code

```
if (value('SE07_03')==1){
goToPage('Kuch');
}
```

11. Könnten Sie sich vorstellen, in Stresssituationen anstelle von Eiscreme Folgendes zu essen?

Mehrere Antworten sind möglich!

- ☐ Fruchtsorbet
- ☐ Smoothie
- ☐ Fruchteis, Wassereis
- ☐ Joghurt, Quark ohne Zuckerzusatz
- ☐ Frisches Obst, Beeren
- ☐ Sonstiges (bitte angeben): ______

Seite 18
Kuch

PHP-Code

```
if (value('SE07_04')==1){
goToPage('Keks');
}
```

12. Könnten Sie sich vorstellen, in Stresssituationen anstelle von Kuchen Folgendes zu essen?

Mehrere Antworten sind möglich!

- ☐ Pudding, Cremespeise
- ☐ Obstkuchen, Biskuit
- ☐ Fruchtkugeln, Energiekugeln
- ☐ Frisches Obst, Beeren
- ☐ Obstkonserve (z.B. Mus, Grütze)
- ☐ Joghurt, Quark ohne Zuckerzusatz
- ☐ Smoothie
- ☐ Müsliriegel, Fruchtriegel
- ☐ Milchbrötchen, Rosinenbrötchen
- ☐ Belegtes Brot
- ☐ Sonstiges (bitte angeben): ____

Seite 19
Keks

PHP-Code

```
if (value('SE07_05')==1){
goToPage('Chips');
}
```

13. Könnten Sie sich vorstellen, in Stresssituationen anstelle von Keksen Folgendes zu essen?

Mehrere Antworten sind möglich!

- ☐ Getrocknetes Obst, Beeren
- ☐ Knäckebrot, Reiswaffeln, Zwieback
- ☐ Müsliriegel, Fruchtriegel
- ☐ Popcorn ohne Salz oder ohne Zuckerzusatz
- ☐ Frisches Obst, Beeren
- ☐ Nuss-Frucht-Mischungen
- ☐ Sonstiges (bitte angeben): ____

Seite 20
Chips

PHP-Code

```
if (value('SE07_06')==1){
goToPage('Nu');
}
```

14. Könnten Sie sich vorstellen, in Stresssituationen anstelle von Chips oder Crackern Folgendes zu essen?

Mehrere Antworten sind möglich!

- [ ] Knäckebrot, Reiswaffeln, Zwieback
- [ ] Nuss-Frucht-Mischungen
- [ ] Frisches Gemüse
- [ ] Oliven
- [ ] Popcorn ohne Salz oder ohne Zuckerzusatz
- [ ] Belegtes Brot
- [ ] Sonstiges (bitte angeben):

Seite 21
Nu

PHP-Code

```
if (value('SE07_07')==1){
goToPage('Pomm');
}
```

15. Könnten Sie sich vorstellen, in Stresssituationen anstelle von gesalzenen Nüssen Folgendes zu essen?

Mehrere Antworten sind möglich!

- [ ] Nuss-Frucht-Mischungen
- [ ] Sesamriegel, Nussriegel
- [ ] Frisches Gemüse
- [ ] Oliven
- [ ] Popcorn ohne Salz oder ohne Zuckerzusatz
- [ ] Knäckebrot, Reiswaffeln, Zwieback
- [ ] Sonstiges (bitte angeben):

Seite 22
Pomm

PHP-Code
```
if (value('SE07_08')==1){
goToPage('Pizz');
}
```

16. Könnten Sie sich vorstellen, in Stresssituationen anstelle von „Frittiertes“ oder Pommes frites Folgendes zu essen?
Mehrere Antworten sind möglich!

- ☐ Kartoffel, Süßkartoffel
- ☐ Sesamriegel, Nussriegel
- ☐ Frisches Gemüse
- ☐ Salat mit Tofu oder magerem Fleisch
- ☐ Knäckebrot, Reiswaffeln, Zwieback
- ☐ Wrap
- ☐ Belegtes Brot
- ☐ Vegetarisches Gericht (z.B. Gemüsepfanne, Reis)
- ☐ Sonstiges (bitte angeben): ____

Seite 23
Pizz

PHP-Code
```
if (value('SE07_09')==1){
goToPage('Alk');
}
```

17. Könnten Sie sich vorstellen, in Stresssituationen anstelle von Hamburgern, Currywurst oder Pizza Folgendes zu essen?
Mehrere Antworten sind möglich!

- ☐ Belegtes Brot
- ☐ Wrap
- ☐ Suppe
- ☐ Kartoffel, Süßkartoffel
- ☐ Salat mit Tofu oder magerem Fleisch
- ☐ Vegetarische Pizza
- ☐ Frisches Gemüse
- ☐ Vegetarischer Döner
- ☐ Knäckebrot, Reiswaffeln, Zwieback
- ☐ Sonstiges (bitte angeben): ____

Seite 24
Alk

PHP-Code

```
if (value('SE07_10')==1){
goToPage('Getr');
}
```

18. Könnten Sie sich vorstellen, in Stresssituationen anstelle von Alkohol Folgendes zu trinken?

Mehrere Antworten sind möglich!

- ☐ Alkoholfreies Bier
- ☐ Fruchtschorle
- ☐ Kokoswasser
- ☐ Infused Water (Wasser mit Obst, Gemüse oder Kräutern)
- ☐ Wasser
- ☐ Light-, Zero-Getränke
- ☐ Sonstiges (bitte angeben):

Seite 25
Getr

PHP-Code

```
if (value('SE07_11')==1){
goToPage('Ener');
}
```

19. Könnten Sie sich vorstellen in Stresssituationen, anstelle von zuckerhaltigen Getränken Folgendes zu trinken?

Mehrere Antworten sind möglich!

- ☐ Wasser
- ☐ Tee ohne Zuckerzusatz
- ☐ Fruchtschorle
- ☐ Infused Water (Wasser mit Obst, Gemüse oder Kräutern)
- ☐ Kokoswasser
- ☐ Light-, Zero-Getränke
- ☐ Sonstiges (bitte angeben):

Seite 26

Ener

PHP-Code

```
if (value('SE07_12')==1){
goToPage('Kaf');
}
```

20. Könnten Sie sich vorstellen, in Stresssituationen anstelle von Energy-Drinks Folgendes zu trinken?

Mehrere Antworten sind möglich!

- ☐ Koffeinfreier Kaffee
- ☐ Tee ohne Zuckerzusatz
- ☐ Fruchtschorle
- ☐ Infused Water (Wasser mit Obst, Gemüse oder Kräutern)
- ☐ Schokomilch ohne Zuckerzusatz
- ☐ Wasser
- ☐ Light-, Zero-Getränke
- ☐ Sonstiges (bitte angeben):

Seite 27

Kaf

PHP-Code

```
if (value('SE07_13')==1){
goToPage('Te');
}
```

21. Könnten Sie sich vorstellen, in Stresssituationen anstelle von Kaffee Folgendes zu trinken?

Mehrere Antworten sind möglich!

- ☐ Koffeinfreier Kaffee
- ☐ Tee ohne Zuckerzusatz
- ☐ Fruchtschorle
- ☐ Infused Water (Wasser mit Obst, Gemüse oder Kräutern)
- ☐ Schokomilch ohne Zuckerzusatz
- ☐ Wasser
- ☐ Light-, Zero-Getränke
- ☐ Sonstiges (bitte angeben):

Seite 28

Te

Teil 4: Technik

In diesem Teil der Befragung interessieren wir uns nun für Ihr **Internet- und Technikverhalten**. Digitale Geräte, wie z.B. Smartphones und Smartwatches können genutzt werden, um **Stress** zu erkennen und über Apps den Stress zu reduzieren. Die folgenden Fragen zielen auf diese Themen ab.

Seite 29

22. Hier finden Sie die Aussagen zu Ihrer Einstellung gegenüber neuen Technologien. Bitte geben Sie an, was am besten auf Sie zutrifft!

Bitte pro Zeile ein Kästchen ankreuzen!

Personal Innovativeness (Persönliche Innovationsfreude)	stimme voll zu	stimme zu	neutral	stimme nicht zu	stimme gar nicht zu
Wenn ich von einer neuen Informationstechnologie höre, suche ich einen Weg mit dieser experimentieren zu können.	○	○	○	○	○
Verglichen mit meinen Bekannten bin ich immer eine/r der Ersten, der/die eine neue Informationstechnologie ausprobiert.	○	○	○	○	○
Im Allgemeinen bin ich zögerlich, neue Informationstechnologien auszuprobieren.	○	○	○	○	○
Ich mag es, mit einer neuen Informationstechnologie zu experimentieren.	○	○	○	○	○

Seite 30

Im Folgenden geht es um Ihr ***Smartphone*** und Ihre ***Smartwatch***!

23. Von welchem Hersteller ist Ihr Smartphone?

- ○ Apple
- ○ Huawei
- ○ OnePlus
- ○ Samsung
- ○ Sony
- ○ Xiaomi
- ○ Andere
- ○ Ich habe kein Smartphone.

Seite 31

24. Besitzen Sie eine Smartwatch?

- ○ ja
- ○ nein

1 aktive(r) Filter
Filter TE05/F1
Wenn eine der folgenden Antwortoption(en) ausgewählt wurde: **2**
Dann nach dem Klick auf "Weiter" direkt zur Seite **%page%** springen

Seite 32

Welche Smartwatch besitzen Sie?
Nur eine Antwort ist möglich!

- ◯ Apple Watch 1-3
- ◯ Apple Watch 4 oder neuer
- ◯ Fitbit Sense / Versa
- ◯ Fossil Carlyle HR / Sport
- ◯ Garmin Venu
- ◯ Huawei Watch
- ◯ Mobvoi TicWatch
- ◯ Motorola Moto
- ◯ Samsung Gear / Galaxy Watch
- ◯ Andere

Seite 33
App

Stress-Apps

Stellen Sie sich eine **App** vor, welche Ihren **Stress** erkennen und lernen könnte, stressige Situationen vorherzusagen. Dies könnte durch die Analyse von Körperwerten wie z.B. **Puls** (um Stress in Echtzeit erkennen zu können) geschehen. Zusätzlich könnten Daten wie **Standort, Anzahl von Kalendereinträgen, Schlafqualität** u.ä. untersucht werden, um Parallelen zu stressigen Tagen ziehen und diese vorhersagen zu können.

Diese **App** könnte Sie auch dabei unterstützen bei Stress eine **gesunde Ernährung** beizubehalten, indem Sie Ihnen gesunde Alternativen vorschlägt.

Seite 34

25. Bitte geben Sie an, was am besten auf Sie zutrifft!
Bitte pro Zeile ein Kästchen ankreuzen!

Perceived Usefulness (Wahrgenommene Nützlichkeit) & Behavioural Intention (Verhaltensabsicht)	stimme voll zu	stimme zu	neutral	stimme nicht zu	stimme gar nicht zu
Ich würde diese App nützlich finden.	◯	◯	◯	◯	◯
Die Verwendung dieser App würde mir ermöglichen, mich gesünder zu ernähren.	◯	◯	◯	◯	◯
Insgesamt finde ich, dass die Nutzung dieser App vorteilhaft wäre.	◯	◯	◯	◯	◯
Die Verwendung dieser App würde es einfacher für mich machen, mich gesünder zu ernähren.	◯	◯	◯	◯	◯
Hätte ich Zugang zu dieser App, dann würde ich beabsichtigen, sie zu benutzen	◯	◯	◯	◯	◯
Hätte ich Zugang zu dieser App, würde ich sie voraussichtlich benutzen.	◯	◯	◯	◯	◯
Ich würde diese App in den nächsten drei Monaten benutzen.	◯	◯	◯	◯	◯

Seite 35

26. Bitte geben Sie an, was am besten auf Sie zutrifft!
Bitte pro Zeile ein Kästchen ankreuzen!

Notifications (Benachrichtigungen in der App)	1 Mal proTag	mehrmals pro Tag	1 Mal pro Woche	mehrmals pro Woche	nie
Wie oft würden Sie gerne Notifications zu Erinnerungen, Daten einzutragen von dieser App erhalten?	○	○	○	○	○
Wie oft würden Sie gerne Notifications zu Informationen zu Ernährungsvorschlägen von dieser App erhalten?	○	○	○	○	○

1 aktive(r) Filter
Filter TE09/F1
Wenn eine der folgenden Antwortoption(en) ausgewählt wurde: **1**
[inaktiv] Keine Filterführung ausgewählt

Seite 36

27. Welche *Daten* würden Sie mit deser App teilen, um die Stresserfassung und -vorhersage zu ermöglichen und zu verbessern?
Bitte pro Zeile ein Kästchen ankreuzen!

Data Sharing (Teilen von Daten)	ja	vielleicht	nein
Puls	○	○	○
Standort	○	○	○
Anzahl der Kalendereinträge	○	○	○
Anzahl eingehender E-Mails	○	○	○
Schrittzähler	○	○	○
Schlaf	○	○	○

Seite 37

Teil 5: Persönlichkeit

In diesem Teil der Befragung geht es um Ihre **Person**.

Seite 38

28. Bitte geben Sie an, was am besten auf Sie zutrifft!

Bitte pro Zeile ein Kästchen ankreuzen!

	trifft überhaupt nicht zu	trifft eher nicht zu	weder noch	eher zutreffend	trifft voll und ganz zu
Ich bin eher zurückhaltend, reserviert.	○	○	○	○	○
Ich schenke anderen leicht Vertrauen, glaube an das Gute im Menschen.	○	○	○	○	○
Ich bin bequem, neige zur Faulheit.	○	○	○	○	○
Ich bin entspannt, lasse mich durch Stress nicht aus der Ruhe bringen.	○	○	○	○	○
Ich habe nur wenig künstlerisches Interesse.	○	○	○	○	○
Ich gehe aus mir heraus, bin gesellig.	○	○	○	○	○
Ich neige dazu, andere zu kritisieren.	○	○	○	○	○
Ich erledige Aufgaben gründlich.	○	○	○	○	○
Ich werde leicht nervös und unsicher.	○	○	○	○	○
Ich habe eine aktive Vorstellungskraft, bin fantasievoll.	○	○	○	○	○

Seite 39

Teil 6: Soziodemographie und Anthropometrie

In diesem Teil der Befragung möchten wir Sie um einige Angaben zu Ihrer **Person** bitten.

Seite 40

29. Was ist Ihr Geschlecht?

○ Weiblich
○ Männlich

30. Wie alt sind Sie?

[ ] Jahre

31. Wie groß sind Sie?

[ ] cm

32. Wie viel wiegen Sie?

[ ] kg

Seite 41

33. Welchen Familienstand haben Sie?

- ◯ Verheiratet und lebe mit meinem/r Ehepartner/in zusammen
- ◯ Verheiratet und lebe mit meinem/r Ehepartner/in getrennt
- ◯ Ledig
- ◯ Geschieden
- ◯ Verwitwet
- ◯ Einen anderen Familienstand und zwar:

34. Haben Sie Kinder?

- ◯ Ja
- ◯ Nein

Seite 42

35. Welchen <u>höchsten allgemeinbildenden</u> Schulabschluss haben Sie?

- ◯ Schüler/in, besuche allgemein bildende Vollzeitschule
- ◯ Schüler/in, besuche eine berufsorientierte Aufbau-, Fachschule o.ä.
- ◯ Von der Schule abgegangen ohne Hauptschulabschluss (Volksschulabschluss)
- ◯ Hauptschulabschluss (Volksschulabschluss)
- ◯ Realschulabschluss (Mittlere Reife)
- ◯ Abschluss der Polytechnischen Oberschule
- ◯ 10. Klasse (vor 1965: 8. Klasse)
- ◯ Fachhochschulreife, Abschluss Fachoberschule
- ◯ Allg./fachgebundene Hochschulreife / Abitur (Gymnasium bzw. EOS, auch EOS mit Lehre)
- ◯ Einen anderen Schulabschluss und zwar:

36. Als was sind Sie derzeit überwiegend tätig?
Nur eine Antwort ist möglich!

- ◯ Angestellte/r, Beamte/r
- ◯ Auszubildende/r
- ◯ Arbeitssuchend
- ◯ Student/in
- ◯ Selbstständige/r
- ◯ Nicht erwerbstätig (z.B. Mutterschutz, Hausmann/-frau, Rente)
- ◯ Sonstiges

Seite 43

37. Möchten Sie uns noch etwas mitteilen? Hier finden Sie Platz für Anregungen, Wünsche oder Kommentare!

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Interesse Studienteilnahme

Haben Sie **Interesse** an unserer **Studie** zum Thema **„Stress-Essen“** teilzunehmen UND besitzen Sie eine **Apple-Smartwatch**?

Dann schreiben Sie uns bitte eine E-Mail an: ***ernaehrungsmedizin.med@tum.de*** mit dem Betreff: „Interesse an StrEss Studie".

Wir werden uns bei Ihnen melden!

Vielen Dank.

Ihr *enable* Studienteam

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Das ist das Ende der Befragung - vielen Dank für Ihre Teilnahme!

Letzte Seite

Vielen Dank für Ihre Teilnahme!

Wir möchten uns ganz herzlich für Ihre Mithilfe bedanken.
Ihre Antworten wurden gespeichert, Sie können das Browser-Fenster nun schließen.

Dr. Sophie Laura Holzmann, Technische Universität München – 2020

List of Scientific Publications

Kaiser, B., Gemesi, K., Holzmann, S. L., Wintergerst, M., Lurz, M., Hauner, H., Groh, G., Böhm, M., Krcmar, H., Holzapfel, C., & Gedrich, K. (2022). Stress-induced hyperphagia: empirical characterization of stress-overeaters. *BMC Public Health*, 22(1), 100. https://doi.org/10.1186/s12889-021-12488-9

Blaurock, J., **Kaiser, B.,** Stelzl, T., Weech, M., Fallaize, R., Franco, R. Z., Hwang, F., Lovegrove, J., Finglas, P. M., & Gedrich, K. (2021). Dietary Quality in Vegetarian and Omnivorous Female Students in Germany: A Retrospective Study. *International Journal of Environmental Research and Public Health*, 18(4), 1888. https://doi.org/10.3390/ijerph18041888

Kaiser, B. M., Stelzl, T., & Gedrich, K. (2020). Nutrition Apps on Focus: A Qualitative Assessment. *European Journal of Public Health Studies*, *3*(1), 9-33. https://dx.doi.org/10.46827/ejphs.v3i1.67

Kaiser, B., & Holzmann, S. H., H Holzapfel, C Gedrich, K. (2020). Nutrition and stress. Overview of selected stress indicators and smart measurement techniques*. Ernaehrungs Umschau* 67(5), 98-107. https://doi.org/10.4455/eu.2020.017

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