# Nutrition and stress

## Overview of selected stress indicators and smart measurement techniques

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### Abstract

Nutritional behaviour is a complex interaction, which can be affected by stress. For the proposed review, various stress indicators have been identified, whereby selected indicators and related measurement tools (e.g. wearables) will be considered in detail. In summary, the combination of data from different stress indicators seems to be a reasonable approach for the measurement of stress. However, the wearables' features need to be improved and further evaluated within appropriate studies using standardized stress stimuli.


**Keywords:** nutrition, stress, smart measurement, wearables, digital


**Citation**

Kaiser B, Holzmann SL, Hauner H, Holzapfel C, Gedrich K: Nutrition and stress. Overview of selected stress indicators and smart measurement techniques. Ernahrungs Umschau 2020; 67(5): 98–107.
This article is available online:
DOI: 10.4455/eu.2020.017

**Peer-reviewed**

Manuscript (original contribution) received: July 25, 2019
Revision accepted: December 09, 2019



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## Background

Nutritional behaviour is a complex biopsychosocial process, which is determined by various factors (e.g. genetic preferences, nutritional education) [1]. This lifelong process is regulated by the interaction of internal physiological (e.g. hunger) and external social and psychological stimuli. Besides, a genetic predisposition and an inconvenient lifestyle can affect that process negatively. A positive energy balance, due to high-energy eating patterns and low levels of physical activity, leads to weight gain in the short-term and to overweight and obesity in the long-term [2]. Moreover, the risk of comorbidities (e.g. metabolic syndrome) increases [3]. Stress is being discussed as an external risk factor for the development of overweight and obesity. Stressful situations have an impact on nutritional behaviour (e.g. increased energy intake) [4] and therefore, can contribute to the development of nutrition-related diseases in the long-term.

### Stress – definition and characteristics

At present, there is no official definition of the term stress. For instance, Selye [5] describes stress as *"non-specific response of the body to any demand for change"*, which exceeds the individual coping skills. Therefore, stress can be seen as a short-term (acute) imbalance between the perceived load and the coping strategies available. A persistence of this imbalance results into a manifestation, called chronic stress [6]. Two types of stress can be differentiated: eustress and distress. While eustress is associated with positive feelings and a healthy condition of the body, distress is accompanied with negative feelings and a disturbed body condition [5].
There are various stress-inducing factors, so-called stressors (e.g. daily life, workload), which can be perceived subjectively or objectively as threat. Reactive and adaptive physiological changes (allostasis) maintain the organism's homeostasis, which can be seen as a survival strategy from an evolutionary point

of view [7]. At the physiological level, stressors activate a cascade of reactions within the autonomic nervous system and the hypothalamic–pituitary–adrenal (HPA) axis [7]. These reactions are needed to set the organism on alert and prepare it for a fight or flight reaction [8]. The activation of the HPA axis triggers the release of the glucocorticoid Cortisol, which enables a rapid energy supply. Within the sympathetic nervous system (SNS) the release of the catecholamines Noradrenalin and Adrenalin is being triggered [7]. Finally, the release of aforementioned stress hormones leads to additional physiological changes like increased heart and breathing rates, as well as a stimulation of the sweat glands [9].

### Smart measurements – use of wearables and smartphones to capture selected stress indicators

Smart (digital) measurement tools, e.g. wearables, can be applied to capture stress-induced changes of respective indicators. Mann [10] describes wearables as minicomputers which can be worn on the body and are always ready for use. Additionally, Gao et al. [11] highlight the ability of wearables to monitor individual activities continuously. Therefore, wearables contain various sensors, enabling the record of physiological and environmental parameters. In the context of stress, physiological measurement values can be established by accessing data from electrocardiograph (ECG), photoplethysmogram (PPG) or plethysmograph sensors [12], which can be integrated in smartwatches, chest straps, smart clothing, or jewellery [13]. Algorithms are used to analyse the sensor signals (raw data) and to translate them into appropriate health-related parameters [14]. Furthermore, smartphones provide the opportunity to capture the individual's stress behaviour. Therefore, traditional paper-pencil questionnaires or single stress-related questions are presented digitally via smartphone to the user [15].

### Nutrition and stress – association and impact

Apart from the digital detection of stress-induced physiological changes, stress can also have an impact on nutritional behaviour. Nutrition is a crucial point to maintain the energy homeostasis of the organism. The feeling of hunger is triggered by an energy deficit, which can be compensated by the intake of food. In contrast to that, appetite can be characterized as "sensually craving" for a specified food (pleasurable experience) and therefore, appears independently of any energy deficit [16]. Moreover, appetite is supressed under acute stress conditions and can be stimulated again after recovery [17]. This may lead to an increased intake of energy-rich comfort foods [18] as well as to an enhanced snacking behaviour [19]. The results of the Hispanic Community Health Study/Study of Latinos (HCHS/SOL) show a positive association between the number of chronic stressors and the energy intake as well as an inverse relation between subjectively perceived stress and the Alternate Healthy Eating Index (AHEI-2010). Thereby, the last-named is being associated with the amount of out-of-home consumption [20]. Sproesser et al. [21] focused on stress-induced, quantitative changes of the nutritional behaviour (food intake) and differentiated between people with hyperphagia/hypophagia (eat more/less) under stress conditions. According to a study among 251 participants, around 40% could be identified as people with hyperphagia and 40% as people with hypophagia. The remaining 20% did not show any significant changes in food intake. Consequently, people with hyperphagia might be a vulnerable group for the development of overweight and obesity [22].

### Stress – approach for personalized nutrition

The investigation of the relation between nutrition and stress and its impact on the onset of overweight and obesity is a subproject of the *enable* competence cluster (→ www.enable-cluster.de), funded by the Federal Ministry of Education and Research (BMBF). One aim of this project is to identify and to evaluate digital approaches for the prevention of stress-related hyperphagia by using wearables to enable the automatic and reliable measurement of stress. Based on learned stress patterns, a virtual dietary advisor can intervene preventively and predictively by giving personalized nutritional recommendations. Thus, it is aimed to prevent an unfavourable nutritional behaviour and the development of overweight and obesity through the application of innovative digital devices. This paper aims to provide a selective overview about stress indicators and its corresponding smart measurements.

## Methods

The scientific data bases Pubmed and Web of Science as well as Google Scholar were screened for reviews on the subject of the measurement of acute distress from December 2018 until February 2019. The following search terms were used: "stress", "measure", "monitor", "detect", "track", "assess" and "review".

Subsequently, indicators and measurements, which were extracted from the respective reviews [23–29], were looked at in detail according to our defined inclusion and exclusion criteria (◆ Table 1). Besides that, the results section includes also single original papers of the reviews. However, only papers published from 2000 on to 2019 were included. Standards for the implementation of Bluetooth, which enables the wireless interoperation between devices, were developed at the turn of the millennium. Therefore, it can be considered as precondition for the development of smart technologies [30].

Further inspection regarding the indicators' suitability to be measured by wearables or smartphones were performed. The most commonly used indicators and their measurements are summarized narratively within this paper.

| Parameter | Inclusion | Exclusion |
|---|---|---|
| study population | healthy adults | children<br>persons with specific diseases |
| study setting | laboratory<br>field trial | medical institution |
| type of stress | distress<br>acute stress | eustress<br>chronic stress |
| stressor | general (e.g. validated stress tasks, everyday life) | specific (e.g. car driving) |
| measurement | non-invasive | invasive<br>biomarker |
| date of publication | 2000 to 2019 | prior to 2000 |

Tab. 1: **Inclusion and exclusion criteria for literature research**

## Results

According to the literature, a variety of stress measurement indicators have been identified. The most commonly used stress indicators are presented in ◆ Figure 1.

These indicators are used as objective or subjective parameters to measure stress and can be assigned to the following categories: biochemical (e.g. hormones), physiological (e.g. heart rate), behavioural (e.g. sleeping duration) and contextual (e.g. weather) indicators as well as the subjective perception of stress.
In the following this paper focuses on the non-invasive measurement of stress using wearables and smartphones.

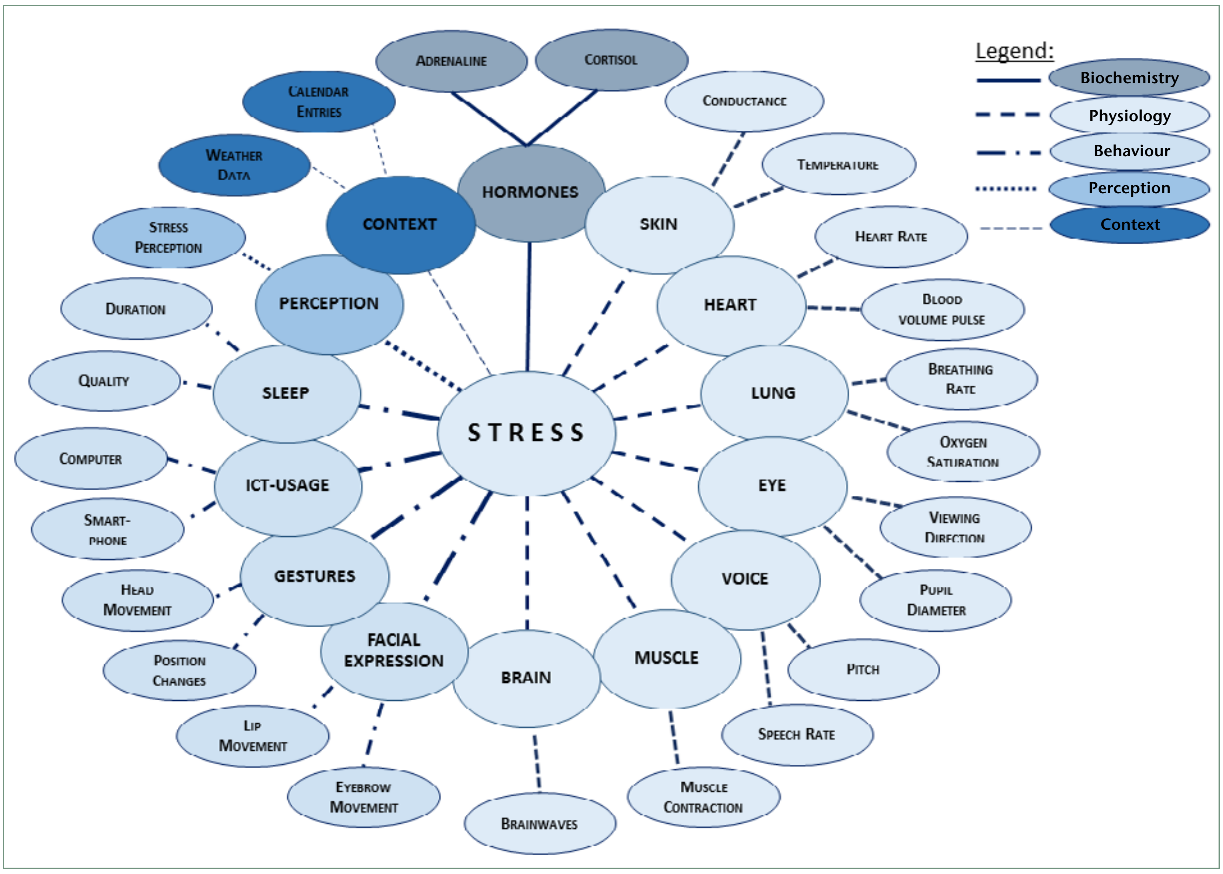


Fig. 1: **Overview of most commonly used indicators for stress measurements**
ICT = information and communication technology

| Organ | Indicator | Measurement |
|---|---|---|
| skin | skin conductance | chest strap<br>smartwatch<br>fitness tracker |
| | skin temperature | chest strap<br>smartwatch<br>fitness tracker |
| heart | heart rate variability | chest strap<br>smartwatch<br>fitness tracker |
| | blood volume pulse | smartwatch<br>fitness tracker |
| lung | breathing rate | chest strap |
| voice | voice variance | microphone |

Tab. 2: **Examples of physiological stress indicators and their measurements**

## Physiological stress indicators

Affected by stress, various physiological changes within the organism, respectively the organs, can be measured. ◆ Table 2 presents selected stress indicators and relevant measurements by organs.

*Skin*

The condition of stress induces an increase of the sweat secretion and a decrease of the body temperature [31]. It is commonly captured by skin-related changes like skin conductance, also referred to as galvanic skin response (GSR). Applying wearables (e.g. at the wrist) is one way to measure GSR [32]. The study by Schmidt et al. [33] investigated the effect of stress (Trier Social Stress Test, TSST) on GSR (chest strap, fitness tracker) among 15 participants. It was demonstrated that non-stress could be differentiated with a sensitivity of about 80%. Ciabattoni et al. [32] detected stress, induced by cognitive tasks, by using a smartwatch (GSR and skin temperature) in a within-subject study design including 10 participants. The combination of skin-related data with additional stress-related parameters like heart rate variability (HRV) resulted into a classification accuracy of around 85% for the overall smart measurement system. Another way to capture skin temperature is the application of thermal sensors within fitness trackers. Ghosh et al. [34] captured everyday stress of 5 participants by using smart wristbands during a 7 day field trial. The results indicate that perceived stress can be detected with a sensitivity of 79% via skin conductance and of 44% via skin temperature. Data based on measurement using a chest strap indicated a sensitivity of 69% for the discrimination of stress and non-stress [33].

*Heart*

There are several studies, which refer to the use of changes in HRV to capture stress. For instance, wearable-integrated ECG-sensors are frequently used for a continuous HRV measurement. Within an experimental trial with 15 participants, stress and non-stress could be distinguished by 85% based on HRV data (chest strap) [33]. Hao et al. [35] captured stress of 12 employees applying fitness trackers. The results indicate a positive correlation ($r > 0.95$) between HRV and subjectively perceived stress. Another heart-related stress indicator is blood volume pulse (BVP), which can be detected via PPG sensors. The study by Ghosh et al. [34] showed, that everyday stress can be detected with a sensitivity of 74% based on the BVP data of a smart wristband.

*Lung*

Stress-related changes in the lung activity can be accessed via the breathing rate. As already stated for skin and heart, chest straps can also be applied for measuring the breathing rate. The results of Schmidt et al. [33] indicate a discrimination of about 90% sensitivity between stress and non-stress situations based on breathing rate data captured by a chest strap. Plarre et al. [36] applied the Stroop Colour Word (SCW) test among 12 participants and investigated changes in the breathing rate. Based on breathing rate data, it was shown that stress can be detected with a sensititvity of 87% (e.g. exhale duration) generated by a chest strap.

*Voice*

The voice, even though not an organ in the proper sense, can be used to capture stress, as well. For instance, variances within the voice can be detected via microphones and used as an indicator for the stress measurement. Adams et al. [37] investigated everyday stress of 7 participants by using smartphone microphones over 10 days. The results indicate a positive correlation ($r > 0.59$) between self-reported stress and voice stress (variances in pitch, speech rate and power). Lu et al. [38] (job-interview, 14 participants) captured stress indicators (e.g. pitch) by using a self-developed app with a sensitivity of 81% (indoor) and 76% (outdoor).

## Behavioural stress indicators

Besides the above addressed physiological changes, stress can be captured by means of behavioural changes. ◆ Table 3 shows an exemplary presentation of behavioural stress indicators and corresponding measurements.

*Information and communication technology (ICT) usage behaviour*

Additional stress indicators can be measured based on the ICT usage behaviour. Firstly, the usage of smartphones is discussed. Usage behaviour can be characterized based on call or short message data (SMS or messenger) and interaction with social media. For example, the

| Behaviour | Indicator | Measurement |
|---|---|---|
| ICT-Usage | smartphone usage behaviour | smartphone |
| sleep | sleep quality | smartphone apps<br>smartwatch<br>fitness tracker<br>questionnaire |

Tab. 3: **Examples of behavioural stress indicators and their measurements**
ICT = information and communication technology

amount, duration, or length of calls or text messages, as well as the number of persons contacted, can be analysed. Additionally, typing behaviour (pressure, speed) can be used as an indicator. According to a 4 month field trial by Muaremi et al. [39] with 35 participants, stress could be detected with an accuracy of 55% based on smartphone usage characteristics.

### *Sleep*

Another behavioural stress indicator is sleep quality, which can be captured by questionnaires. The results of Sano & Picard [40] indicate an inverse correlation between sleep quality and subjective stress perception using the Pittsburgh Sleep Quality Index (PSQI). Furthermore, sleep quality (e.g. sleep latency, movement profile, ambient brightness) can be captured digitally via wearables. Ben-Zeev et al. [41] investigated the relation between the daily stress level and the smartphone-captured sleep duration during a 10 week cohort study among 47 participants. A significant inverse relation between stress and sleep duration was demonstrated.

## Subjective stress perception

In addition to the objective (physiological) indicators listed above, questionnaires are a possibility to capture the subjective stress perception. ◆ Table 4 presents a selection of validated questionnaires, which are also available in a German version.

The selected questionnaires are freely available and assess the perceived load or the stress level. They can be distinguished according to the number of items and the period of recording, for instance. The subjective stress level is evaluated by the calculation of scores, which are then translated into certain categories, e.g. low, moderate, or high perceived stress (PSS).

Moreover, smartphones can be used to assess the subjective stress in a digital manner. Plarre et al. [36] applied smartphones to 21 participants within a laboratory setting and evaluated the emotional state (e.g. nervous, stressed) based on 4-point scale. The results indicate a positive correlation (r = 0.72) between the subjective stress perception (via smartphone) and the objectively measured stress indicators (HRV and breathing rate).

### *Stress types*

As already mentioned, stress situations can cause different changes of the nutritional behaviour. Therefore, it is important to characterize stress induced nutritional behaviour and to identify stress types. Emotional eating behaviour can be captured through questionnaires like the Dutch Eating Behavior Questionnaire (DEBQ) [50] or the *Fragebogen zum Essverhalten* (FEV) [51]. Furthermore, questionnaires to capture stress can be used (◆ Table 4). Up to now, there are only a few validated German questionnaires assessing stress-induced nutritional behaviour and thus enabling a classification of different stress types. For instance, the validated Salzburg Stress Eating Scale (SSES) assesses the changes in food intake at stressful situations [52]. Based on 10 questions, a score is calculated to identify an increase or decrease in food intake.

| Questionnaire | Items | Content | German Version<br>*Original publication* |
|---|---|---|---|
| *Alltagsbelastungsfragebogen* (ABF) (Daily Stress Inventory, DSI) | 58 | objective burdensome everyday experiences within the last 24 hours | Traue, Hrabal, Kosarz 2000 [42]<br>*Brantley et al. 1987 [43]* |
| Perceived Stress Questionnaire (PSQ) | 30<br>20 | current subjectively experienced stress load | Fliege et al. 2001 [44]<br>*Levenstein et al. 1993 [45]* |
| Perceived Stress Scale (PSS) | 10 | perceived stress experience within the last month | Klein et al. 2016 [46]<br>*Cohen et al. 1983 [47]* |
| Stress Appraisal Measure (SAM) | 28 | evaluation of current stress causing events | Delahaye et al. 2015 [48]<br>*Peacock, Wong 1990 [49]* |

Tab. 4: **Selection of validated questionnaires to capture subjective stress perception, with German translations**

A preliminary validation study indicated that the average SSES score is higher in women compared to men, accordingly they tend to eat more when stressed. Furthermore, there was a positive association between the SSES score and the BMI for persons with a high subjective stress perception [52].

## Discussion

This paper shows that wearables, as a daily companion, offer the opportunity to track various stress indicators continuously. In the wake of the digital health movement, wearables are being further developed and improved due to the implementation of new techniques and features. As most wearables are not declared as medical devices, they are not subject to the Act on Medical Devices (MPG) [53]. Therefore, many wearables lack scientific evidence regarding the development of health-related contents and features. The study by Peake et al. [27] demonstrates that only 5% of the investigated wearables were validated against an acknowledged standard measurement method. Scalise and Cocili [54] emphasize the small amount of studies and the lack of standard protocols evaluating the accuracy and validity of health- and fitness-related wearables. An approach to determine the validity of wearables is the inter-device comparison of selected indicators. Stahl et al. [55] compared HRV data captured by fitness trackers from different manufacturers with HRV data measured via ECG of a chest strap. The results indicate different correlation values for the different models ranging from 0.93–0.96. Results of the study by Wang et al. (56) presume an over- or underestimation of HRV according to differences between the models of selected fitness trackers used.

Mantua et al. [57] compared sleep-related data of fitness trackers with data of a polysomnograph. Their results indicate a variance between different fitness trackers concerning the loss of data (e.g. caused by misfitting devices or incorrect data input). Regarding sleep duration, a strong correlation between data of fitness trackers and polysomnographic data was shown (range from 0.84–0.94 according to different devices). On the contrary, data on the efficacy of sleep showed only a weak correlation (range from 0.21–0.34 according to different devices used).

The results of the studies afore-mentioned prove that some indicators (e.g. HRV and sleep duration) can be estimated quite precisely via features of wearables, whereas discrepancies between the precision of different wearables still exist. Other indicators (e.g. voice variance) still lack scientific research in terms of validation of the measurement capabilities of wearables on the basis of standardized measurement methods. Furthermore, the measurement values of wearables can be influenced due to their localization. Schmidt et al. [33] recorded the same indicators using different measurement devices (chest strap and fitness tracker). Concerning skin conductance and temperature a higher sensitivity was shown for data of the chest strap sensors, compared to those of the fitness tracker (measurement accuracy GSR: chest strap 82%, fitness tracker 78%). More recent wearables are already equipped with systems to estimate the stress level by the manufacturer [58]. Up to now, the number of scientific studies validating features for the measurement of stress within commercial wearables is limited.

In addition, wearables also differ on the underlying algorithms, which analyse the signals captured by the sensors (raw data) to generate a (stress-related) output. Missing data can potentially lead to inaccuracies, which can be caused by a loss of contact of the sensors to the skin due to movement [59]. For instance, the accuracy of video and microphone signals can be affected by ambient noises [37].

Besides the validation of wearable features to measure specific parameters, this paper also focuses on selected indicators to objectively measure stress. Within the investigated studies everyday stress has been detected subjectively (e.g. based on questionnaires) or has been generated on the basis of a (scientific) stress test (e.g. TSST). To detect potential relations, specific indicators have been measured simultaneously to the event of stress.

Schmidt et al. [33] analysed various indicators (BVP, GSR, HRV, breathing rate, temperature, muscle contraction) and identified breathing rate as the most exact indicator in relation to stress. Results were confirmed by Plarre et al. [36], who also calculated the highest measurement accuracy for the breathing rate as a stress detection indicator. The results of Palanisamy et al. [60] showed the highest accuracy for HRV compared to temperature, GSR, and muscle contraction to identify stress. Mohino-Herranz et al. [61] compared HRV and breathing rate and demonstrated a lower error rate for stress measurement based on HRV data. Ghosh et al. [34] compared BVP, heart rate, skin temperature, and GSR, identifying the last-named as most accurate indicator for the measurement of stress. It was demonstrated that the indicator skin temperature shows the lowest accuracy compared to data of the subjective stress perception within various studies [33, 34].

Thereby the listed indicators are not only influenced by stress, but by other factors as well. HRV and GSR can for example be affected by physical activity [62]. Ambient temperature and humidity can have an impact on GSR [62]. To reduce the effects of interfering factors, data of various indicators can be jointly analysed. This reduces systematic errors and improves the precision of the measurement of stress. Muaremi et al. [39] demonstrated that stress could be measured based on smartphone usage data with 55% accuracy. Combining the data with HRV data, the accuracy could be improved up to 61%. The findings of Ghosh et al. [34] showed a measurement precision for

stress of 44% based on skin temperature and 79% based on GSR. The combination of various indicators (HRV, BVP, GSR) resulted into a precision of 89%. Adding contextual factors (activity, emotions, events) a further improvement up to 91% could be attained. Other potentially contextual factors to specify the measurement of stress are GPS, weather data, or calendar entries [63].
Discrepancies between the results might be explained by the application of different measurements (smart watch, fitness tracker, chest strap) from various manufacturers, as well as by the usage of various evaluation methods (e.g. one-way ANOVA, random forest) and classification models (binary: stress – no stress; tripartite: baseline – stress – relaxed). Moreover, the precision of individual parameters is mainly based on the sensitivity (as true positive rate). Information on specificity (as true negative rate) or correct classification rate are mostly missing in the results. Finally, as standardized measurement requirements are missing and external interfering factors have barely been considered or looked upon differently, a general ranking of the indicators is not possible.

## Limitations

This paper addresses a selection of stress indicators and their smart measurement methods and focuses on indicators which can be captured by wearable features. As we did not aim to run a systematic literature search, this paper might be prone to a selection bias and therefore, completeness cannot be claimed. Consequently, ◆ Figure 1 solely presents an overview of indicators, which have been addressed within the selected studies. Other important stress-related indicators, as functional magnetic resonance imaging (fMRI) and blood parameters, were not used within the selected studies and therefore are not included in this overview. Furthermore, it has to be mentioned that the selected studies were of a small sample size and the inclusion has been limited to studies published after the year 2000. Besides, stress was provoked through different stimuli (e.g. everyday stress, validated stress test in laboratory). Consequently, the results are only comparable to a limited extent. In addition, stress was differentiated most often categorically within the selected studies and not based on a possible stress continuum. Taken together, no final evaluation on the indicators can be done and no overall recommendation for the measurement of stress can be given.

## Conclusion

The objective of this paper was to identify stress indicators, which can be measured with wearables. The performed research demonstrates that especially physiological and behavioural indicators can be captured by wearable features. Results of the selected studies indicate a high measurement accuracy for some indicators like breathing rate and HRV which can be optimized by combining various indicators. Additionally, standardized questionnaires on the subjective stress perception can provide further information about the individual stress level. Up to now, comparisons on wearable features to detect stress based on standardized measurement methods are only focused on single indicators (HRV, sleep). For a valid selection of appropriate stress indicators, measured with a high accuracy via wearables, further research on the features of wearables with regard to the selected stress indicators is required. Therefore, standardized stress stimuli should be applied within large study cohorts.
The combination of various smart features to measure selected stress indicators (e.g. HRV, GSR) seems to provide an objective detection of stressful situations. Smartphone-based questionnaires on subjective stress perceptions can be used to add further value. Additionally, stress-related nutritional questionnaires (e.g. SSES) can be used to assign persons to different categories of stress-related nutritional behaviour. Based on these findings a future virtual dietary advisor should be able to detect stress situations based on the combination of different variables and measurements and hence generate situational and individual nutritional advices according to contextual personalized nutrition.

**Conflict of Interest**
Hans Hauner is a member of the expert advisory board of the Oviva AG, Christina Holzapfel is a member of the expert advisory board of the 4sigma GmbH. The remaining authors declare no conflict of interest.

**Financing**
This work has been supported by the competence cluster of nutritional research *enable* which has been funded by the Federal Ministry of Education and Research (Funding code: 01EA1807A, 01EA1807H; *enable* publication number: 042).

**Acknowledgement**
We would like to thank our cooperating partners of the technical university of Munich who gave their suggestions to the manuscript: Georg Groh, Monika Wintergerst, Markus Böhm, Martin Lurz, Gudrun Klinker, and Christian Eichhorn.

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**DOI: 10.4455/eu.2020.017**