Understanding and Changing Eating Behavior: In-the-Moment Assessments Provide New Perspectives for Health Promotion

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2. Referent: Prof. Dr. Harald T. Schupp
Danksagung

„In jede hohe Freude mischt sich eine Empfindung der Dankbarkeit.“

(Marie von Ebner-Eschenbach, 1911)

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Teilergebnisse dieser Dissertation wurden bereits in folgenden Beiträgen vorgestellt:

Publikationen


Konferenzbeiträge


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Summary

The rising prevalence of non-communicable diseases challenges health psychology research to find effective intervention strategies to change people’s health behaviors. It is particularly important to change eating behavior since this constitutes one of the most important preventive health behaviors. To facilitate eating behavior changes, new technologies such as smartphone applications (apps) are booming and are increasingly being considered in intervention development. App-based mobile interventions not only include a wide range of technical options along with the capability to reach a broad spectrum of the population, but also the possibility to intervene in real-life and real-time.

In order to use these advantages and open up new perspectives for changing eating behavior, the present dissertation aims to determine and quantify the potential of app-based mobile interventions for changing eating behavior by synthesizing the existing evidence. Moreover, deriving conclusions for future intervention development first requires a comprehensive understanding of eating behavior and its underlying psychological determinants as a necessary initial step towards changing it. For this purpose, the core determinants of daily eating behavior, including in-the-moment eating motives and eating happiness, are examined using an Ecological Momentary Assessment approach.

The first step of the present dissertation is to determine the potential of app-based mobile interventions as an effective strategy for achieving changes in eating behavior in a large spectrum of the population. For this purpose, a systematic review and meta-analysis is conducted, including 41 studies and comprising 6,348 participants and 373 investigated outcomes. This shows that app-based mobile interventions are effective in changing eating behavior, including positive effects on fruit and vegetable intake. Moreover, positive changes in nutrition-related health outcomes such as obesity indices and clinical parameters are observed, showing small-to-moderate effect sizes. Overall, the present evidence confirm the high potential of app-based mobile interventions for health promotion, and can support both research and practice in further exploiting their full potential.

In a second and third step, the core psychological determinants of daily eating behavior are investigated by analyzing in-the-moment eating motives and eating happiness experienced in-the-moment to achieve a comprehensive understanding of the targeted behavior. In both studies, a smartphone-based Ecological Momentary Assessment is
conducted over the course of a week to assess eating behavior, along with eating motives and eating happiness. Moreover, in addition to this real-life and real-time assessment approach, the present dissertation aims to point out new paths for data analysis, and a new visualization approach is introduced to handle the resulting high-dimensional data and allow an analysis at the between- and within-person levels. By combining the ecological valid assessment method with this comprehensive data analysis, the present dissertation gains considerable insight into the psychological determinants of daily eating behavior.

The investigation of eating motives as core motivators for daily food choices reveals differences between why people think they eat (dispositional assessment) and why they actually eat in the moment of consumption (in-the-moment assessment). In particular, visual appeal, liking, and pleasure show a high impact on in-the-moment eating behavior and can therefore contribute to the development of future app-based mobile interventions. Moreover, a more sophisticated analysis on the person and motive levels indicates considerably inter- and intra-individual differences, highlighting the importance of tailoring interventions not only to the individual but also to the situation.

Further, the investigation of eating happiness experienced in-the-moment as one important determinant of daily food choices indicates promising results for health promotion. Comparing eating happiness among different food categories reveals that healthy food choices such as fruits and vegetables evoke at least comparable to or even higher eating happiness than unhealthy food choices. Out of 14 different food categories, vegetable consumption contributes the largest proportion of total eating happiness, which indicates a ‘happy = healthy’ association. On the basis of these findings, it can be concluded that healthy food choices seem to also be happy food choices, and that the consumption of fruits and vegetables has both immediate and long-term beneficial psychological effects.

Bringing the present findings together, could pave the way towards a new approach in health promotion. By using in-the-moment interventions, eating happiness could be promoted as an important motivator that both drives human food choices and acts as an important cue for healthy eating. This might constitute an innovative intervention strategy that not only triggers healthy but also happy eating behaviors and enables the focus to be shifted towards a more positive and wellbeing-centered perspective on eating behavior.
Zusammenfassung


In einem zweiten und dritten Schritt werden situationsbezogene Essmotive und im Moment erlebte Esszufriedenheit als zentrale Determinanten des alltäglichen Ernährungsverhaltens untersucht, um ein tiefergehendes Verständnis von Ernährung zu etablieren. In zwei verschiedenen Studien werden zu diesem Zweck Smartphone-basierte Ecological Momentary Assessments (EMA) implementiert, um Essverhalten, Essmotive und Esszufriedenheit im Alltag zu untersuchen. Um den Umgang mit den daraus resultierenden


In ihrer Gesamtheit lassen sich diese Ergebnisse in eine neue, innovative Strategie zur Veränderung von Ernährungsverhalten integrieren, welche gewinnbringend für die Gesundheitsförderung eingesetzt werden kann. Die Verwendung von App-basierten mobilen Interventionen ermöglicht es, situationsbezogene Essmotive als bedeutende Determinanten alltäglichen Ernährungsverhaltens anzusprechen und Esszufriedenheit in der Essenssituation selbst zu fördern. Dieser vielversprechende Ansatz beinhaltet das Potential sowohl gesunde als auch glückliche Essensentscheidungen zu evozieren und ermöglicht somit eine positive Perspektive auf die Veränderung von Ernährungsverhaltensweisen.
General Introduction
1. General Introduction

1.1 Health and the Importance of Health Behaviors

Health represents one of the ultimate goods in human life (World Health Organization, 2018a), but there are many different risks that threaten its integrity. The leading current causes of morbidity and premature mortality are non-communicable diseases (NCDs) such as cardiovascular diseases, cancer, chronic respiratory diseases, or diabetes, which together account for over half of annual deaths worldwide (World Health Organization, 2008, 2010). NCDs are a global burden that challenges public health, but they also offer new opportunities for health promotion. Compared to communicable diseases, which are caused by pathogenic microorganisms, NCDs are strongly related to individual behavior (M. Conner & Norman, 2005; Fisher et al., 2011; World Health Organization, 2018b), and evidence suggests that behaviors such as healthy eating, physical activity, and non-smoking are important determinants for the prevention of NCDs (Covolo, Ceretti, Moneda, Castaldi, & Gelatti, 2017; Khaw et al., 2008; Loprinzi, Smit, & Mahoney, 2014), which could potentially reduce all-cause mortality risk by 66% (Loef & Walach, 2012).

However, studies across different countries and samples have shown that less than 15% of the population follows a healthy overall lifestyle (Ford, Bergmann, Boeing, Li, & Capewell, 2012; S. Keller, Maddock, Hannöver, Thyrian, & Basler, 2008; King, Mainous, Carnemolla, & Everett, 2009; Reeves & Rafferty, 2005). Unhealthy eating behavior in particular is a major concern (World Health Organization, 2019) and only a small percentage of the western population’s eating behaviors follows dietary recommendations (Krebs-Smith, Guenther, Subar, Kirkpatrick, & Dodd, 2010). For instance, less than one quarter of adults eat a sufficient amount of fruits and vegetables, whereas more than 80% show an increased consumption of high-energy-low-density foods (S. Keller et al., 2008; Moore & Thompson, 2015; Reeves & Rafferty, 2005).

On account of these alarming figures, which represent a high prevalence of unhealthy diets (Vandelanotte et al., 2016), changing individual eating behavior has become a public health challenge (Dietz et al., 2015; Fisher et al., 2011; Lim et al., 2012; Mirmiran, Mirbolooki, & Azizi, 2002; Rodgers, Watts, Austin, Haines, & Neumark-Sztainer, 2017). Research, the media, and policy-makers are all focused on the question of how eating behavior can be changed (Beaglehole et al., 2011; Ferrão et al., 2018; Hollands et al.,
2013; Pettigrew, 2016), but improving the initiation, adaption, and maintenance of health behaviors such as eating is often challenging and difficult to achieve (Bouton, 2014; Kelly & Barker, 2016).

As part of this search for new opportunities, ‘mobile health’ (m-Health) strategies are currently being suggested as the future of health behavior change (Fogg, 2007; Schembre, Liao, O’Connor, et al., 2018; West et al., 2017).

1.2 Changing Health Behaviors through M-Health Interventions

Within the last few years, m-Health interventions have become acknowledged as an innovative approach to changing health behaviors. M-health interventions aim to improve health, support health behaviors, and facilitate health behavior changes by employing mobile devices including smartphones, patient monitoring devices, personal digital assistants (PDAs), and other wireless devices (Albrecht, 2016; Eysenbach & Diepgen, 2001; Olson, 2016; World Health Organization, 2011). In particular, app-based mobile health interventions, which are delivered via smartphones, are attracting considerable interest, and are becoming an increasingly important part of both research and practice.

1.2.1 The Promising Potential of App-Based Mobile Interventions

Four main advantages of app-based mobile interventions as a new delivery mode for health promotion are summarized in Figure 1.1 and discussed below.

Firstly, smartphones are widely distributed across all demographic groups, as shown by the fact that 66% of the world’s population own and use a smartphone (Zenith, 2017). This makes it possible to reach a broad spectrum of the population and address a great variety of target groups, including both the general population and specific, high-risk audiences. Large-scale health interventions can therefore be delivered in a low-cost way compared to costly stationary treatment or face-to-face counselling (Albrecht, 2016; Becker et al., 2014; Zhao, Freeman, & Li, 2016). App-based mobile interventions therefore contain the potential to become a comparably cost-effective intervention strategy (Whittaker, Merry, Dorey, & Maddison, 2012).
Secondly, the permanent use of smartphones in daily life allows interventions to be delivered ‘on the go’ and integrated into people’s daily routines, which importantly means that interventions can be delivered in real-life. They can also be conducted anywhere, and in the person’s natural environment (DiFilippo, Huang, Andrade, & Chapman-Novakofski, 2015; Heron & Smyth, 2010). This enhanced convenience reduces the burden of taking part in an intervention, for both participants and investigators (European Comission, 2014; Whittaker et al., 2012).

Thirdly, in addition to the real-life component of app-based mobile interventions, they make it possible to enter data in real-time, capturing important day-to-day situations. Since data is processed simultaneously, interventions can take place immediately when they are needed, e.g. when people are making decisions that will affect their health (Free et al., 2013; Klasnja & Pratt, 2012; Schembre, Liao, Robertson, et al., 2018; Schoeppe et al., 2016). This facilitates the implementation of just-in-time interventions including time-sensitive behavior change strategies, such as giving instant feedback or providing helpful advice in tempting situations (Nahum-Shani, Hekler, & Spruijt-Metz, 2015; Nahum-Shani et al., 2014; Spruijt-Metz & Nilsen, 2014). It also makes it possible to utilize data at a personal level, allowing interventions that are tailored to the individual rather than relying on one-size-fits-all intervention approaches. For instance, individual goal-setting or personalized messages can improve adherence and user engagement, and subsequently intervention effects (Klasnja & Pratt, 2012; Schembre, Liao, Robertson, et al., 2018; Vandelanotte et al., 2016; Whittaker et al., 2012).

Fourthly, smartphone’s sophisticated capabilities can be fruitfully implemented for a bidirectional and interactive communication between researchers and study participants. Moreover, embedded sensors such as GPS functions or audio and video recordings, can be used for both research and practice (Elliston, Ferguson, Schüz, & Schüz, 2017; Rehg, Murphy, & Kumar, 2017). For instance, eating behavior assessments can be facilitated by taking pictures of the food being consumed (Boushey, Spoden, Zhu, Delp, & Kerr, 2017; Maringer et al., 2018) and sensor data can be used to tailor interventions to specific locations or settings (Elliston & Ferguson, 2018). These continuously expanding technological capabilities not only reduce the burden on participants and enhance the quality of the data collected but also make the health behavior interventions more effective.
These benefits show that smartphone apps could potentially be an innovative delivery mode for interventions (Mummah, 2016; Payne, Lister, West, & Bernhardt, 2015). However, to fully tap this potential for health promotion, it is necessary to determine how effective app-based mobile interventions are at changing eating behavior.

Figure 1.1. Major benefits of app-based mobile interventions.

1.2.2 Evidence for the Effectiveness of App-Based Mobile Interventions

More than 300,000 health apps are currently available for download worldwide. Despite this growing popularity, a large quantity of commercially-available health apps have not been empirically evaluated (Albrecht, 2013, 2016; Van Heerden, Tomlinson, & Swartz, 2012). They rarely include evidence-based strategies for behavior change (Bardus, van Beurden, Smith, & Abraham, 2016; Olson, 2016; Rivera et al., 2016) or reflect best practice guidelines for behavioral interventions (Albrecht, 2016; Cohn, Hunter-Reel, Hagman, & Mitchell, 2011; Gan & Allman-Farinelli, 2011; Hebden, Cook, van der Ploeg, & Allman-Farinelli, 2012). For instance, Rivera et al. (2016) showed in their scoping review of 393 apps that only 0.8% involved a scientific evaluation. Moreover, Chen, Cade, and Allman-Farinelli (2015) pointed out that the 28 highly-rated apps they reviewed lacked an adequate scientific perspective, and lacked any evidence-based behavior change strategies.
To overcome these issues, an increasing number of scientific trials have been published that explore the effectiveness of app-based mobile interventions at changing health behaviors and outcomes. Initial attempts have been made in the form of systematic reviews and meta-analyses to summarize the available literature and give an estimate of their effectiveness.

Reviews of early-stage evidence have already indicated the beneficial effects of mobile interventions (Bacigalupo et al., 2013; Buchholz, Wilbur, Ingram, & Fogg, 2013; Free et al., 2013). Further reviews extended these findings by adding positive effects on the improvement of health behaviors (Afshin et al., 2016; Schoeppe et al., 2016; Zhao et al., 2016), including smoking (Whittaker, McRobbie, Bullen, Rodgers, & Gu, 2016), substance abuse (M. Mason, Ola, Zaharakis, & Zhang, 2015), and physical activity (Eckerstorfer et al., 2018). These positive effects suggest that mobile interventions have a promising potential, and lead to the conclusion that they offer good preconditions to be implemented for health promotion (Covolo et al., 2017; Lyzwinski, 2014; Mateo, Granado-Font, Ferré-Grau, & Montaña-Carreras, 2015).

Nevertheless, there is still considerable uncertainty regarding the empirical evidence of app-based mobile interventions for changing eating behavior. Reviews and meta-analyses that investigated the effectiveness of mobile interventions on eating behavior are summarized in Table 1.1. They were selected by assessing the relevance of their target sample and behavior, and whether they included a sufficient number of studies. However, as Table 1.1 illustrates, the existing reviews and meta-analyses are still difficult to integrate due to a large degree of heterogeneity. On one hand, they differ in the type and number of implemented delivery modes (e.g. only app vs. multiple delivery modes) and focus on different study and sample characteristics (e.g. specific target groups vs. healthy people). On the other, they include various target behaviors (e.g. fruit and vegetable intake vs. caloric intake). Above all, one of the major issues is that most reviews and meta-analysis primarily targeted nutrition-related health outcomes such as weight loss or blood parameters, which did not allow conclusions about preceding eating behavior changes to be drawn. However, as health-related outcomes such as body weight are consequences of behaviors (Michie & Johnston, 2012), interventions cannot lead directly to changes in health outcomes: rather, they are mediated by preceding changes in health behaviors. Hence, in order to change
health outcomes such as obesity indices, preceding changes in health behaviors such as eating are necessary.

Therefore, based on the current state of research, the core question of how effective app-based mobile interventions are at promoting eating behavior changes cannot be satisfactorily answered. Although the majority of reviews and meta-analyses revealed positive effects (see Table 1.1), empirical evidence is not conclusive and there has been no systematic quantification of the effectiveness of app-based mobile intervention in changing eating behavior (Marcolino et al., 2018).

Besides the quantification of effectiveness, it is also important to determine which intervention characteristics are effective at inducing eating-behavior changes in app-based mobile interventions. To address this goal, it is first necessary to understand how health behaviors change and the factors by which they are determined. Therefore, in the following, health behavior theories and models will be discussed as a theoretical basis for health behavior changes.
Table 1.1

*Overview of reviews and meta-analyses targeting the effectiveness of mobile health interventions.*

<table>
<thead>
<tr>
<th>Author</th>
<th>Type</th>
<th>Mobile Device</th>
<th>Targeted Outcomes</th>
<th>Included Studies</th>
<th>Sample</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Afshin et al. (2016)</td>
<td>Systematic evaluation</td>
<td>Internet, mobile phone, personal sensors, and computer software</td>
<td>Diet, physical activity (PA), adiposity, tobacco, alcohol use</td>
<td>N=224 RCT and quasi-experimental studies Published: 1990 - 2013</td>
<td>Healthy adults</td>
<td>Internet and mobile interventions showed improvements in lifestyle behaviors up to 1 year</td>
</tr>
<tr>
<td>Bacigalupo et al. (2013)</td>
<td>Systematic review</td>
<td>Portable mobile technologies, e.g. palmtop computers, mobile phones, PDAs</td>
<td>Weight loss</td>
<td>N=21 RCTs Published: 1998 - 2011</td>
<td>Overweight and obese adults</td>
<td>Strong evidence was shown for weight loss in the short-term and moderate in the medium-term</td>
</tr>
<tr>
<td>Coughlin et al. (2015)</td>
<td>Literature review</td>
<td>Mobile phone apps</td>
<td>Healthy diet, PA, weight loss</td>
<td>N=12 RCTs and qualitative studies; Published: up to 2015</td>
<td>Adults without disease (except obesity)</td>
<td>Apps showed improved dietary compliance for low calorie, low fat, high fiber foods, and higher PA activity levels, resulting in more weight loss</td>
</tr>
<tr>
<td>Covolo et al. (2017)</td>
<td>Systematic review</td>
<td>Mobile phone apps, other supporting technologies (e.g. websites)</td>
<td>Weight management, PA, healthy eating, sun protection, stopping smoking, alcohol consumption</td>
<td>N=40 RCTs Published: up to 2016</td>
<td>People both healthy or at risk for chronic diseases</td>
<td>Apps showed modest efficacy for health promotion</td>
</tr>
<tr>
<td>Study</td>
<td>Type</td>
<td>Technology</td>
<td>Health Behaviors</td>
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<td>Study Results</td>
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</tr>
<tr>
<td>Free et al. (2013)</td>
<td>Systematic review</td>
<td>Any mobile technology including mobile phones, smartphones, portable devices</td>
<td>Disease management, stopping smoking, PA, calorie intake, sexual behavior, alcohol consumption</td>
<td>N=75 RCTs with 26 for health behaviors Published: 1990 - 2010</td>
<td>Adults (any age) Interventions showed suggestive benefits but results were not consistent</td>
<td></td>
</tr>
<tr>
<td>Heron &amp; Smyth (2010)</td>
<td>Review</td>
<td>Palmtop computer and mobile phone apps</td>
<td>Smoking, weight loss, anxiety, eating disorders, alcohol, healthy eating, PA</td>
<td>N=27 with 1 for diet</td>
<td>All Evidence found that EMI are efficacious for treating a variety of health behaviors and physical symptoms</td>
<td></td>
</tr>
<tr>
<td>Liu et al. (2015)</td>
<td>Meta-analysis</td>
<td>Mobile phone, SMS/MMS</td>
<td>Weight loss (body weight and BMI)</td>
<td>N=14 RCTs Published: up to 2014</td>
<td>Overweight and obese adults Interventions showed significant changes in body weight and BMI</td>
<td></td>
</tr>
<tr>
<td>Lunde et al. (2018)</td>
<td>Systematic review and meta-analysis</td>
<td>Mobile phone apps aiming to monitor PA and/or dietary habits (lasting for at least 3 month)</td>
<td>PA, physical fitness, dietary habits, quality of life, HbA1c; Meta-analysis only for HbA1c</td>
<td>N=9 RCTs and non-RCTs Published: up to 2017</td>
<td>Adults with NCDs Apps showed significant effects on HbA1c in both the short- and long-term</td>
<td></td>
</tr>
<tr>
<td>Lyzwinski (2014)</td>
<td>Systematic review and meta-analysis</td>
<td>Portable devices including smartphones, PDA, iPods and Mp3 players</td>
<td>Weight loss (BMI, waist circumference, body fat), dietary intake, PA</td>
<td>N=17 RCTs with 9 for diet and PA Published: up to 2013</td>
<td>Adults without pre-specified co-morbidities Interventions showed medium significant effect size for weight loss</td>
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<tr>
<td>Study</td>
<td>Study Type</td>
<td>Intervention Focus</td>
<td>Sample Size</td>
<td>Sample Characteristics</td>
<td>Key Findings</td>
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<tr>
<td>Mateo et al. (2015)</td>
<td>Systematic review and meta-analysis</td>
<td>Mobile phone apps, Weight, BMI, waist circumference, and PA</td>
<td>N=12 mostly RCTs (83.3%) Published: up to 2015</td>
<td>Healthy individuals (except obesity)</td>
<td>Apps showed significant changes in body weight and BMI</td>
<td></td>
</tr>
<tr>
<td>Schoeppe et al. (2016)</td>
<td>Systematic review</td>
<td>Mobile phone apps, Diet, PA, sedentary behavior, health outcomes</td>
<td>N=27 mostly RCTs (70%) with 13 for diet Published: 2006 - 2016</td>
<td>Adults and children</td>
<td>Apps showed modest evidence for diet, PA and sedentary behaviors</td>
<td></td>
</tr>
<tr>
<td>Schippers et al. (2017)</td>
<td>Meta-analysis</td>
<td>Mobile phones, Weight loss</td>
<td>N=12 RCTs Published: from 1996</td>
<td>16 years or older</td>
<td>Interventions showed modest reduction in body weight</td>
<td></td>
</tr>
<tr>
<td>Teasdale et al. (2018)</td>
<td>Systematic review and meta-analysis</td>
<td>‘Remotely delivered’ (including self-monitoring and tailored feedback)</td>
<td>N=26 RCTs Published: 1990 - 2017</td>
<td>Adults without history of eating disorders</td>
<td>Interventions showed small but significant effects on dietary improvements</td>
<td></td>
</tr>
<tr>
<td>Zhao et al. (2016)</td>
<td>Evidence review</td>
<td>Mobile phone apps, Mental health, alcohol addiction, PA, weight control, diet, medication management, lifestyle improvement</td>
<td>N=23 RCT, case-control and cohort studies with 4 for diet, PA, weight control Published: 2010 - 2015</td>
<td>All</td>
<td>17 studies reported statistically significant effects in the direction of the targeted behavior change</td>
<td></td>
</tr>
</tbody>
</table>

*Note.* Data are presented as reported in the primary article.
1.3 How to Change Health Behaviors?

1.3.1 Psychological Health Behavior Theories

Psychological health behavior theories try to explain how, when and why behavior or behavior changes occur. They attempt to predict the initiation of a healthy behavior, or changes from an unhealthy to a healthy one, through different behavioral determinants including key psychological variables and motives (Peters, De Bruin, & Crutzen, 2015). Moreover, they specify causal links between these behavioral determinants to explain processes of behavior change. These theories therefore provide useful insights into how behaviors change and serve as a theoretical basis for health behavior interventions.

Different health behavior theories exist. While most of these theories seem to encompass distinct concepts they show clear overlaps among their predictors and determinants, even if their terminology differs (Lippke & Renneberg, 2006; Noar, Chabot, & Zimmerman, 2008). An overview of classical health behavior theories is given below (see also Table 1.2). For a more detailed summary of health behavior theories, see e.g. Brinkmann (2014), M. Conner & Norman (2005), Lippke & Renneberg (2006), and Schwarzer (2004).

Health behavior theories can generally be systematized as either continuum or stage theories. Continuum theories include the Health Belief Model (HBM; Becker et al., 2014) and the Protection Motivation Theory (PMT; Rogers, 1975). Both include fear appeals as an important mechanism that determines behavior and behavior changes. The Theory of Reasoned Action (TRA; Ajzen & Fishbein, 1980), which was further developed into the Theory of Planned Behavior (TPB; Ajzen, 1985, 1991), as well as the Social Cognitive Theory (SCT; Bandura, 1986, 1998) can also be assigned to the group of continuum theories. In comparison to the HBM and the PMT, they focus more on social-cognitive determinants such as attitudes, outcome expectancies, perceived behavioral control (self-efficacy), and social components such as subjective norms and social support. Continuum theories are based on the assumption that individuals are located on a continuum of the likelihood of performing a behavior, with the different determinants predicting the formation of an intention to perform the respective behavior. However, evidence for the validity of these motivational theories shows that intention and health behavior only offer a medium correlation of 0.46 (Godin & Kok, 1996), and that intentions only account for 20 to 25% of the behavioral
variance (Sheeran, 2002). This means that the forming of intentions does not inevitably lead to the performance of a health behavior (M. Conner & Sparks, 2005; Renner & Schwarzer, 2003; Schwarzer, 2008; Sheeran & Webb, 2016), indicating the existence of an intention-behavior gap.

Continuum theories are contrasted with stage theories, which are represented by theories like the Transtheoretical Model (TTM; J. O. Prochaska, 2013; J. O. Prochaska, DiClemente, & Norcross, 1992; J. O. Prochaska & Velicer, 1997). Stage theories are characterized by the assumption that individuals pass through different qualitative stages when changing their behaviors.

One health behavior theory that integrates the different assumptions by targeting both a motivational and volitional stages is the Health Action Process Approach (HAPA; Schwarzer, 1992, 2004, 2008). The HAPA can be seen as a ‘hybrid model’ (Lippke & Renneberg, 2006). The motivational stage includes the formation of an intention, whereas the volitional stage explains the realization of this intention into actual behavior. The HAPA integrates important predictors from other health behavior theories, including self-efficacy, risk perception, and outcome expectancy (for an overview, see Table 1.2). Moreover, the intention-behavior gap is addressed by including further important determinants in the volitional stage, specifying phase-specific self-efficacy (Schwarzer & Renner, 2000) and planning mechanisms such as action and coping planning (Sniehotta, Scholz, & Schwarzer, 2005; Sniehotta, Schwarzer, Scholz, & Schüz, 2005). This integration of different determinants for intention formation and action initiation allows the HAPA to provide useful and evidence-based insights into how behaviors change (Schwarzer et al., 2007; Sniehotta, Scholz, et al., 2005; Sniehotta, Schwarzer, et al., 2005).

In conclusion, psychological health behavior theories represent a theoretical basis for deriving important strategies to support behavior changes. In addition to these theories, different taxonomies and protocols have been developed to summarize the existing behavior change strategies (see e.g. Bartholomew, Parcel, & Kok, 1998; Eldredge et al., 2016; Michie, Johnston, Francis, Hardeman, & Eccles, 2008). One of the most comprehensive approaches can be found in the Behavior Change Technique taxonomy (Abraham & Michie, 2008; Michie et al., 2013).
Table 1.2

Overview of social-cognitive determinants included in major psychological health behavior theories.

<table>
<thead>
<tr>
<th>Theory</th>
<th>Self-Efficacy</th>
<th>Outcome Expectancy</th>
<th>Risk Perception</th>
<th>Goals</th>
<th>Planning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Health Belief Model (HBM)</td>
<td>-</td>
<td>X</td>
<td>X</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Protection Motivation Theory (PMT)</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>-</td>
</tr>
<tr>
<td>Theory of Planned Behavior (TPB)</td>
<td>X</td>
<td>X</td>
<td>-</td>
<td>X</td>
<td>-</td>
</tr>
<tr>
<td>Social Cognitive Theory (SCT)</td>
<td>X</td>
<td>X</td>
<td>-</td>
<td>X</td>
<td>-</td>
</tr>
<tr>
<td>Transtheoretical Model (TTM)</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Health Action Process Approach (HAPA)</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
</tbody>
</table>

Note. The table is based on Lippke and Renneberg (2006).

1.3.2 The Behavior Change Technique (BCT) Taxonomy

The BCT taxonomy developed by Abraham and Michie (2008) aims at providing a standardized vocabulary to define and describe intervention characteristics (i.e. ‘active ingredients’) as observable and replicable components of behavior change interventions. The BCT taxonomy represents a hierarchical classification system for reliably specifying those components. The most recent version of this taxonomy (BCTtv1) lists 93 different strategies that facilitate behavior changes and organizes them into 16 main groups (Michie et al., 2013).

Empirical evidence indicates that implementing BCTs successfully leads to health behavior changes (Bert, Giacometti, Gualano, & Siliquini, 2014; Hasman, 2011; West et al., 2017; West et al., 2013), and specific strategies are beginning to gain attention in the context of app-based mobile interventions. Setting personal goals, receiving feedback, and reviewing relevant goals have proven to be successful strategies for promoting eating behavior changes (Direito et al., 2014; Samdal, Eide, Barth, Williams, & Meland, 2017). Moreover, self-monitoring is proclaimed as an effective strategy even though self-monitoring is included in almost all apps as a prerequisite for assessing eating behavior.

Although current evidence indicates that BCTs are associated with positive intervention effects, they are not sufficiently embedded in existing health behavior theories. As described above, BCTs represent the ‘active ingredients’ of interventions, summarized in a
comprehensive taxonomy. Central components of major health behavior theories such as the HBM, PMT, SCT, TPB, and HAPA are reflected in this taxonomy. Linking BCTs to theoretically-derived behavioral determinants such as self-efficacy can explain their effects on a targeted behavior (e.g. changing eating behavior). These links are referred to as ‘mechanisms of action’ (MoA). Figure 1.2 illustrates these mechanisms of action, which link the active ingredients of interventions with their theoretical basis (Michie et al., 2017). This conceptualization describes the processes through which a BCT as an active ingredient of an intervention can influence a target behavior by affecting behavioral determinants.

![Diagram](image.png)

**Figure 1.2.** Framework for the suggested relationship between BCTs, health behavior theories and models, and their mechanism of action on the target behavior.

In addition to BCTs and psychological health behavior theories, a more dynamic perspective on behavior and behavior changes is provided by the Fogg Behavior Model (Fogg, 2009b). In contrast to psychological health behavior theories, the Behavior Grid (Fogg, 2009a, 2018) further distinguishes different behavioral characteristics and different ways in which behaviors can change (see Figure 1.2 and Figure 1.3).

### 1.3.3 The Fogg Behavior Model (FBM) and Behavior Grid

The FBM (Fogg, 2009b) highlights the co-occurrence of three determinants that increase the likelihood of performing a behavior: Motivation, ability, and trigger. Motivation refers to an individual’s intention to perform the target behavior, whereas ability refers to the simplicity of the behavior (e.g. how easy the behavior is to perform). The manifestation of motivation and ability increases or decreases the likelihood of performing the target behavior.
(see Figure 1.3, left). Triggers are then needed to finally perform the behavior (Fogg, 2009b).

In addition, the Behavior Grid (Fogg, 2009a, 2018) distinguishes between different target behaviors and considers the fact that not all behaviors are alike. Although both are health behaviors, smoking less from now on might include different tasks and challenges than arranging a once-off cancer screening. The Behavior Grid (Fogg, 2009a, 2018) therefore differentiates between fifteen types of behavior, based on their characteristics (see Figure 1.3, right). The Behavior Grid’s axes combine two dimensions of the behavior; first the duration, which is referred to in the rows, and second the characteristics, which are referred to in the columns. Behavior duration includes one-time (dots), limited-period (spans), and prolonged period behaviors (paths). Behavior characteristics include initiating a new (green), or familiar (blue) behavior, increasing (purple) or decreasing (gray) behavior intensity, or stopping a behavior (black). These two dimensions can then be combined to define the type of behavior, e.g. a ‘purple path behavior’ aims at increasing a familiar behavior from now on. This differentiation is of great importance for health promotion since methods for getting people to buy a bicycle helmet or try a new food item once (green dot behavior) are different from methods getting people to wear this helmet or increase their fruit and vegetable intake over a prolonged period (green or purple span behavior). Comparing the different types of behaviors shows that target behaviors can differ considerably in their characteristics.

![Figure 1.3. The Fogg Behavior Model and Behavior Grid (Fogg, 2009a, 2009b, 2018).](image-url)
Returning to the initial aim of changing eating behavior through app-based mobile interventions, a necessary first step is therefore to identify and define the targeted aspect of eating behavior that is to be changed. This requires a thorough understanding of eating as it occurs in daily life. For this purpose, developing a real-time and real-life understanding of eating behavior and its psychological determinants becomes both a fundamental prerequisite and a crucial endeavor to effectively change it (Atkins & Michie, 2015; Bardus, Smith, Samaha, & Abraham, 2015; M. Conner & Norman, 2005; Heimlich & Ardoin, 2008; Jacquier, Bonthoux, Baciu, & Ruffieux, 2012; Maringer et al., 2018; Salah, Lepri, Pentland, & Canny, 2013).

### 1.4 Understanding Eating Behavior in Order to Change It

Eating is a core aspect of our everyday life (Stok et al., 2017) and people spend up to 133 Minutes per day eating and drinking (Statista, 2018a). Moreover, eating is not only a basic human need but also one of the most frequently experienced daily temptations (Hofmann, Vohs, & Baumeister, 2012). Even though each individual starts consuming only one food item – milk – (Rozin, 1996), consumption possibilities then extend to an endless variety of food items. With over 10,000 products available in German and over 30,000 in U.S. supermarkets (Food Marketing Institute, 2018; Statista, 2018b), the eating environment is characterized by an almost endless variety of food items together with an omnipresent abundance and easy accessibility of food (McCrory et al., 1999; Rozin, 2005). Eating no longer serves the sole function of supplying vital nutrition and energy, it is shaped by psychological, social, economic, and environmental factors (De Castro, 1996; McCrory et al., 1999; Rozin, 2005; Schütz, Revell, Hills, Schütz, & Ferguson, 2017; Stok et al., 2017), and can therefore be considered as a rather complex behavior (Fischler, 1980; Hummel & Hoffmann, 2016; Rozin, 1996). Due to this multidimensionality of factors influencing day-to-day food choices (Stok et al., 2017; Symmank et al., 2017), the question why we eat what we eat becomes increasingly important (Renner, Sproesser, Strohbach, & Schupp, 2012).

#### 1.4.1 Eating Motives

Although hunger is one of the most important motives for eating, there is a multitude of other compelling motives that drive human food choices and determine daily eating
behavior (Renner et al., 2012). For example, do people decide to eat chocolate bars because they are hungry, or because they look so appealing? Research identified social (e.g. because a food item was offered by a friend), situational (e.g. because the food looks appealing), emotional (e.g. to reward oneself), personal (e.g. because of weight concerns) and economic (e.g. because it was affordable) motives that regulate eating behavior beside hunger (see e.g. Jackson, Cooper, Mintz, & Albino, 2003; Renner et al., 2012; Steptoe, Pollard, & Wardle, 1995; Van Strien, Frijters, Bergers, & Defares, 1986).

When attempting to understand real-world eating motives, it is important to investigate their day-to-day manifestations. So far, eating motives have been measured by psychometric scales such as The Eating Motivation Survey (TEMS; Renner et al., 2012). These measurements commonly make assessments at one specific point in time, focusing on a person’s dispositional eating motives. This provides important insights into inter-individual differences, which is of great importance since individuals can strongly differ in the motives determining their daily food choices (Adriaanse, de Ridder, & de Wit, 2009; Heimlich & Ardoin, 2008). For instance, the eating behavior of individual A might be strongly influenced by weight concerns, whereas the eating behavior of individual B might be strongly influenced by how much the food costs.

However, since daily eating behavior is characterized by situational and context-dependent fluctuations (Chambers et al., 2016; Elliston et al., 2017; Phan & Chambers, 2016, 2018; Schüz, Schüz, & Ferguson, 2015; Villinger, Wahl, Sproesser, Schupp, & Renner, 2017; Wahl, Villinger, Sproesser, Schupp, & Renner, 2017) it is also suggested that intra-individual differences in eating motives exist. Therefore, it is also important to assess intra-individual variability. For this purpose, an assessment of eating motives across different eating situations is necessary.

In addition to a dispositional assessment, the question why people eat what they eat should therefore be repeatedly assessed throughout the day to capture in-the-moment eating situations. This combined perspective of dispositional and in-the-moment assessed eating motives could shed new light on the core determinants of daily eating behavior and provide important insights for changing eating behavior.
1.4.2 Eating Happiness

One of the most important and salient characteristics of daily eating behavior is the happiness derived from eating (Cornelis, Tordoff, El-Sohemy, & van Dam, 2017; Drewnowski, 1997; Glanz, Basil, Maibach, Goldberg, & Snyder, 1998; Phan & Chambers, 2016; Renner et al., 2012). When we eat, we expect emotional responses such as pleasure and satisfaction (L. G. Block et al., 2011; Pettigrew, 2016). These positive emotions experienced during eating play a considerable role in predicting eating behavior. It is therefore suggested that eating happiness constitutes an important psychological determinant for eating behavior.

However, eating is often considered as a trade-off between eating happiness experienced in-the-moment and future health benefits. On the one hand, consumers believe and the media promotes the belief that unhealthy foods are supposed to be particularly tasty and evoke a higher eating pleasure (Raghunathan, Naylor, & Hoyer, 2006). This assumption that unhealthy, high-caloric foods such as chocolate and cakes are more palatable and result in higher eating happiness compared to other food types, is called the ‘unhealthy = tasty’ intuition. On the other hand, the positive long-term effects of healthy food choices intensify. For instance, the consumption of fruits and vegetables is reputed to have both physical benefits and a positive impact on psychological well-being (Brookie, Best, & Conner, 2018; T. S. Conner, Brookie, Carr, Mainvil, & Vissers, 2017; Rooney, McKinley, & Woodside, 2013; Warner, Frye, Morrell, & Carey, 2017). The association between fruit and vegetable consumption and general well-being is shown not only in cross-sectional studies (Blanchflower, Oswald, & Stewart-Brown, 2013) but also in time-lagged correlations from daily diary studies, demonstrating that a higher consumption of fruits and vegetables is positively associated with improvements in positive affects for the subsequent day (White, Horwath, & Conner, 2013). Moreover, since longitudinal and long-term linkages between fruit and vegetable intake and well-being have been confirmed (Mujcic & Oswald, 2016), eating fruits and vegetables can be seen as an investment in future well-being. However, the pathways from eating fruits and vegetables to long-term well-being remain obscure. Physiological and biochemical effects of specific food elements or nutrients on well-being have been discussed (Rooney et al. 2013), while an alternative explanation might be that fruits and vegetables are also associated with high eating happiness experienced in-the-moment, which cumulates and in turn increases long-term well-being (Rooney et al. 2013).
This raises the question of whether the consumption of healthy food choices can also be associated with high eating happiness experienced in-the-moment, which would clearly contrast with the ‘unhealthy = tasty’ intuition. Initial evidence indeed supports this new perspective by showing that the mood-enhancing effects of eating are not necessarily related to unhealthy foods (Strahler & Nater, 2018; Wagner, Ahlstrom, Redden, Vickers, & Mann, 2014; Werle, Trendel, & Ardito, 2013). To examine the assumption that it is not just unhealthy foods that are tasty and make us happy, eating happiness needs to be comprehensively investigated in the moment of consumption. For this purpose, data collection should take place under real-life conditions to explore which food items and meal types are associated with daily eating happiness.

1.5 An In-the-Moment Approach to Assess Eating Motives and Eating Happiness

Investigating eating motives and eating happiness as underlying psychological determinants of daily food choices necessitates a real-life and real-time assessment of eating motives and eating happiness.

Mobile technologies offer an excellent means of capturing these in-the-moment assessments. In line with promising technological developments for changing behaviors, the same technologies can also be implemented to measure behaviors and behavioral determinants. Mobile assessments, often referred to as Ecological Momentary Assessments (EMA; Shiffman, Stone, & Hufford, 2008; Stone, Shiffman, Atienza, & Nebeling, 2007) or Ambulatory Assessments (AA; Trull & Ebner-Priemer, 2013, 2014), emerged from paper-pencil approaches that were combined with random prompts and became part of everyday life (for very early approaches see e.g. Fluegel; 1925; Csikszentmihalyi, Larson, & Prescott, 1977; Prescott & Csikszentmihalyi, 1981). Present approaches focus on digital technologies, including for instance smartphone-based assessments.

These smartphone-based assessments can be leveraged to advance psychological research. They can assess thoughts, feelings, behaviors, and environments in daily life to investigate how individuals feel, think, and behave in-the-moment (Geukes & Back, 2018), removing the problem of recall or memory biases (Garbinsky, Morewedge, & Shiv, 2014; Redelmeier & Kahneaman, 1996; Robinson, 2014; Robinson, Blissett, & Higgs, 2011) since the assessment takes place in the ‘hot’ moment of behavior or experience (Fahrenberg, Myrtek, Pawlik, & Perrez, 2007; Jezior, Lesher, & Popper, 1990). In terms of eating, motives
and happiness can both be assessed in the moment of consumption, together with the eating behavior itself, to capture the whole diversity of daily food intake across different eating situations, meal types, and foods categories, ensuring a high measurement accuracy and maximizing ecological validity (Shiffman et al., 2008; Stone et al., 2007; Trull & Ebner-Priemer, 2013, 2014).

However, despite their advantages, in-the-moment assessments are also accompanied by some problematic issues that go beyond ethical concerns and privacy issues (Albrecht, 2016; Harari et al., 2016; Short et al., 2018). For instance, low compliance rates can impede the accuracy of the measurement. However, compliance across different studies, including time- and event-based designs, is reported to be reasonable with compliance rates of over 70 to 80% (De Smet, Cardon, de Bourdeaudhuij, & Crombez, 2018; Ferrar et al., 2018; Hofmann et al., 2012; Short et al., 2018; Ziesemer et al., 2017).

Moreover, although in-the-moment assessments can take fluctuations in and the dynamics of eating behavior into account (Elliston et al., 2017; Schüz, Schüz, et al., 2015; Villinger et al., 2017; Wahl, Villinger, Sproesser, et al., 2017), they also challenge research to find new, elaborated methods of analyzing these high-dimensional data (Hamaker & Wichers, 2017; Short et al., 2018). An important achievement is therefore to develop methods that force data analyses to go beyond aggregated mean values and consider the between- and within-person levels. A new approach is proposed by Blumenschein et al. (2018), who developed an interactive and customized visualization tool called ‘Smart Explore’ (Blumenschein et al., 2018; for an illustration see Figure 1.4), which presents a sophisticated tabular-based visualization, and includes intuitive and interactive possibilities for analyzing high-dimensional data. Using tools such as ‘Smart Explore’ for data analysis in psychological research helps to gain a deeper understanding of in-the-moment assessed phenomena, including an understanding of clusters, correlations, and complex patterns of behaviors and experiences based on the raw data.

Taken together, the reported advantages of smartphone-based measures in combination with new analysis and visualization techniques show that in-the-moment assessments are a promising approach for measuring eating motives and eating happiness as important psychological determinants of daily eating behavior.
In the ‘Smart Explore’ tool, descriptors (e.g. means or variances) are normalized by dimension or subspace and mapped onto a color map. Algorithms extend the visualization and support the analysis of clusters, correlations, outliers, and patterns. Statistical measures are computed and visualized, along with missing values (for a detailed explanation, see Blumenschein et al., 2018).

1.6 Outline and Research Aims of the Present Dissertation

The overall aim of the present dissertation is to examine new opportunities and perspectives for changing eating behavior by taking an in-the-moment approach to first understanding and then changing eating behavior. To meet this objective, it explores the potential of app-based mobile interventions as delivery modes to induce changes in eating behavior. It further seeks to form a deeper understanding of eating behavior so that it can be changed effectively. And finally, by using an Ecological Momentary Assessment approach, preceding eating motives and resulting experienced eating happiness are investigated as important psychological determinants of in-the-moment eating behavior (see Figure 1.5).
The first goal is to determine the potential of app-based mobile interventions for changing eating behavior across a broad spectrum of the population by conducting a systematic review and meta-analysis, including both generally healthy and clinical samples. For this purpose, existing global evidence, which evaluates the effects of app-based mobile interventions on eating behavior changes, is synthesized and their effectiveness at changing eating behavior is quantified. Primary outcomes encompass nutrition behaviors such as the consumption of fruits and vegetables or caloric intake. Secondary outcomes include nutrition-related health outcomes such as obesity indices and clinical parameters. App features and intervention characteristics are also examined to identify the building blocks of successful interventions. For this purpose, interventions are evaluated according to the BCT taxonomy (Michie et al., 2013). Different moderators are also analyzed, including study characteristics such as study design, sample size, and study duration and intervention characteristics such as intervention duration, type of app, additional treatment components, and the number of implemented BCTs.

The second goal is to further illuminate eating motives as important determinants of daily food choices. Two different measurement approaches are used to investigate eating motives by comparing the 15 repeated in-the-moment assessed basic eating motives of TEMS (Renner et al., 2012) to a single-time-point dispositional assessment of the same motives. This combined approach allows the identification of differences between why people think they eat and why they actually eat in-the-moment. Moreover, an in-the-moment assessment of eating motives makes it possible to address both inter- and intra-individual differences to identify person- and situation-specific determinants for daily eating behavior. A visualization tool called ‘Smart Profile Explorer’ is then developed to facilitate the handling of the high-dimensional data resulting from this study, which builds on the ‘Smart Explore’ tool and aims to illustrate new and sophisticated ways of analyzing and visualizing in-the-moment assessed data. The ‘Smart Profile Explorer’ includes a person x motive data matrix, which allows inter- and intra-individual differences based on the raw data to be considered. Moreover, by providing an open-access online tool with sorting and filtering functions, it also supports an interactive and highly transparent data sharing approach.

The third goal of this dissertation is to examine eating happiness experienced in-the-moment in relation to different meal types and food categories to shed further light on the prevailing ‘unhealthy = tasty’ intuition. The aim is to investigate whether eating happiness is
specifically induced by unhealthy foods, and whether comparable eating happiness can be induced by healthy foods. Confirming a ‘healthy = happy’ association would indicate that eating happiness is associated with both long-term and in-the-moment happiness, which would offer a new perspective on eating behavior. For this purpose, eating happiness is assessed in the moment of consumption, using a smartphone-based EMA design. To assess the whole diversity of food intake, daily eating behavior is recorded together with the experienced eating happiness over the course of a week. Eating happiness assessed in-the-moment is then compared across different food categories and meal types.

In summary, the present dissertation aims to understand in-the-moment eating behavior and its psychological determinants in order to change it effectively. For this purpose, eating motives and eating happiness are examined as important psychological determinants of eating behavior in daily life using an in-the-moment assessment approach. Moreover, the potential of app-based mobile interventions to change eating behavior is determined. Since the findings of the present dissertation can serve to improve intervention practice, it also discusses how the present findings can be integrated into an app-based mobile intervention approach.
App-Based Mobile Interventions

The Effectiveness of App-Based Mobile Interventions on Nutrition Behaviours and Nutrition-Related Health Outcomes: A Systematic Review and Meta-Analysis

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2. App-Based Mobile Interventions

2.1 Abstract

A systematic review and meta-analysis was conducted to assess the effectiveness of app-based mobile interventions for improving nutrition behaviours and nutrition-related health outcomes, including obesity indices (e.g. BMI) and clinical parameters (e.g. blood lipids). Seven databases were searched for studies published between 2006 and 2017. Forty-one of 10,132 identified records were included, comprising 6,348 participants and 373 outcomes with sample sizes ranging from ten to 833, including 27 RCTs. A beneficial effect of app-based mobile interventions was identified for improving nutrition behaviours ($g = 0.19$, $CI = 0.06-0.32$, $p = 0.004$) and nutrition-related health outcomes ($g = 0.23$, $CI = 0.11-0.36$, $p < 0.001$), including positive effects on obesity indices ($g = 0.30$, $CI = 0.15-0.45$, $p < 0.001$), blood pressure ($g = 0.21$, $CI = 0.01-0.42$, $p = 0.043$), and blood lipids ($g = 0.15$, $CI = 0.03-0.28$, $p = 0.018$). Most interventions were comprised of four Behaviour-Change-Techniques (BCTs) clusters, namely ‘Goals/Planning’, ‘Feedback/Monitoring’, ‘Shaping Knowledge’, and ‘Social Support’. Moderating effects including study design, type of app (commercial/research app), sample characteristics (clinical/non-clinical sample) and intervention characteristics were not statistically significant. The inclusion of additional treatment components besides the app or the number or type of BCTs implemented did not moderate the observed effectiveness, which underscores the potential of app-based mobile interventions for implementing effective and feasible interventions operating at scale for fighting the obesity epidemic in a broad spectrum of the population.
2.2 Introduction

2.1 billion people worldwide were classified as overweight or obese in 2013 (Ng et al., 2014), which equates to 27.5% of all adults. Since being overweight or obese is associated with both physical and mental health consequences (Corica et al., 2015; Mokdad et al., 2003; Must et al., 1999) and huge economic costs (Withrow & Alter, 2011), it is one of today’s most crucial health issues. Since nutrition-related behaviours are well-established as major risk factors in becoming overweight (Rodgers et al., 2017; Thorpe, 2009), accounting for a considerable percentage of global disability-adjusted life years (Lim et al., 2012), preventing obesity and being overweight are not only personal matters but also of social, societal, and governmental interest (Bleich et al., 2017).

To fight the obesity epidemic, it is important to scale effective, feasible and affordable interventions that address a broad spectrum of the population. New intervention delivery modes such as e-Health (web-based) and m-Health (mobile) technologies are booming, and have even evoked a ‘self-track-trend’ (Servick, 2015). The term ‘m-Health’ refers to the concept of using mobile devices, such as mobile phones, personal digital assistants (PDAs), tablets, wireless devices, and smartphones, in medicine and public health. Early functionalities of these devices were text messaging (SMS), paging, and voice communication (Ali, Chew, & Yap, 2016). However, with the emergence of smartphones, more advanced functionalities including fully-automated applications (apps) were developed. App-based mobile health interventions are a particularly promising method of changing nutrition behaviours and nutrition-related health outcomes due to the high level of global smartphone penetration and the ease of installing apps in all kinds of mobile devices (Ali et al., 2016). The advantages of app-based mobile interventions are numerous, including the possibility of intervening in ‘real-life’ and ‘real-time’, while also offering interactivity (Heron & Smyth, 2010; Nahum-Shani et al., 2015; Riley et al., 2011), the ability to tailor interventions to personal needs, and the potential to provide effective and feasible interventions to different target groups (Rehg et al., 2017; Servick, 2015). So far, however, most users and patients have relied on commercially-available app-based mobile health interventions that have not been empirically evaluated, and rarely include evidence-based strategies for behaviour change (Bardus et al., 2016; Rivera et al., 2016). The effectiveness of app-based mobile health interventions must be determined to enable evidence-based
decisions, and to evaluate the potential contribution of app-based mobile interventions as large-scale health prevention measures.

While an increasing number of systematic reviews have examined technology-based interventions, a considerable gap exists in the research since most of these reviews have examined combined intervention delivery modes using various e- and m-Health technologies simultaneously (Afshin et al., 2016; Bardus et al., 2015; Cotie et al., 2018; Fedele, Cushing, Fritz, Amaro, & Ortega, 2017; Hutchesson et al., 2015; Lyzwinski, 2014; Olson, 2016; Roberts, Fisher, Smith, Heinrich, & Potts, 2017; Rose et al., 2017; Teasdale et al., 2018; Wang, Xue, Huang, Huang, & Zhang, 2017). In addition, they have a specific focus on study selection, target population, and outcome measure. More specifically, most reviews combine different target behaviours (e.g. diet and physical activity, see e.g. Afshin et al., 2016; Free et al., 2013; Heron & Smyth, 2010; Palmer et al., 2018; Schoeppe et al., 2016; Stephens & Allen, 2013; Zhao et al., 2016), they focus on specific audiences (e.g. adults with overweight or obesity, see e.g. Bacigalupo et al., 2013; Liu et al., 2015; with diabetes, see e.g. Kitsiou, Paré, Jaana, & Gerber, 2017; Liang et al., 2011) or patients with cancer, see e.g. Roberts et al., 2017) or research designs (e.g. randomized controlled trials, see e.g. Bacigalupo et al., 2013; Covolo et al., 2017; Hutchesson et al., 2015; Liu et al., 2015; Lyzwinski, 2014; Mateo et al., 2015; Palmer et al., 2018; Schippers, Adam, Smolenski, Wong, & Wit, 2017), or examine single nutrition-related health outcomes (e.g. weight loss, see e.g. Bacigalupo et al., 2013; Hutchesson et al., 2015; Liu et al., 2015; Schippers et al., 2017). The few reviews which specifically look at app-based mobile interventions are also heterogeneous in scope; some concentrate on single nutrition-related health outcomes (e.g. weight loss (Mateo et al., 2015), diabetes (Bonoto et al., 2017; Y. Wu et al., 2017), or glycaemic control (L. Wu et al., 2018)) or a specific target group (e.g. healthy adults, see e.g. DiFilipetto et al., 2015), while others combine multiple health behaviours (e.g. diet and physical activity, see e.g. Coughlin et al., 2015; Covolo et al., 2017; Lunde et al., 2018; Schoeppe et al., 2016; Zhao et al., 2016). Almost all previous reviews analysed the studies narratively and the number of intervention studies that they included was rather limited, ranging from four (DiFilipetto et al., 2015) to 27 (Schoeppe et al., 2016). Not surprisingly, this leads to findings that are divergent, difficult to integrate, and limited in their ability to provide quantified effect sizes on the effectiveness of app-based mobile health interventions. Only six previous meta-analyses, which included between seven and 22 studies, revealed that app-based mobile interventions were associated with significant weight loss (El Khoury
et al., 2019; Mateo et al., 2015; Schippers et al., 2017), and improved diabetes indicators (Bonoto et al., 2017; Lunde et al., 2018; I. Wu et al., 2018). Based on these findings, app-based mobile interventions might be a promising approach for combating obesity and nutrition-related diseases but, to our knowledge, no conclusions about the effects of app-based mobile interventions on nutrition behaviours and nutrition-related health outcomes have yet been drawn, and there have been no attempts to quantify the effects. Addressing both nutrition behaviours and nutrition-related health outcomes provides a more comprehensive picture of the effectiveness of mobile interventions using a fully-automated mobile dietary application, as intervention studies often target multiple outcomes within the same study.

Therefore, the aim of this systematic review and meta-analysis was to address these research gaps by evaluating the effectiveness of mobile interventions using a fully-automated mobile dietary application on nutritional outcomes in both healthy and clinical audiences. Nutritional outcomes included (1) nutrition behaviours (primary outcomes) such as nutrition scores, calorie intake and (2) consequent nutrition-related health outcomes (secondary outcomes) such as obesity indices (e.g. BMI) and clinical metabolic parameters (e.g. blood lipids). Unlike most previous reviews that have narratively summarised empirical evidence, we add to the literature by conducting both a systematic review and a meta-analysis using a random effects model for quantifying intervention effects. In addition, we extended the scope of previous reviews by examining relevant moderator effects such as sample characteristics and the duration of the intervention, and assessing the ‘building blocks’ of app-based mobile interventions that target nutrition behaviours and nutrition-related health outcomes by coding the intervention characteristics according to implemented Behaviour Change Techniques (BCTs; Michie et al., 2013).

2.3 Methods

The systematic review of the literature and quantitative meta-analysis to evaluate the effectiveness of app-based mobile interventions on nutrition behaviours and nutrition-related health outcomes were conducted according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Moher, Liberati, Tetzlaff, Altman, & Group, 2009) (see Appendix 2.1 for the completed PRISMA checklist).
2.3.1 Search Strategy and Selection Criteria

To investigate the effectiveness of app-based mobile dietary interventions for both clinical and healthy samples in changing nutrition behaviours and nutrition-related health outcomes, studies were eligible if they (1) included a mobile intervention using a fully-automated mobile application, (2) the app assessed any kind of nutrition behaviour, (3) the measured outcome was nutrition-related, including either nutrition behaviours or nutrition-related health outcomes, and (4) targeted adolescents or adults.

Any intervention study design or study population from clinical and healthy audiences was considered for inclusion. All types and units of measurement for nutrition behaviours and nutrition-related health outcomes were acceptable (e.g. self-report, objective measures, calories, kilograms). The app intervention could be a stand-alone intervention using apps only, or a multi-component intervention where the use of an app was one of several intervention components (e.g. face-to-face counselling, dietary education). Randomized controlled trials (RCTs) and pre-post studies were included if they encompassed an intervention that was delivered through an app that targeted nutrition behaviours or nutrition-related health outcomes. We considered both between (control-intervention) and within (pre-post) comparisons for the quantitative meta-analyses. We looked at studies between 2006 and June 2017, since smartphones and apps are a recent development over the last ten years. Studies were excluded if they were (1) not available in English language, (2) published before 2006, (3) targeting children (12 years of age or younger), (4) papers, study protocols or conference presentations that did not report empirical data, or (5) the app did not assess any kind of nutrition behaviour.

To ensure that the literature search was multidisciplinary and comprehensive, we searched databases from the fields of medicine, nutrition and sport (MEDLINE, PubMed, PsycInfo, PsycIndex, PsycArticle, SPORTDiscus, and Web of Science) using a predefined systematic database search protocol developed in cooperation with a scientific literature specialist from the university library. The search strategy incorporated both keywords and a controlled vocabulary (e.g. Medical Subject Headings, MeSH terms) and free-text search terms. The complete search terms as well as a specification of the search strategy are provided in Appendix 2.2. We also searched reference lists of relevant review papers and retraced study protocols and conference presentations to identify other potentially eligible studies.
After removing duplicates, articles were selected in a three-step process (see Figure 2.1). Firstly, trained reviewers independently screened titles and abstracts according to the four eligibility criteria, with no reviewer screening both the title and abstract of the same paper. The full-text articles that remained after this first selection were then screened independently by two authors (KV/DW), who also screened a random sample of 25 studies to ensure that the four eligibility criteria were being applied consistently. Disagreements were resolved through discussion by the authors until a consensus was reached.

2.3.2 Data Extraction

A standardized manual for data extraction was developed by the authors, and two authors (KV/DW) independently extracted key study and sample characteristics (including study design, number and type of participants, and dropout rate), intervention characteristics (including type of intervention, duration, Behaviour Change Techniques (BCTs, Michie et al., 2013), and type of app used), nutrition assessment (including quantity and type of food assessed, assessment method), and prespecified outcomes. The information was then entered into a customized Excel database and discussed by the authors. The coders were trained in recognising BCTs as defined by the v1 taxonomy and reference list (Michie et al., 2013). The v1 taxonomy includes a total of 93 BCTs such as “Goal Setting for Behaviours” (BCT 1.1), which describes a behaviour goal such as eating five pieces of fruit per day, or “Goal Setting for Outcome” (BCT 1.3), representing a positive outcome of a wanted behaviour, e.g. a weight loss goal of 0.5 kg over one week as an outcome of a changed eating pattern. Both BCTs belong to the BCT cluster “Goals & Planning” (BCT 1). In total, the v1 taxonomy includes 93 BCTs which are grouped into 16 BCT clusters. The coders independently extracted and coded the 93 BCTs and 16 BCT clusters, and disagreements were resolved through discussions between the authors until a consensus was reached. Since missing details in the descriptions of the interventions made it impractical to only analyse BCTs that were implemented in the app, additional treatments were also considered when classifying the implemented intervention strategies. In order to retrieve as much detail and information about the interventions and BCTs as possible, we used three sources: (1) the description and information provided in the retrieved articles, (2) the original apps used in the included studies (which we downloaded for data extraction where possible), and (3) in case of incomplete reports, we contacted the authors and asked for the missing information.
Hence, we took a great deal of effort to retrieve as much information as possible, so we could make objective and non-contentious decisions. Neither authorship, publication journal nor study results were blinded for data extraction.

2.3.3 Outcomes

Our primary outcomes were changes in nutrition behaviours, including changes in overall nutrition (e.g. healthy eating score), the consumption of specific foods (e.g. fruit and vegetables), nutrient intake (e.g. vitamin C), and caloric intake. Secondary outcomes were nutrition-related health outcomes including obesity indices (e.g. body weight, BMI) and clinical parameters (e.g. blood lipids, blood pressure). See also Appendix 2.8 for the identified outcomes included in the present meta-analysis (three right-hand columns).

2.3.4 Study Quality Assessment

The quality of the included studies was independently evaluated by two authors (KV/DW) according to the 25 criteria outlined by the CONSORT 2010 checklist (Schulz, Altman, & Moher, 2010). Criteria and respective items are related to the background and objectives, methods (including participant selection and outcome measures), study analysis and results, and potential selection bias or bias from funding (see Figure 2.2 and Appendix 2.4 for a definition of all 25 criteria). While the CONSORT checklist is intended for controlled trials, most criteria are applicable to other study designs and the weaker study designs justifiably received a lower score than studies using a controlled trial design. This approach has been used in other reviews (Maher et al., 2014; Schoeppe et al., 2016). Each item of the 25 criteria was rated as 1 (fulfilled), 0.5 (only partially fulfilled), 0 (not fulfilled), or not applicable to the study design. For example, criterion 2 ‘Background & Objectives’ entails two items with item 2a ‘Scientific Background and Explanation of Rationale’ and item 2b ‘Specific Objectives or Hypotheses’. Items were averaged per criterion. Adapted from previous reviews (Davies, Spence, Vandelanotte, Caperchione, & Mummery, 2012; Maher et al., 2014; Schoeppe et al., 2016), study quality was classified as ‘high’, ‘fair’, and ‘low’ based on an ‘overall study quality score’ (sum of points). Non-applicable criteria were discounted from the ‘overall study quality score’, and as a result the highest attainable quality score was not 25 for all studies. The study quality score for each study was divided by the highest
attainable score and multiplied by 100 to give a percentage of fulfilled criteria, with more than 66.6% = ‘high’, 50 to 66.6% = ‘fair’ and less than 50% = ‘low’ study quality (Figure 2.2). In addition, two authors (KV/DW) independently assessed the risk of bias according to the International Cochrane Collaboration criteria (Higgins et al., 2011). All study criteria were dual-coded, and any discrepancies were resolved by consensus.

2.3.5 Data Analysis and Synthesis

Standardized effect sizes were calculated to conduct quantitative meta-analyses. Effect sizes were calculated based on two approaches to account for between group (control-intervention) and within group (pre-post) comparisons (Morris & DeShon, 2002). Effect sizes were calculated separately for each measured primary and secondary outcome. Referring to Higgins and Green (2005), outcomes reported for subsamples (e.g. gender) and for studies with more than two groups were pooled to create single pair-wise comparisons to address the unit-of-analysis error due to ‘double counts’. Specifically, we combined all relevant intervention groups of a study into a single group, and combined all relevant control groups into a single control group. Cohen’s $d$ (Cohen, 1988) was calculated to provide a standardized effect size, and converted into Hedges’ $g$ to correct for the slight upward sample bias (Hedges, 1981). Hedges’ $g$ is a variation of Cohen’s $d$ that corrects for biases due to small sample sizes (Hedges, 1981). However, the effect sizes calculated in Cohen’s $d$ (see Appendix 2.11) or Hedges’ $g$ (see Appendix 2.12) were highly comparable and did not show marked statistical changes. The magnitude of Hedges’ $g$ is interpreted using Cohen’s convention as small (0.2), medium (0.5), and large (0.8; Cohen, 1988). The standardized mean difference was prioritized for between-group comparisons, and the standardized mean change was preferred for within-group comparisons. Reported effect sizes (e.g. odds ratios) were transformed into Cohen’s $d$. Furthermore, where possible, effect sizes were calculated from the statistics provided (Kontopantelis & Reeves, 2009; Polanin & Snislstveit, 2016). Positive effect sizes refer to intended changes by the intervention, indicating for example weight loss or an increase in fruit consumption.

The standardized effect sizes were synthesized using a meta-analysis model with random effects (Borenstein, Hedges, Higgins, & Rothstein, 2011). The choice of a fixed effect or a random effects statistical model affects the method used to calculate the total overall estimate, and hence the interpretation of the summary estimates. A fixed effect meta-analysis...
assumes all studies are estimating the same (fixed) intervention effect, whereas a random effects meta-analysis allows for differences in the intervention effect from study to study (see for example Riley et al. (2011) and Borenstein et al. (2011). Thus, random effects meta-analysis models address heterogeneity in the interventions effects caused by differences in study populations, interventions received, follow-up length, and other factors. However, random effects commonly yield a wider scatter of effect estimates and substantially wider confidence intervals than fixed effect models because each effect size has two components of variation, one due to sampling error, and one from the underlying distribution. In one study (G. Block et al., 2015), the within-group comparison effect sizes for weight ($d = 46.57$) and BMI ($d = 15.00$) deviated markedly from other studies, and these two outcomes effects were therefore excluded from the analyses. To address within-study dependencies, effect sizes of studies measuring multiple outcomes were aggregated using the univariate procedure developed by Borenstein et al. (2011; BHHR), which is considered the most precise and least biased (Hoyt & Del Re, 2015). Heterogeneity was investigated by $Q$-statistics and Higgins $I^2$.

The meta-analysis was conducted in a three-step process to account for the heterogeneity of study designs and outcome variables: (1) Firstly, an all-encompassing data set was created to calculate an overall effect size across all 373 identified primary and secondary outcomes, including both between- and within-group comparisons. Here, both within and between-group comparisons within a study were included. Sensitivity analyses were then computed following the recommendation of Viechtbauer and Cheung (2010) for outlier and influence diagnostic procedures to determine the stability of conclusions. Publication bias was assessed by a visual inspection of the funnel plot and Egger’s test (Egger, Smith, Schneider, & Minder, 1997). Subgroup analyses were conducted by type of comparison (between or within group). (2) Secondly, an adjusted data set was created which prioritized between-group comparisons over within-group comparisons (Cuijpers, Weitz, Cristea, & Twisk, 2017; Morris & DeShon, 2002). If a primary or secondary outcome was measured as both a between- and within-group comparison, the between-group comparison was prioritized and included in the data set. Within-group comparisons were only included when no between-group comparisons were provided for the outcome. Follow-up intervals from the baseline were calculated and grouped into short-term (less than three months), intermediate (three to six months), and long-term (more than six months) effects (Higgins & Green, 2005). In cases where an outcome (e.g. BMI) was measured multiple times within a
follow-up interval, the shortest in duration within the respective follow-up interval was prioritized. Subgroup analyses were performed for the three different follow-up intervals. Meta-regressions were also conducted for a-priori identified moderators, including study design (RCT vs. no-RCT), sample size and characteristic (clinical vs. non-clinical), study and intervention duration, dropout rate, and the number of included outcomes, as well as intervention characteristics including the type of app (commercial vs. research app), the inclusion of treatment components in addition to the app (stand-alone app (app only) vs. app combined with another intervention (app+)), and the number of BCTs implemented as intervention strategies. Furthermore, we conducted meta-regressions for samples including adolescents vs. adults and the quality of the studies according to the 25 CONSORT criteria (high vs. fair). We conducted additional moderation analysis to get more insights into the question of whether the presence or absence of each BCT identified in the included intervention studies impacts on the effect size estimates (see Goodwin, Ostuzzi, Khan, Hotopf, and Moss-Morris (2016), Tang, Smith, McSharry, Hann, and French (2018), and Williams and French (2011) for a similar approach). (3) Thirdly, to get more detailed insights into intervention effects, primary and secondary outcomes were analysed separately and further subdivided into short-, intermediate- and long-term follow-up intervals. In addition, constituent outcomes of nutrition behaviours and nutrition-related health outcomes were analysed separately (given a sufficient number of studies was available for the respective outcome), including caloric and fruit/vegetable intake as well as obesity indices (including body weight, BMI, body fat, hip, waist, and arm circumference), blood pressure, blood lipids (cholesterol, LDL, HDL, triglyceride), and blood sugar (including fasting (plasma) glucose, glucose, HbA1c, glucose/HbA1c).

All analyses were conducted in SPSS (version 24) and R using the packages compute.es, metafor, MAd and altmeta.

2.4 Results

The search identified a total of 11,707 electronic records. After removing duplicates, 10,132 titles were screened and the full text of 101 potentially eligible articles were retrieved (see Figure 2.1). Studies were excluded for multiple reasons, such as not having an intervention component (see Appendix 2.3 for a list of the excluded studies). In total, 41 studies (see Appendix 2.8) had investigated the effectiveness of app-based mobile
interventions for improving nutrition behaviours or nutrition-related health outcomes, and
met all four eligibility criteria. These 41 studies were then included in the systematic review
and quantitative meta-analysis.

| Identification | 11,707 records identified through database search
| | 8,765 through MEDLINE and Web of Science
| | 2,942 through PubMed, PsycINFO, PsycINDEX, PsycArticle, SPORTDiscus
| | 1,575 removed duplicates
| Screening | 10,132 titles screened
| | 9,004 excluded based on title
| | 1,128 abstracts screened
| | 1,027 excluded based on abstract
| | 339 no intervention
| | 98 no app used
| | 519 no results (e.g., study protocol)
| | 71 no nutrition-related outcome
| Eligibility | 101 full-text articles assessed for eligibility
| | 60 full-text articles excluded
| | 11 no intervention
| | 19 no app or automated feedback
| | 10 no results reported
| | 17 no nutrition-related outcome
| | 2 insufficient data
| Inclusion | 41 studies included in review and meta-analysis

*Figure 2.1. Study selection process.*

### 2.4.1 Study Quality

A detailed summary of quality assessments of the studies included according to the
CONSORT 2010 checklist (Schulz et al., 2010) is presented in Figure 2.2, and depicted as
a heat map. The 25 CONSORT criteria show a considerable variation across the 41 studies
(see Appendix 2.4 for criteria definitions and details). Overall, study quality ranged from
high (29 studies) to fair (12 studies) (see Figure 2.2 for study details). While the study quality
of 89% of the 27 RCT intervention studies was classified as ‘high’, 43% of the non-RCT
intervention studies were classified as being of ‘high’ quality. On average, the studies
included fulfilled 74% of the quality assessment criteria (range: 51% to 92%). Most studies
(at least 85%) met the CONSORT criteria requirements of providing a clear scientific
rationale and describing their scientific background and objectives (criterion 2), delivered
interventions (criterion 5), statistical methods (criterion 12), sample characteristics (criterion
15), and number analysed (criterion 16); they also considered limitations (criterion 20) and provided a consistent and balanced interpretation of their results (criterion 22). A majority of the studies (at least 63%) reported a detailed and complete description of the study design, participants, and outcomes as specified by the CONSORT criteria (criterion 3, 4, 6, 13, 14, 17). Fewer studies reported sample size calculations (criterion 7) and included randomization (criterion 8, 9, 10). Most of the studies did not include blinding procedures in their study design (criterion 11). Therefore, the results of the evaluation of risk of bias according to the six International Cochrane Collaboration criteria (Higgins et al., 2011) indicate a high or unclear risk of bias for the two blinding procedures criteria and the allocation concealment criterion. Risk of bias due to incomplete data or random sequence generation was low (36 studies and 27 studies, respectively). See Appendix 2.5 and 2.6.
Figure 2.2. Heat map visualizing the assessment of the 25 CONSORT criteria of study quality for the 41 studies included. Colours range from dark blue (item fulfilled) to light blue (item not fulfilled or unclear) and grey (not applicable). *Wharton et al., 2014: semi-randomized trial.
2.4.2 Study and Sample Characteristics

Overall, the 41 studies contained a total of 6,348 participants, yielded 373 primary and secondary outcomes, and were published between 2006 and 2017 (80.5% in 2014 or later). Of these, 27 studies were RCTs with either a 2-arm (19 studies), 3-arm (7 studies) or 4-arm (1 study) design. The remaining 14 studies were either single-arm, pre-post studies (8 studies) or studies with different control group designs (6 studies). Sample size in the studies ranged from ten to 833 ($M = 154.83; SD = 177.80$), with an average attrition rate of 18.7% ($SD = 16.27$; range: 0 to 72%). Sample descriptions were provided for 5,701 participants. The mean age was 41.51 years ($SD = 13.44$; range: 14 to 68 years) and 3,678 (64.5%) of the sample population were women. 38 studies focused on adults and three included adolescents aged between 13 to 19 years of age (Appel, Huang, Cole, James, & Ai, 2014; Froisland, Arsand, & Skarderud, 2012) and 13 to 17 years (Jensen et al., 2016). The average BMI of the sample population was 30.77 kg/m$^2$ ($SD = 3.73$; range: 22.25 to 36.40 kg/m$^2$). Most of the studies focused on clinical samples, with 16 studies including participants classified as being overweight or obese, and eight including patients diagnosed with diabetes or pre-diabetes. In addition, one study focused on survivors of endometrial and breast cancer (McCarroll et al., 2015) and one on smokers (Gordon et al., 2017). The remaining 15 studies focused on non-clinical, generally healthy samples. Study durations ranged from 20 days (Appel et al., 2014) to 24 months (Godino et al., 2016; Svetkey et al., 2015), with an average duration of 24 weeks ($SD = 21.71$). Intervention duration ($M = 21.05; SD = 21.17$) ranged from two weeks (Rabbi, Pfammatter, Zhang, Spring, & Choudhury, 2015) to 96 weeks (Godino et al., 2016; Svetkey et al., 2015).

A total of 30 different smartphone apps were used across the studies, mostly running on Android (9 studies), iOS (8 studies) or both (13 studies). To implement the intervention, 17 studies developed their own research app, while 15 used pre-existing, commercial apps. Two studies modified a pre-existing app to fit their study purposes, and seven did not provide respective information. Eighteen studies included an exclusively app-based intervention and 23 studies included additional treatment components which were delivered to participants either before (13 studies), during (23 studies) and/or after (2 studies) the app-based intervention.
2.4.3 Classification of Implemented Behaviour Change Techniques (BCTs)

The classification of implemented intervention strategies for achieving outcome changes according to the Behaviour Change Techniques (BCTs) taxonomy (Michie et al., 2013) showed that in total, nine of the 16 different BCT clusters with an average of 3.88 ($SD = 1.29$, range: 1 to 6) were employed across the 41 studies. Figure 2.3 depicts the frequency of BCT clusters implemented across the 41 studies and Table 2.1 the frequency of inclusion of single BCTs. A detailed summary of BCTs for each study is provided in Appendix 2.7.

As Figure 2.3 illustrates, the BCT intervention strategy clusters ‘Feedback & Monitoring’ (BCT 2, 41 studies), ‘Goals & Planning’ (BCT 1, 31 studies), ‘Social Support’ (BCT 3, 28 studies), and ‘Shaping Knowledge’ (BCT 4, 25 studies) were implemented in the majority of the 41 studies, while ‘Associations’ (BCT 7, 17 studies), ‘Reward & Threat’ (BCT 10, nine studies), and ‘Comparison of Behaviour’ (BCT 6, six studies) were less prominent, and the BCT clusters ‘Antecedents’ (BCT 12) and ‘Self-Belief’ (BCT 15) were only implemented in one study each.

In addition to the 16 main BCT clusters of the BCT taxonomy, intervention strategies can be further classified into 93 BCTs. The number of implemented BCTs across the 41 studies ranged from two to 11, with an average of 6.9 ($SD = 2.46$). For example, the frequently-implemented BCT cluster ‘Goals & Planning’ (BCT 1) includes nine different BCTs, of which seven were actually implemented across the 41 studies with ‘Goal Setting for Behaviours’ (BCT 1.1, 28 studies), ‘Goal Setting for Outcome’ (BCT 1.3, 14 studies), and ‘Review Behaviour Goal(s)’ (BCT 1.5, 20 studies) being realized the most frequently. The intervention strategies ‘Problem Solving’ (BCT 1.2, 6 studies), ‘Action Planning’ (BCT 1.4, 2 studies), and ‘Review Outcome Goal(s)’ (BCT 1.7, 8 studies) were implemented less often, and strategies such as ‘Discrepancy between Current Behaviour and Goal’ (BCT 1.6), ‘Behavioural Contract’ (BCT 1.8) and ‘Commitment’ (BCT 1.9) were implemented in none of the studies. The BCT cluster ‘Feedback & Monitoring’ includes seven different BCTs, of which five were actually implemented across the 41 studies. The most frequently implemented strategies were ‘Feedback on Behaviour’ (BCT 2.2, 37 studies), ‘Self-monitoring of Behaviour’ (BCT 2.3, 41 studies), ‘Self-monitoring of Outcome(s) of Behaviour’ (BCT 2.4, 17 studies), ‘Feedback on Outcome(s) of Behaviour’ (BCT 2.7, 11 studies), while the three remaining strategies were implemented either infrequently or not at all. The third main intervention strategy cluster
‘Social Support’, used in 28 studies, encompasses the three BCTs ‘Unspecified Social Support’ (BCT 3.1, 12 studies), ‘Practical Social Support’ (BCT 3.2, 10 studies), and ‘Emotional Social Support’ (BCT 3.3, 12 studies).

Figure 2.3. Absolute frequency of BCT clusters implemented across studies (k = 41) and relative proportion of implemented BCTs within each of the BCT cluster, as classified in the Behaviour Change Technique taxonomy (BCTs, Michie et al., 2013). The number before the decimal point denotes the BCT cluster; decimal and colour denote the specific BCT. Note. Only nine out of the 16 BCT clusters were implemented across the 41 studies. See Table 1 and Appendix 2.7 for absolute frequencies of implemented BCTs.

2.4.4 Assessment of Nutrition Behaviour

Of the 41 studies, 29 included an app-based assessment of the total nutrition intake (Ahn, Bae, & Kim, 2016; Allen, Stephens, Dennison Himmelfarb, Stewart, & Hauck, 2013; Appel et al., 2014; Balk-Moller, Poulsen, & Larsen, 2017; Brindal, Hendrie, Taylor, Freyne, & Noakes, 2016; Burke et al., 2017; Carter, Burley, Nykjaer, & Cade, 2013; Froisland et al., 2012; Fukuoka, Gay, Joiner, & Vittingoff, 2015; Gilson et al., 2017; Hales et al., 2016; Holmen et al., 2014; Ipjian & Johnston, 2017; Jensen et al., 2016; Kim, Faw, & Michaelides, 2017; Laing et al., 2014; Lee, Chae, Kim, Ho, & Choi, 2010; McCarroll et al., 2015; Rabbi et al., 2015; Recio-Rodriguez et al., 2016; Ross & Wing, 2016; Spring et
al., 2017; Stephens, Yager, & Allen, 2017; Svetkey et al., 2015; Thomas & Wing, 2013; Torbjørsen et al., 2014; Turner-McGrievy & Tate, 2011; Wharton, Johnston, Cumingham, & Sterner, 2014; Willey & Walsh, 2016), nine an assessment of specific foods (G. Block et al., 2015; Duncan et al., 2014; Gordon et al., 2017; Hebden et al., 2014; Mummah, Marthur, King, Gardner, & Sutton, 2016; Partridge, McGeechan, Baumann, Phongsavan, & Allman-Farinelli, 2017; Partridge et al., 2015; Steinert et al., 2016; Widmer, Allison, Lerman, & Lerman, 2015) such as vegetables or specific food consumption patterns (e.g. adherence to specific guideline-based recommendations), one assessed meal replacements (Brindal et al., 2013), and two did not provide further information (Godino et al., 2016; Johnston, Rost, Miller-Kovach, Moreno, & Foreyt, 2013). Twenty-one of the 32 studies which provided information about the features implemented for nutrition assessment included a database which participants could search to select the food items and meals they had consumed. Other features included a photo function (11 studies), a barcode scan (13 studies), an open format description of food items (10 studies), and the selection of food icons for specific foods (3 studies). In addition, 26 studies included a quantitative assessment of the amount of food consumed, with 20 studies providing further details about the assessment. All 20 studies used pre-defined amounts or quantities specified by the implemented databases, and nine studies also offered users the option to insert their own estimations of the amounts consumed.

2.4.5 Quantitative Synthesis of Primary and Secondary Outcomes

373 outcome effect sizes were reported in the 41 studies, covering a broad range of different primary and secondary outcomes (see Appendix 2.8, right-hand columns, as well as Appendix 2.12). The primary outcome, nutrition behaviours, was assessed through both general and specific nutrition scores (e.g. Healthy Eating Index (HEI) as a measure of diet quality, which reflects the concordance of dietary pattern with key dietary recommendations from the Dietary Guidelines for Americans; see Kennedy, Ohls, Carlson, & Fleming, 1995), total caloric intake, the consumption of specific foods (e.g. fruits, low-fat milk), consumption of meal types (e.g. take-away meals), or the intake of specific nutrients (e.g. sodium). Secondary outcomes also included a broad range of indicators ranging from obesity indices (e.g. body weight, BMI, body fat, waist circumference) to clinical metabolic parameters (e.g. blood pressure, glucose, or triglyceride).
The random effects meta-analyses based on the all-encompassing data set including all 373 primary and secondary outcomes effect sizes across the 41 studies showed an overall significant small-to-medium positive effect for app-based mobile interventions, with overall Hedges’ $g = 0.33$ ($CI = 0.21 - 0.44, p < 0.001$).

To assess the robustness of the effect, we conducted a sensitivity analysis including and excluding outliers (Viechtbauer & Cheung, 2010). One study was identified as an outlier (G. Block et al., 2015; Hedges’ $g = 1.80$). However, removing this study did not appreciably change the overall effect size (Hedges’ $g = 0.27$, $CI = 0.20 – 0.35$). Therefore, we kept the study in the analysis, given our interest in providing a comprehensive assessment of the overall impact of app-based mobile interventions on nutrition behaviours.

The investigation of publication bias, analysed by a visual examination of the funnel plot with the observed effect size $g$ on the horizontal axis plotted against the standard error, revealed no asymmetry (see Appendix 2.9). In addition, Egger’s regression coefficient (Egger et al., 1997) did not suggest a publication bias ($z = 0.47$, $p = 0.636$). However, since the $Q$ statistic for the overall effect across the 373 effects sizes was significant, indicating considerable heterogeneity between the 41 studies with $Q (40) = 312.19, p < 0.001$ and $I^2 = 86.79\%$, the type of comparison (between- or within-group) was further examined as a moderator. Analyses indicated a significant moderating effect, $Q (1) = 13.13, p < 0.001$, explaining $R^2 = 3.63\%$ of the among-study heterogeneity. Subsequent separate subgroup analyses yielded a significant small effect size of Hedges’ $g = 0.22$ ($CI = 0.08 - 0.36, p = 0.002$, $Q (27) = 200.61, p < 0.001$, $I^2 = 83.61\%$) for between-group comparisons ($k = 28$, outcome $n = 190$), and a significant medium-to-large effect size with Hedges’ $g = 0.47$ ($CI = 0.29 - 0.65, p < 0.001$, $Q (33) = 390.52, p < 0.001$, $I^2 = 93.61\%$) for within-group comparisons ($k = 34$, outcome $n = 183$). As the type of comparison (between- or within-group) was identified as a significant moderator, further analyses were conducted with the adjusted data set, which prioritized between-group effects.
### Table 2.1

Comparisons between effect sizes, according to whether specific BCT clusters and single BCTs were present or absent in the intervention study.

<table>
<thead>
<tr>
<th>Moderator</th>
<th>Present</th>
<th>Absent</th>
<th>Estimate</th>
<th>SE</th>
<th>p</th>
<th>CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>K</td>
<td>g</td>
<td>k</td>
<td>g</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BCT 1</td>
<td>31</td>
<td>10</td>
<td>0.27</td>
<td>0.06</td>
<td>0.13</td>
<td>0.663 -0.19 - 0.30</td>
</tr>
<tr>
<td>BCT 1.1</td>
<td>28</td>
<td>13</td>
<td>0.26</td>
<td>0.02</td>
<td>0.12</td>
<td>0.875 -0.21 - 0.25</td>
</tr>
<tr>
<td>BCT 1.2</td>
<td>6</td>
<td>35</td>
<td>0.30</td>
<td>0.04</td>
<td>0.15</td>
<td>0.803 -0.26 - 0.33</td>
</tr>
<tr>
<td>BCT 1.3</td>
<td>14</td>
<td>27</td>
<td>0.20</td>
<td>-0.10</td>
<td>0.11</td>
<td>0.396 -0.32 - 0.13</td>
</tr>
<tr>
<td>BCT 1.4</td>
<td>2</td>
<td>39</td>
<td>0.30</td>
<td>0.05</td>
<td>0.27</td>
<td>0.854 -0.48 - 0.58</td>
</tr>
<tr>
<td>BCT 1.5</td>
<td>20</td>
<td>21</td>
<td>0.26</td>
<td>0.00</td>
<td>0.11</td>
<td>0.973 -0.21 - 0.22</td>
</tr>
<tr>
<td>BCT 1.7</td>
<td>8</td>
<td>33</td>
<td>0.28</td>
<td>-0.11</td>
<td>0.13</td>
<td>0.391 -0.37 - 0.15</td>
</tr>
<tr>
<td>BCT 2</td>
<td>41</td>
<td>0</td>
<td>0.26</td>
<td>0.07</td>
<td>0.20</td>
<td>0.717 -0.32 - 0.46</td>
</tr>
<tr>
<td>BCT 2.2</td>
<td>37</td>
<td>4</td>
<td>0.23</td>
<td>0.05</td>
<td>0.11</td>
<td>0.623 -0.16 - 0.27</td>
</tr>
<tr>
<td>BCT 2.4</td>
<td>17</td>
<td>24</td>
<td>0.29</td>
<td>-0.29</td>
<td>0.29</td>
<td>0.330 -0.86 - 0.29</td>
</tr>
<tr>
<td>BCT 2.6</td>
<td>2</td>
<td>39</td>
<td>-0.06</td>
<td>0.02</td>
<td>0.12</td>
<td>0.895 -0.25 - 0.22</td>
</tr>
<tr>
<td>BCT 2.7</td>
<td>11</td>
<td>30</td>
<td>0.25</td>
<td>0.03</td>
<td>0.12</td>
<td>0.831 -0.21 - 0.27</td>
</tr>
<tr>
<td>BCT 3</td>
<td>10</td>
<td>13</td>
<td>0.24</td>
<td>0.10</td>
<td>0.12</td>
<td>0.381 -0.13 - 0.33</td>
</tr>
<tr>
<td>BCT 3.1</td>
<td>12</td>
<td>29</td>
<td>0.32</td>
<td>-0.16</td>
<td>0.13</td>
<td>0.209 -0.40 - 0.09</td>
</tr>
<tr>
<td>BCT 3.2</td>
<td>10</td>
<td>31</td>
<td>0.14</td>
<td>-0.06</td>
<td>0.11</td>
<td>0.608 -0.28 - 0.17</td>
</tr>
<tr>
<td>BCT 3.3</td>
<td>12</td>
<td>29</td>
<td>0.22</td>
<td>0.01</td>
<td>0.11</td>
<td>0.116 -0.04 - 0.38</td>
</tr>
<tr>
<td>BCT 4</td>
<td>25</td>
<td>16</td>
<td>0.32</td>
<td>0.17</td>
<td>0.11</td>
<td>0.116 -0.04 - 0.38</td>
</tr>
<tr>
<td>BCT 4.1</td>
<td>25</td>
<td>16</td>
<td>0.32</td>
<td>0.17</td>
<td>0.11</td>
<td>0.116 -0.04 - 0.38</td>
</tr>
<tr>
<td>BCT 5</td>
<td>6</td>
<td>35</td>
<td>0.08</td>
<td>-0.22</td>
<td>0.15</td>
<td>0.142 -0.51 - 0.07</td>
</tr>
<tr>
<td>BCT 6</td>
<td>4</td>
<td>37</td>
<td>-0.02</td>
<td>-0.29</td>
<td>0.19</td>
<td>0.118 -0.66 - 0.08</td>
</tr>
<tr>
<td>BCT 6.3</td>
<td>3</td>
<td>38</td>
<td>0.11</td>
<td>-0.13</td>
<td>0.20</td>
<td>0.524 -0.52 - 0.26</td>
</tr>
<tr>
<td>BCT 7</td>
<td>17</td>
<td>24</td>
<td>0.28</td>
<td>0.05</td>
<td>0.11</td>
<td>0.665 -0.17 - 0.26</td>
</tr>
<tr>
<td>BCT 7.1</td>
<td>17</td>
<td>24</td>
<td>0.28</td>
<td>0.05</td>
<td>0.11</td>
<td>0.665 -0.17 - 0.26</td>
</tr>
<tr>
<td>BCT 10</td>
<td>9</td>
<td>32</td>
<td>0.12</td>
<td>-0.17</td>
<td>0.13</td>
<td>0.189 -0.42 - 0.08</td>
</tr>
<tr>
<td>BCT 10.1</td>
<td>2</td>
<td>39</td>
<td>-0.19</td>
<td>-0.46</td>
<td>0.26</td>
<td>0.074 -0.96 - 0.05</td>
</tr>
<tr>
<td>BCT 10.3</td>
<td>7</td>
<td>34</td>
<td>0.16</td>
<td>-0.07</td>
<td>0.14</td>
<td>0.647 -0.35 - 0.22</td>
</tr>
</tbody>
</table>

*Note.* BCT cluster and single BCTs as classified in the Behaviour Change Technique taxonomy (BCTs; Michie et al., 2013). Comparisons were only made if the BCT cluster or single BCT was at least included in two intervention studies; $k =$ number of studies; $g =$ Hedges' $g$. 
The random effects meta-analyses based on the adjusted data set across the 41 studies including 224 effects sizes revealed an overall significant small but positive effect of Hedges’ $g = 0.26$ ($CI = 0.15 - 0.36$, $p < 0.001$). The $Q$ and $I^2$ statistics indicated considerable heterogeneity across studies with $Q(40) = 220.98$, $p < 0.001$ and $I^2 = 80.94\%$ (see Figure 2.4). Separate meta-regressions were conducted to identify moderating effects of study design (RCT vs. no-RCT), study quality (high vs. fair), sample size and characteristic (non-clinical vs. clinical sample; adolescents vs. adults), study and intervention duration, dropout rate, and the number of included outcomes, along with intervention characteristics including the type of the app, the inclusion of treatment components in addition to the app, and the number of BCTs implemented as intervention strategies. The meta-regressions revealed no significant effects, with $0.875 \leq p \geq 0.120$ (see Appendix 2.10). In addition to testing whether or not the number of BCTs implemented had a moderating effect, it was additionally tested whether specific BCTs were a predictor of the pooled effect size (see for a similar approach Goodwin et al. (2016), Tang et al. (2018), and Williams and French (2011)). The separate meta-regressions for the implemented BCT clusters and single BCTs (technique present vs. not present in the intervention) yielded no significant effect, with $0.973 \leq p \geq .074$ (see Table 2.1).
<table>
<thead>
<tr>
<th>Author(s) and Year</th>
<th>Hedges g [95% CI]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ahn et al., 2016</td>
<td>-0.22 [-0.76, 0.33]</td>
</tr>
<tr>
<td>Allen et al., 2013</td>
<td>0.09 [-0.42, 0.59]</td>
</tr>
<tr>
<td>Appel et al., 2014</td>
<td>0.64 [0.25, 1.03]</td>
</tr>
<tr>
<td>Balk-Moller et al., 2017</td>
<td>0.09 [-0.09, 0.27]</td>
</tr>
<tr>
<td>Block et al., 2015</td>
<td>1.19 [1.01, 1.37]</td>
</tr>
<tr>
<td>Brindal et al., 2013</td>
<td>0.17 [-0.28, 0.61]</td>
</tr>
<tr>
<td>Brindal et al., 2016</td>
<td>0.28 [0.10, 0.46]</td>
</tr>
<tr>
<td>Burke et al., 2017</td>
<td>0.67 [0.32, 1.02]</td>
</tr>
<tr>
<td>Carter et al., 2013</td>
<td>0.29 [0.00, 0.57]</td>
</tr>
<tr>
<td>Duncan et al., 2014</td>
<td>0.07 [-0.21, 0.34]</td>
</tr>
<tr>
<td>Froiland et al., 2012</td>
<td>0.21 [0.58, 0.99]</td>
</tr>
<tr>
<td>Fukuo et al., 2015</td>
<td>0.35 [0.05, 0.74]</td>
</tr>
<tr>
<td>Gilson et al., 2017</td>
<td>0.01 [-0.46, 0.49]</td>
</tr>
<tr>
<td>Godino et al., 2016</td>
<td>0.08 [-0.06, 0.22]</td>
</tr>
<tr>
<td>Gordon et al., 2017</td>
<td>0.24 [0.03, 0.45]</td>
</tr>
<tr>
<td>Hales et al., 2016</td>
<td>0.33 [0.04, 0.70]</td>
</tr>
<tr>
<td>Hebden et al., 2014</td>
<td>0.01 [-0.41, 0.43]</td>
</tr>
<tr>
<td>Holmen et al., 2014</td>
<td>0.06 [0.33, 0.45]</td>
</tr>
<tr>
<td>Ipjan &amp; Johnston, 2017</td>
<td>0.23 [0.41, 0.86]</td>
</tr>
<tr>
<td>Jensen et al., 2016</td>
<td>0.11 [0.47, 0.69]</td>
</tr>
<tr>
<td>Johnston et al., 2013</td>
<td>0.72 [0.51, 0.92]</td>
</tr>
<tr>
<td>Kim et al., 2017</td>
<td>0.16 [0.07, 0.24]</td>
</tr>
<tr>
<td>Laing et al., 2014</td>
<td>0.11 [-0.10, 0.32]</td>
</tr>
<tr>
<td>Lee et al., 2010</td>
<td>0.76 [0.35, 1.17]</td>
</tr>
<tr>
<td>Mc Caroll et al., 2015</td>
<td>0.02 [0.20, 0.34]</td>
</tr>
<tr>
<td>Mummah et al., 2016</td>
<td>0.37 [0.32, 1.07]</td>
</tr>
<tr>
<td>Partridge et al., 2015</td>
<td>0.16 [0.06, 0.37]</td>
</tr>
<tr>
<td>Partridge et al., 2017</td>
<td>0.59 [0.39, 0.80]</td>
</tr>
<tr>
<td>Rabbi et al., 2015</td>
<td>0.75 [0.19, 1.69]</td>
</tr>
<tr>
<td>Recio-Rodriguez et al., 2016</td>
<td>-0.01 [-0.15, 0.14]</td>
</tr>
<tr>
<td>Ross &amp; Wing, 2016</td>
<td>0.60 [0.13, 1.07]</td>
</tr>
<tr>
<td>Spring et al., 2017</td>
<td>-0.36 [-0.78, 0.06]</td>
</tr>
<tr>
<td>Steinert et al., 2016</td>
<td>0.58 [0.12, 1.04]</td>
</tr>
<tr>
<td>Stephens et al., 2017</td>
<td>0.01 [-0.46, 0.48]</td>
</tr>
<tr>
<td>Svetkey et al., 2015</td>
<td>-0.07 [-0.27, 0.13]</td>
</tr>
<tr>
<td>Thomas &amp; Wing, 2013</td>
<td>0.59 [0.13, 1.06]</td>
</tr>
<tr>
<td>Torgeson et al., 2014</td>
<td>-0.12 [-0.58, 0.34]</td>
</tr>
<tr>
<td>Turner-McGrievy &amp; Tate, 2011</td>
<td>0.16 [-0.15, 0.48]</td>
</tr>
<tr>
<td>Wharton et al., 2014</td>
<td>-0.34 [-0.91, 0.24]</td>
</tr>
<tr>
<td>Wider et al., 2015</td>
<td>0.35 [-0.17, 0.87]</td>
</tr>
<tr>
<td>Willey &amp; Walsh, 2016</td>
<td>0.70 [0.04, 1.35]</td>
</tr>
</tbody>
</table>

**Figure 2.4.** Forest plot showing the effects of app-based mobile interventions on nutrition behaviours and nutrition-related health outcomes ($k = 41$, outcome $n = 224$; adjusted data set).
2.4.6 Primary Outcomes

Twenty-one of the 41 studies assessed at least one primary outcome, addressing the effect of app-based mobile interventions on nutrition behaviours, resulting in 24 analysed behavioural outcomes (see Figure 2.5). Analysing the effect of app-based mobile interventions on behavioural outcomes \((k = 21, \text{outcome } n = 24)\) showed a small significant effect size, Hedges’ \(g = 0.19\) \((CI = 0.06 - 0.32, \rho = 0.004)\), with considerable heterogeneity of \(Q(20) = 57.41, \rho < 0.001\) and \(I^2 = 62.96\%\). Based on the number of available studies, behavioural outcomes were further separated into calorie \((k = 8, \text{outcome } n = 9)\) and fruit and vegetable intake \((k = 8, \text{outcome } n = 27)\). For a detailed summary, see Appendix 2.12 and 2.13. While both outcomes yielded overall positive effects, only the effect for fruit and vegetable intake reached statistical significance with Hedges’ \(g = 0.32\) \((CI = 0.15 - 0.50, \rho < 0.001, Q(7) = 11.83, \rho = 0.106, I^2 = 24.19\%\).

2.4.7 Secondary Outcomes

Thirty-four of the 41 studies included at least one secondary, nutrition-related health outcome, resulting in 42 analysed outcomes (see Figure 2.6). The effect size for nutrition-related health outcomes was small-to-medium, with Hedges’ \(g = 0.23\) \((CI = 0.11 - 0.36, \rho < 0.001)\). Effects sizes showed considerable heterogeneity between studies, \(Q(33) = 202.39, \rho < 0.001\) and \(I^2 = 84.15\%\). Furthermore, based on the number of available studies, assessed nutrition-related health outcomes were divided into obesity indices (e.g. body weight, BMI), blood pressure, blood lipids, and blood sugar (see also Appendix 2.12 and 2.13). The strongest effect was found for obesity indices with Hedges’ \(g = 0.30\) \((CI = 0.15 - 0.45, \rho < 0.001, Q(31) = 230.49, \rho < 0.001, I^2 = 87.88\%, k = 32, \text{outcome } n = 76)\). Separate analyses for body weight and BMI also revealed comparable effect sizes with an effect of Hedges’ \(g = 0.27\) for body weight \((CI = 0.13 - 0.41, \rho < 0.001, Q(30) = 125.59, \rho < 0.001, I^2 = 81.93\%, k = 31, \text{outcome } n = 39)\) and an effect of Hedges’ \(g = 0.37\) for BMI \((CI = 0.18 - 0.55, \rho < 0.001, Q(16) = 66.35, \rho \leq 0.001, I^2 = 81.55\%, k = 17, \text{outcome } n = 21)\). The effects for the other health indicators were also significantly positive but less pronounced, with blood pressure showing an overall effect of Hedges’ \(g = 0.21\) \((CI = 0.01 - 0.42, \rho = 0.043, Q(6) = 20.99, \rho = 0.002, I^2 = 73.81\%, k = 7, \text{outcome } n = 19)\), and blood lipids of Hedges’ \(g = 0.15\) \((CI = 0.03 - 0.28, \rho = 0.018, Q\).
(4) = 1.67, \( p = 0.797, \ I^2 = 0.00\%, \ k = 5, \ outcome \ n = 22 \). For cholesterol, a significant positive overall effect was found with Hedges’ \( g = 0.37 \) (\( CI = 0.04 - 0.71, \ p = 0.031, \ Q (4) = 21.99, \ p < 0.001, \ I^2 = 72.81\%, \ k = 5, \ outcome \ n = 7 \). The effect for blood sugar was also positive, but not statistically significant, Hedges’ \( g = 0.18, \ p = 0.429 (k = 7, \ outcome \ n = 10) \). We did not conduct separate meta-analyses for the remaining single health outcomes, since the numbers of studies and outcomes were too small.

2.4.8 Follow-Up Intervals: Short-Term, Intermediate, and Long-Term Effects

Effect sizes for different follow-up intervals were also examined. Assessing short-, intermediate- and long-term effects separately by subgroup analysis revealed positive effects for all follow-up intervals. However, only studies targeting short-term and/or intermediate follow-up intervals yielded significant small effect sizes (short-term: Hedges’ \( g = 0.27, \ CI = 0.12 - 0.43, \ p = 0.001, \ Q (12) = 22.34, \ p = 0.034, \ I^2 = 48.53\% \ k = 13, \ outcome \ n = 57 \); intermediate Hedges’ \( g = 0.28, \ CI = 0.15 - 0.40, \ p < 0.001, \ Q (28) = 186.20, \ p < 0.001, \ I^2 = 83.85\% \ k = 29, \ outcome \ n = 136 \)). The effects for long-term intervals did not reach statistical significance (Hedges’ \( g = 0.08, \ CI = -0.10 - 0.39, \ p = 0.404, \ Q (8) = 27.84, \ p = 0.001, \ I^2 = 72.99\% \ k = 9, \ outcome \ n = 31 \)). In a subsequent step, the effects of different follow-up intervals were examined separately for primary and secondary outcomes (see Figure 2.5 and 2.6). For nutrition behaviours (primary outcome), the effect for the intermediate follow-up interval was statistically significant with Hedges’ \( g = 0.25 \) (\( CI = 0.10 - 0.39, \ p < 0.001, \ Q (12) = 28.32, \ p = 0.005, \ I^2 = 52.32\% \ k = 13, \ outcome \ n = 49 \). The effect for nutrition-related health outcomes (secondary outcome) was also significant and small with Hedges’ \( g = 0.26 \) (\( CI = 0.12 - 0.40, \ p < 0.001, \ Q (24) = 167.52, \ p < 0.001, \ I^2 = 84.68\% \ k = 25, \ outcome \ n = 86 \). Effects of short- and long-term intervals did not reach statistical significance for either outcome. An overview of the different levels of analysis and corresponding statistical characteristics is summarised in Appendix 2.12.
Figure 2.5. Forest plot showing the effects of app-based mobile interventions on nutrition behaviours (primary outcome) for short-, intermediate-, and long-term follow-up intervals ($k = 21$, outcome $n = 24$; adjusted data set).
Figure 2.6. Forest plot showing the effects of app-based mobile interventions on nutrition-related health outcomes (secondary outcome) for short-, intermediate-, and long-term follow-up intervals ($k = 34$, outcome $n = 42$; adjusted data set).
2.5 Discussion

This meta-analysis of data from 41 studies, which included more than 6,300 participants, showed that app-based mobile interventions can be effective for changing nutrition behaviours and their main nutrition-related health outcomes in a wide range of study settings, with both clinical and generally healthy samples. The study extends previous work by including 373 primary and secondary outcomes addressing nutrition behaviours, obesity indices, and clinical metabolic parameters, revealing small-to-moderate positive effect sizes.

To make the results as relevant and robust as possible to inform prevention and clinical practice, we prioritized between group effects, which also resulted in a significant positive effect with Hedges’ $g = 0.26$ ($CI = 0.15 - 0.36$). We found no evidence that the inclusion of additional treatment components besides the app or the number of BCTs implemented moderated the observed effectiveness, which underscores the potential of app-based mobile interventions for implementing effective and feasible, cost-effective interventions with a high reach of target groups.

Although the results of studies comparing app-based mobile intervention versus control and pre-post comparisons yielded broadly consistent positive results on their relative effectiveness, a substantial diversity was observed in the range of efficacy across measured outcomes. In view of the rapid increase in the prevalence and disease burden of obesity worldwide, it is particularly encouraging that the results of app-based mobile interventions revealed a positive effect size for changing obesity indices with Hedges’ $g = 0.30$ ($CI = 0.15 - 0.45$) pooled across 32 studies. This confirms previous reviews summarising the effectiveness of various types of mobile interventions on obesity indices (El Khoury et al., 2019; Liu et al., 2015; Lyzwinski, 2014; Mateo et al., 2015; Schippers et al., 2017). This effectiveness was also observed for clinical metabolic parameters including blood lipids and blood pressure, although with smaller effect sizes, while a positive, non-significant effect was observed for blood sugar. This differential efficacy across nutrition-related health outcomes might reflect heterogeneous mechanisms and causes, smaller numbers of studies on clinical metabolic parameters, or different methodological issues affecting studies targeting obesity indices and clinical metabolic parameters. New developments in sensor technology, e.g. continuous glucose measurement, seem to offer promising avenues for improving the assessment of the clinical metabolic parameters implicated in body weight regulation (Koydemir & Ozcan, 2018).
2.5.1 Implications for Intervention Research and Clinical Practice

While the pooled effect size indicates a significant overall effect on nutrition behaviours and related health outcomes (Hedges’ $g = 0.26$, $CI = 0.15$ - $0.36$), converting this statistical significance into clinical significance is not unequivocally possible. Nakagawa and Cuthill (2007) and other researchers suggested taking multiple criteria into account besides comparisons to benchmarks values (e.g. Cohen’s classification), such as comparing effect sizes values of the current work with previous research and practical meaningful measures.

Comparing the effects size values of the current study with previous research shows that the observed effects coincide with m-Health interventions in the same and other domains. For example, Schippers et al. (2017) reported a pooled body weight reduction of $d = -0.23$, $CI = -0.38$ to $-0.08$ based on 12 studies, which is comparable to the present pooled obesity indices estimate which includes 32 studies (Hedges’ $g = 0.30$, $CI = 0.15$ - $0.45$). The effects size value is also comparable with effects sizes found in previous meta-analyses of weight loss interventions either using mobile phones (Khokhar et al., 2014; Lyzwinski, 2014) or not using mobile phones (Franz et al., 2007). A comparison with other domains leads to similar conclusions. For example, a recent meta-analysis in the domain of physical activity by Eckerstorfer et al. (2018) found a small overall effect of Hedges’ $g = 0.29$, ($CI = 0.20$ - $0.37$), which agrees with another recent meta-analysis of m-Health physical activity interventions (Direito, Carraça, Rawstorn, Whittaker, & Maddison, 2016).

As pooled overall estimates are based on standardized effects sizes converted from measures with different units (e.g. body weight loss in kg, BMI change etc.), translating them into physiological and clinical significance is not directly possible. However, effect sizes in original units, e.g. body weight loss in kg as a result of the intervention, can be obtained from reported changes in the intervention arms (see also Schippers et al., 2017). Summarizing the 13 intervention studies reporting changes in BMI (kg/m$^2$) in intervention arms (see Appendix 2.14, Table 14a), the average weighted BMI weight loss was $-0.90$ kg/m$^2$, ranging from $0.21$ kg/m$^2$ (Ahn et al., 2016) to $-1.41$ kg/m$^2$ (Hales et al., 2016). In the 29 studies reporting body weight changes in kilograms (or lbs) in intervention arms (see Appendix 2.14, Table 14b), the reduction in the intervention arm ranged from $0.64$ kg (Ahn et al., 2016) to $-9.65$ kg (Thomas & Wing, 2013) with an average weight loss of $-2.69$ kg. This weighted effect size for body weight reduction is similar to those reported in previous
meta-analysis of mobile or e-Health interventions within adults with chronic diseases (-2.45 kg; El Khoury et al., 2019), adults (-3.1 kg; Schippers et al., 2017), and adults with overweight or obesity (-2.70 kg; Hutchesson et al., 2015). Whether this is or is not enough to result in physiologically relevant effects or clinically meaningful health improvements probably depends on the situation and context (Nakagawa & Cuthill, 2007). For some individuals with overweight or obesity, this weight loss might be insufficient. However, from a public health perspective, small changes might also be considered as relevant (see Fisher et al. (2011) for a discussion).

The overall effectiveness of the interventions did not significantly vary in dependence of whether the interventions were based on apps as stand-alone or they were combined with additional intervention components. Eighteen of the 41 interventions studies (44%) used an app as a stand-alone intervention delivery method, while a larger proportion of interventions used an app in combination with other intervention strategies such as groups sessions (Burke et al., 2017), weekly meetings and online tools (Johnston et al., 2013), coaching calls, text messages and emails (Partridge et al., 2017), or face-to-face contact (Ross & Wing, 2016; Thomas & Wing, 2013) (see Appendix 2.8 for a detailed study description). Also the eleven most successful interventions studies (Appel et al., 2014; G. Block et al., 2015; Brindal et al., 2016; Burke et al., 2017; Johnston et al., 2013; Lee et al., 2010; Partridge et al., 2017; Ross & Wing, 2016; Steinert, Haesner, Tetley, & Steinhagen-Thiessen, 2016; Thomas & Wing, 2013; Willey & Walsh, 2016), which demonstrated a significant and positive overall pooled effect size, included four interventions studies (Appel et al., 2014; Lee et al., 2010; Steinert et al., 2016; Willey & Walsh, 2016) using an app as stand-alone strategy (36%). Comparing the effect sizes between these “success models” shows an overall comparable result pattern for stand-alone interventions (range: Hedges’ $g = 0.58$ (Steinert et al., 2016) to Hedges’ $g = 0.76$ (Lee et al., 2010)) compared to combined interventions (range: Hedges’ $g = 0.28$ (Brindal et al., 2016) to Hedges’ $g = 1.19$ (G. Block et al., 2015)).

A major finding of our analysis is that app-based mobile interventions are effective in changing nutrition behaviours, which is an essential prerequisite for changes in obesity indices and clinical metabolic parameters (Lyzwinski, 2014; Olson, 2016). However, the number and type of assessed behavioural outcomes varied between studies, which limited the calculation of effect sizes for all specific behavioural outcomes except for caloric and fruit and vegetable intake. A positive effect was found for these two behavioural outcomes,
but the pooled effect was only significant for fruit and vegetable intake (Hedges’ $g = 0.32$, CI = 0.15 - 0.50), which is one of the most commonly-measured dietary change indicators.

Studies showed substantial variations in the nutrition assessment methods, which are often study- and/or country-specific, and are not harmonized (Brug et al., 2017). This diversity in methods for assessing dietary intake might have contributed to the identified heterogeneity and the smaller effects sizes compared with nutrition-related health outcomes. It is therefore desirable to harmonize and standardize dietary assessment methods to enable better cross-study comparisons.

Behaviour assessments also provide a major input for creating tailored feedback implemented in mobile interventions (Schembre, Liao, Robertson, et al., 2018). So far, however, the full potential of mobile technology for dietary assessment has barely been realized. The focus is often on conventional food frequency questionnaires relying on retrospective self-reports, including memory bias (Boushey et al. 2017; Renner, Klusmann, & Sproesser, 2015). Mobile devices utilizing image-based methods offer in-the-moment dietary assessments, and it is likely that automated food identification and portion size estimation will allow more a comprehensive and accurate assessment of the quality and quantity of dietary intake (Boushey et al., 2017).

Considering that on average only four of the 16 different Behaviour Change Technique clusters were implemented in the interventions and that mobile devices impose excessive restrictions on message length and interaction-duration (Andrews, Ellis, Shaw, & Piwek, 2015; Fogg, 2009a, 2009b), the generally positive effects we observed across nutrition behaviours and major health outcomes were induced by a highly-focused intervention effort. The BCT clusters that were utilized, which form the central ‘building blocks’ of interventions, mainly encompassed goal setting, feedback & self-monitoring, information, and social support provision, which coincides with successful conventional individual and group-based interventions (Michie, Abraham, Whittington, McAteer, & Gupta, 2009) and reviews on m-Health interventions (Direito et al., 2016; Direito et al., 2014; Lyzwinski, 2014; Matthews, Win, Oinas-Kukkonen, & Freeman, 2016; Middelweerd, Mollee, van der Wal, Brug, & Te Velde, 2014; Samdal et al., 2017; Schippers et al., 2017; Schoeppe et al., 2016). Setting goals, monitoring behaviour, receiving feedback, and reviewing relevant goals in the light of feedback are central to self-management and behavioural control, as specified by control theories (Carver & Scheier, 1981; Gollwitzer & Oettingen, 2012). Considering that app-
based mobile interventions can operate at scale and at lower comparable implementation costs than individual and group-based interventions, they offer the potential to be a cost-effective method for improving nutrition behaviours and health indicators. A recent systematic review of economic evaluations of m-Health solutions (Iribarren, Cato, Falzon, & Stone, 2017) found a consistent overall reporting of positive economic outcomes (e.g. increase in life-years gained, cost savings, cost-effectiveness). Of 35 intervention studies using m-Health as primary intervention component, 26 (74%) reported a positive costing outcome. This supports the notion that mobile intervention might be a viable alternative to more cost-intensive face-to-face intervention formats, offering a potentially more effective alternative to common non-mobile interventions.

Although the number of single BCTs implemented varied from two to eleven between studies, the results did not show the association which some studies have suggested between greater effectiveness and an increasing number of BCTs (Direito et al., 2014; Middelweerd et al., 2014; Samdal et al., 2017; Tang et al., 2018; Webb, Joseph, Yardley, & Michie, 2010). We conducted additional moderation analysis to get more insights into the question of whether or not the presence of each of the 24 BCTs identified impacts on the effect size estimates (see Goodwin et al. (2016), Tang et al. (2018), and Williams & French (2011)). Whilst we identified 19 BCTs, which were implemented in two or more interventions studies, we did not find evidence that any of the BCTs predicted the pooled effect size. Hence, there does not appear to be a single effective approach to changing nutrition behaviours and their main nutrition-related health outcomes (see also Goodwin et al. (2016) for similar results but see Olander et al. (2013), Tang et al. (2018), and Williams and French (2011) for significant results). However, the effect of a single BCT may generally be very small (Michie, West, Sheals, & Godinho, 2018). For example, according to control theories (Carver & Scheier, 1981; Gollwitzer & Oettingen, 2012), setting and reviewing goals in the light of feedback are central to self-management, behavioural control, and ultimately behaviour changes. Accordingly, techniques revolving around goal setting and reviewing of goals are likely to be more effective if implemented conjointly in an intervention. However, ‘Goal Setting’ (BCT 1.1 and BCT 1.3) was implemented more commonly than ‘Review of Goals’ (BCT 1.5 and BCT 1.7).

The BCT taxonomy, while already complex with 16 different theory-based BCT clusters and 93 single BCTs, is mainly focusing on static concepts. However, since mobile
interventions distinguish themselves by being interactive, adaptive, time-sensitive, and intra-individually dynamic (Riley et al., 2011), more dynamic concepts including the timing of information provision, feedback, and reminders, or tailoring tasks and goals to individual progress and capacities as specified in persuasive technology, might be essential ingredients of effective focused mobile interventions (Fogg, 2009a, 2009b; Nahum-Shani et al., 2015; Riley et al., 2011; König, 2018; Wahl, Villinger, König et al., 2017). Hence, while mobile phones are a promising platform for accessible and cost-effective interventions, further development and innovation is required to ensure that the medium’s possibilities are leveraged to ensure efficacious changes (Schippers et al., 2017; Servick, 2015).

2.5.2 Study Strengths and Limitations

To the best of our knowledge, this is one of the most comprehensive and up-to-date reviews and meta-analyses to evaluate the effects of app-based mobile interventions on both major nutrition-related health outcomes and intermediate nutrition behaviours across a broad spectrum of the population, combining data from 41 studies, 6,348 participants and 373 outcomes with sample sizes ranging from ten to 833 participants and including 27 RCTs. The meta-analyses should therefore provide sufficiently reliable estimates of the intervention effects associated with app-based mobile interventions targeting nutrition behaviours and related health outcomes. By analysing the currently-available evidence for app-based mobile intervention studies and reporting results separately for study designs and characteristics, we address the observed heterogeneity and provide estimates across the whole range of interventions studies. We report results separately for two outcomes (nutrition behaviours and nutrition-related health outcomes), each according to short-term, intermediate, and long-term follow-up intervals. Importantly, results showed consistency between study designs, clinical and generally healthy samples, and between the different forms of analysis.

However, our review and meta-analysis has limitations. Since we strived to cover all the globally-available evidence on app-based mobile interventions targeting nutrition behaviours and nutrition-related health outcomes, considerable heterogeneity in the results could be due to methodological differences restricting the interpretation. Firstly, the systematic review is based on 30 different apps, with 15 studies using commercial apps. Although meta-regression did not yield a significant difference in effectiveness between
commercial and research apps, considerable heterogeneity within both types of apps might still be of concern. Secondly, estimated intervention effects were smaller in between-group comparisons than in within-group comparisons, which are associated with less precise estimations due to within-subject correlations and potentially confounding variables (Cuijpers et al., 2017; Morris & DeShon, 2002). Thirdly, although the pooled effect size did not vary in dependence of the study or intervention duration (see also Schippers et al. (2017) for similar findings for weight loss interventions), the effects sizes varied between short-term, intermediate-, and long-term follow-ups as for the latter, effect sizes were generally smaller and non-significant. There are several possible explanations for this, as many factors may have caused lower effectiveness for long-term outcomes. This differential efficacy might indicate a smaller number of studies with long-term follow-ups, a decrease in the maintenance of changes (Partridge et al., 2017), or a general lack of effectiveness (Balk-Moller et al., 2017; Godino et al., 2016; Spring et al., 2017; Svetkey et al., 2015). Specifically, systematic reviews and meta-analyses have shown that the efficacy of both traditional and technology-based weight loss interventions is greatest during the first six months (Hutchesson et al., 2015; Wadden, Butryn, Hong, & Tsai, 2014), which might be due to a well-documented decline in engagement with intervention modalities (Okorodudu, Bosworth, & Corsino, 2015). Another possible explanation could be bias in conducting, analysing, or reporting. In our analysis, neither dropout rate, sample size, study quality, intervention duration, number or type of included BCTs, or outcomes were associated with differential effectiveness. Also, the funnel plot did not provide consistent evidence for publication bias (see Appendix 2.9). However, such plots are known to be insensitive, and it is possible that a small study bias (Hopewell, Loudon, Clarke, Oxman, & Dickersin, 2009) might have led to an overestimation of the magnitude of the effectiveness.

Considering the BCTs, we have identified four core clusters including ‘Goals/Planning’, ‘Feedback/Monitoring’, ‘Shaping Knowledge’, and ‘Social Support’, but not all interventions using these strategies were more effective. There are various possible reasons for this. The BCTs may be implemented very differently in one study versus another. Since meta-analyses are reliant on published descriptions of intervention and control conditions, a further “drill-down” was limited. We included information from the articles, authors, and apps to decrease the likelihood of missing out on actually implemented BCTs. Since these are different data sources, the surplus of having more detailed information available comes with the downside that the available information differs between studies. As one anonymous reviewer
suggested, some apps might, for example, vary the information included depending on how they are used (e.g. some interactive apps trigger specific BCTs after repeated and constant use), which might explain why some BCTs are not coded. Methodological limitations may also have contributed. A certain number of studies and a sufficient variation among them in terms of intervention components and effect sizes is needed to have a chance of detecting relevant associations (see also Michie et al. (2018) for a detailed discussion). Specifically, there was insufficient variation between the 41 available studies for the assessment of the relative effectiveness of BCTs or evaluating different BCT combinations.

The potential for sample selection bias is another concern for the quality of mobile intervention studies (Schippers et al., 2017). In this respect, most of the studies scored in the moderate to high range on CONSORT criteria and neither study quality (high vs. fair quality) nor study design (RCT vs. no-RCT) moderated the effects. Moreover, the type of study sample did not reveal a significant moderating effect, indicating that the effects were comparable for studies with both clinical and generally healthy samples and across adolescents and adults. Overall, the findings suggest a high potential for app-based mobile interventions across multiple audiences, offering confidence that app-based mobile interventions are a promising method for fighting the obesity epidemic in a broad spectrum of the population.

2.5.3 Conclusion

The present findings represent one of the most comprehensive currently available evidence bases demonstrating that app-based mobile interventions are effective and highly promising for changing nutrition behaviours and nutrition-related health outcomes, which is essential for conquering the obesity epidemic. The overall pooled effect size was positive and, in general, the effects were relatively consistent across different outcomes, which provides some confidence in the conclusion that the effects are likely to be small but, to a certain degree, reliable and of practical relevance. Moreover, the present results do not indicate that this generally positive effect is limited to certain populations (healthy vs. clinical samples; adolescents vs. adults), intervention strategies (app only vs. app+ ; number or type of BCTs), or type of app (commercial vs. research). Considering that app-based mobile interventions can operate at scale and at lower comparable implementation costs than individual and group-based interventions, they offer the potential to be a cost-effective method for improving nutrition behaviours and health indicators in a wide range of target groups.
However, long-term follow-up effect sizes were generally smaller and non-significant. Hence, increasing engagement with intervention modalities might be a key avenue for future developments. Mobile technologies offer the possibility of realizing more dynamic concepts with interactive, adaptive, time-sensitive, and intra-individually dynamic strategies. However, all statements comparing the merits of mobile, app-based interventions with other delivery modes must be tempered by the potential limitations of the methodology (Ioannidis, 2008), the complexity of specific populations, and treatment settings. These findings raise important questions around intervention design. Additional research to unpack the effective ingredients of mobile interventions would be helpful to identify which intervention components might be the most likely to be universally effective, and which are more contextually dependent.
2.6 Acknowledgements

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Author’s Contributions

KV, DW, HS, and BR designed the systematic review, KV, DW, and BR did the search, KV & DW did the screening, data extraction process, assessed data quality and analysed data with critical comments from BR, HS, and HB. KV, DW and BR drafted the manuscript with input from HS and HB. All authors read, commented on and approved the draft and final manuscripts.

Competing Interests

No conflicts of interest are declared by the authors.

Role of the Funding Source

This research was supported by the Federal Ministry of Education and Research and the German Research Foundation within the research projects SmartAct (BMBF Grant 01EL1820A) and RiskDynamics (DFG Grant FOR 2374) granted to BR & HS. The funding source had no involvement in the study’s design; the collection, analysis, and interpretation of data; the writing of the report; or the decision to submit this article for publication.

Data sharing

No additional data available.
2.7 Appendix

Review

Appendix 2.1: PRISMA checklist.

Appendix 2.2: Search strategy.

Appendix 2.3: List of excluded studies and reasons \( (k = 60) \).

Appendix 2.4: CONSORT 2010 checklist with definitions.

Appendix 2.5: Cochrane risk of bias assessment across studies.

Appendix 2.6: Cochrane risk of bias assessment for each study.

Appendix 2.7: Behaviour Change Techniques (BCTs) for each study.

Appendix 2.8: Detailed description of included studies and analysed outcomes.

Meta-Analysis

Appendix 2.9: Funnel plot.

Appendix 2.10: Meta-regression and moderation effect results.

Appendix 2.11: Effect sizes (Cohen’s \( d \)) for all analysis levels and outcomes.

Appendix 2.12: Effect sizes (Hedges’ \( g \)) for all analysis levels and outcomes.

Appendix 2.13: Forest plots for outcomes (I. Nutrition behaviours, Figure 2.13a, 2.13b; II. Nutrition-related health outcomes, Figure 2.13c – 2.13i). 

Appendix 2.14: Weighted mean differences for BMI (Table 2.14a) and body weight (Table 2.14b).
Appendix 2.1

PRISMA checklist (Moher et al., 2009).

<table>
<thead>
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<th>Section/topic</th>
<th>#</th>
<th>Checklist item</th>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Title</td>
<td>1</td>
<td>Identify the report as a systematic review, meta-analysis, or both.</td>
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<td><strong>ABSTRACT</strong></td>
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<td></td>
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<tr>
<td>Structured summary</td>
<td>2</td>
<td>Provide a structured summary including, as applicable: background; objectives; data sources; study eligibility criteria, participants, and interventions; study appraisal and synthesis methods; results; limitations; conclusions and implications of key findings; systematic review registration number.</td>
<td>Yes</td>
</tr>
<tr>
<td><strong>INTRODUCTION</strong></td>
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<td></td>
<td></td>
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<td>Rationale</td>
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<td>Describe the rationale for the review in the context of what is already known.</td>
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<tr>
<td>Objectives</td>
<td>4</td>
<td>Provide an explicit statement of questions being addressed with reference to participants, interventions, comparisons, outcomes, and study design (PICOS).</td>
<td>Yes</td>
</tr>
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<td><strong>METHODS</strong></td>
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<td>Protocol and registration</td>
<td>5</td>
<td>Indicate if a review protocol exists, if and where it can be accessed (e.g., Web address), and, if available, provide registration information including registration number.</td>
<td>The review was conducted in accordance to a pre-defined but not published protocol</td>
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<td>Eligibility criteria</td>
<td>6</td>
<td>Specify study characteristics (e.g., PICOS, length of follow-up) and report characteristics (e.g., years considered, language, publication status) used as criteria for eligibility, giving rationale.</td>
<td>Yes</td>
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<td>Information sources</td>
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<td>Describe all information sources (e.g., databases with dates of coverage, contact with study authors to identify additional studies) in the search and date last searched.</td>
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<td>Search</td>
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<td>Present full electronic search strategy for at least one database, including any limits used, such that it could be repeated.</td>
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<td>Study selection</td>
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<td>State the process for selecting studies (i.e., screening, eligibility, included in systematic review, and, if applicable, included in the meta-analysis).</td>
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<td>Data collection process</td>
<td>10</td>
<td>Describe method of data extraction from reports (e.g., piloted forms, independently, in duplicate) and any processes for obtaining and confirming data from investigators.</td>
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<td>Data items</td>
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<td>List and define all variables for which data were sought (e.g., PICOS, funding sources) and any assumptions and simplifications made.</td>
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<td>Describe methods used for assessing risk of bias of individual studies (including specification of whether this was done at the study or outcome level), and how this information is to be used in any data synthesis.</td>
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<tr>
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<td>State the principal summary measures (e.g., risk ratio, difference in means).</td>
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<td>Synthesis of results</td>
<td>14</td>
<td>Describe the methods of handling data and combining results of studies, if done, including measures of consistency (e.g., $I^2$ for each meta-analysis).</td>
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<td>Risk of bias across studies</td>
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<td>Specify any assessment of risk of bias that may affect the cumulative evidence (e.g., publication bias, selective reporting within studies).</td>
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<td>Additional analyses</td>
<td>16</td>
<td>Describe methods of additional analyses (e.g., sensitivity or subgroup analyses, meta-regression), if done, indicating which were pre-specified.</td>
<td>Yes</td>
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</table>

**RESULTS**

| Study selection        | 17 | Give numbers of studies screened, assessed for eligibility, and included in the review, with reasons for exclusions at each stage, ideally with a flow diagram.                                                           | Yes |
| Study characteristics  | 18 | For each study, present characteristics for which data were extracted (e.g., study size, PICOS, follow-up period) and provide the citations.                                                                                       | Yes |
| Risk of bias within studies | 19 | Present data on risk of bias of each study and, if available, any outcome level assessment (see item 12).                                                                                          | Yes |
| Results of individual studies | 20 | For all outcomes considered (benefits or harms), present, for each study: (a) simple summary data for each intervention group (b) effect estimates and confidence intervals, ideally with a forest plot. | Yes |
| Synthesis of results   | 21 | Present results of each meta-analysis done, including confidence intervals and measures of consistency.                                                                                                  | Yes |
| Risk of bias across studies | 22 | Present results of any assessment of risk of bias across studies (see Item 15).                                                                                                                              | Yes |
| Additional analysis    | 23 | Give results of additional analyses, if done (e.g., sensitivity or subgroup analyses, meta-regression [see Item 16]).                                                                                     | Yes |
### DISCUSSION

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<td>Limitations</td>
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<td>Conclusions</td>
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<td>Provide a general interpretation of the results in the context of other evidence, and implications for future research.</td>
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### FUNDING

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<td>Describe sources of funding for the systematic review and other support (e.g., supply of data); role of funders for the systematic review.</td>
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### Appendix 2.2

Search strategy with general search terms used in the searches.

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<td>Outcomes</td>
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<td>Terms excluded</td>
<td>anti endomysial antibody OR IgA-endomysium antibodies OR eugenyl methacrylate OR epithelial membrane antigen OR ethylmethacrylate OR European Medicines Agency OR serum endomysial antibodies OR mental health</td>
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**MEDLINE and Web of Science**

**Search Term:**

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TOPIC: ((ambulatory assessment OR ecological momentary assessment OR EMA OR mHealth OR mobile health OR smartphone OR smart phone OR smartphone intervention OR smartphone application OR mobile application OR smartphone app OR mobile app OR mobile intervention OR mobile technology OR mobile technologies OR mobile phone OR mobile device) AND (healthy eating OR diet OR dietary OR food OR foods OR nutrition OR eating OR fruit OR fruits OR vegetable OR vegetables OR snack OR snacks OR snacking OR energy intake OR calorie intake OR caloric intake OR dietary intake OR dietary behavior OR food intake OR nutrient intake OR nutritional intake OR BMI OR body mass index OR adiposity OR weight OR body weight OR weight management OR weight loss OR weight reduction OR obesity OR obese OR health behavior OR health behavior change) NOT (anti endomysial antibody OR IgA-endomysium antibodies OR eugenyl methacrylate OR epithelial membrane antigen OR ethylmethacrylate OR European Medicines Agency OR serum endomysial antibodies OR mental health))
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Limits:
- Publication date: 01/01/2006 – 01/06/2017
- Language: English
- Search for: Topic

Hits:
- n = 8 765

PubMed

Search Term:

Limits:
- Publication date: 01/01/2006 – 01/06/2017
- Language: English
- Search for: Title and abstract

Hits:
- n = 1 679
Search Term:

(ambulatory assessment OR ecological momentary assessment OR EMA OR mHealth OR mobile health OR smartphone OR smart phone OR smartphone intervention OR smartphone application OR mobile application OR smartphone app OR mobile app OR mobile intervention OR mobile technology OR mobile technologies OR mobile phone OR mobile device ) AND ( healthy eating OR diet OR dietary OR food OR foods OR nutrition OR eating OR fruit OR fruits OR vegetable OR vegetables OR snack OR snacks OR snacking OR energy intake OR calorie intake OR calorific intake OR dietary intake OR dietary behavior OR food intake OR nutrient intake OR nutritional intake OR BMI OR body mass index OR adiposity OR weight OR body weight OR weight management OR weight loss OR weight reduction OR obesity OR obese OR health behavior OR health behavior change ) NOT ( anti endomysial antibody OR IgA-endomysium antibodies OR eugenyl methacrylate OR epithelial membrane antigen OR ethylmethacrylate OR European Medicines Agency OR serum endomysial antibodies OR mental health)

Limits:

- Publication date: 01/01/2006 – 01/06/2017
- Language: English
- Search for: All fields

Hits:

- \( n = 1263 \)
Appendix 2.3

List of excluded studies and reasons ($k = 60$).

$k = 19$: No app or automated feedback

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<th>Study</th>
<th>Reason</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blackburne, T., Rodriguez, A., &amp; Johnstone, S. J. (2016).</td>
<td>A serious game to increase healthy food consumption in overweight or obese adults: Randomized controlled trial.</td>
<td><em>JMIR Serious Games, 4</em>(2), e10. doi:10.2196/games.5708</td>
</tr>
</tbody>
</table>


\( k = 10 \): No results reported / no study conducted


$k = 11$: No intervention


$k = 1$: No nutrition related outcome targeted


$k = 17$: Abstract / proposal / statement


Watterson, T. A. (2012). Changes in attitudes and behaviors toward physical activity, nutrition, and social support for middle school students using the AFIT app as a supplement to instruction in a physical education class. (Graduate Theses and Dissertations). University of South Florida, United States of America.


$k = 2$: Insufficient data/method for assessing eating behavior in app

Elbert, S. P., Dijkstra, A., & Oenema, A. (2016). A mobile phone app intervention targeting fruit and vegetable consumption: The efficacy of textual and auditory tailored health information tested in a randomized controlled trial. *Journal of Medical Internet Research, 18*(6), e147. doi:10.2196/jmir.5056

**CONSORT 2010 checklist (Schulz et al., 2010) with definitions.**

<table>
<thead>
<tr>
<th>#</th>
<th>Item</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Title and Abstract</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1a</td>
<td>Identification as a randomized trial in the title</td>
<td></td>
</tr>
<tr>
<td>1b</td>
<td>Structured summary of trial design, methods, results, and conclusions</td>
<td></td>
</tr>
<tr>
<td><strong>Introduction</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2a</td>
<td>Background &amp; objectives</td>
<td>Scientific background and explanation of rationale</td>
</tr>
<tr>
<td>2b</td>
<td>Specific objectives or hypotheses</td>
<td></td>
</tr>
<tr>
<td><strong>Methods</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3a</td>
<td>Trial design</td>
<td>Description of trial design (such as parallel, factorial) including allocation ratio</td>
</tr>
<tr>
<td>3b</td>
<td>Important changes to methods after trial commencement (such as eligibility criteria), with reasons</td>
<td></td>
</tr>
<tr>
<td>4a</td>
<td>Participants</td>
<td>Eligibility criteria for participants</td>
</tr>
<tr>
<td>4b</td>
<td>Settings and locations where the data were collected</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Interventions</td>
<td>The interventions for each group with sufficient details to allow replication, including how and when they were actually administered</td>
</tr>
<tr>
<td>6a</td>
<td>Outcomes</td>
<td>Completely defined pre-specified primary and secondary outcome measures, including how and when they were assessed</td>
</tr>
<tr>
<td>6b</td>
<td>Any changes to trial outcomes after the trial commenced, with reasons</td>
<td></td>
</tr>
<tr>
<td>7a</td>
<td>Sample size</td>
<td>How sample size was determined</td>
</tr>
<tr>
<td>7b</td>
<td>When applicable, explanation of any interim analyses and stopping guidelines</td>
<td></td>
</tr>
<tr>
<td>8a</td>
<td>Random sequence generation</td>
<td>Method used to generate the random allocation sequence</td>
</tr>
<tr>
<td>8b</td>
<td>Type of randomization; details of any restriction (such as blocking and block size)</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>Allocation concealment</td>
<td>Mechanism used to implement the random allocation sequence (such as sequentially numbered containers), describing any steps taken to conceal the sequence until interventions were assigned</td>
</tr>
<tr>
<td>10</td>
<td>Implementation</td>
<td>Who generated the random allocation sequence, who enrolled participants, and who assigned participants to interventions</td>
</tr>
<tr>
<td>11a</td>
<td>Blinding</td>
<td>If done, who was blinded after assignment to interventions (for example, participants, care providers, those assessing outcomes) and how</td>
</tr>
<tr>
<td>11b</td>
<td></td>
<td>If relevant, description of the similarity of interventions</td>
</tr>
<tr>
<td>Item</td>
<td>Category</td>
<td>Description</td>
</tr>
<tr>
<td>------</td>
<td>----------</td>
<td>-------------</td>
</tr>
<tr>
<td>12a</td>
<td>Statistical methods</td>
<td>Statistical methods used to compare groups for primary and secondary outcomes</td>
</tr>
<tr>
<td>12b</td>
<td>Statistical methods</td>
<td>Methods for additional analyses, such as subgroup analyses and adjusted analyses</td>
</tr>
</tbody>
</table>

**Results**

<table>
<thead>
<tr>
<th>Item</th>
<th>Category</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>13a</td>
<td>Participant flow</td>
<td>For each group, the numbers of participants who were randomly assigned, received intended treatment, and were analyzed for the primary outcome</td>
</tr>
<tr>
<td>13b</td>
<td>Participant flow</td>
<td>For each group, losses and exclusions after randomization, together with reasons</td>
</tr>
<tr>
<td>14a</td>
<td>Recruitment</td>
<td>Dates defining the periods of recruitment and follow-up</td>
</tr>
<tr>
<td>14b</td>
<td>Recruitment</td>
<td>Why the trial ended or was stopped</td>
</tr>
<tr>
<td>15</td>
<td>Baseline data</td>
<td>A table showing baseline demographic and clinical characteristics for each group</td>
</tr>
<tr>
<td>16</td>
<td>Numbers analysed</td>
<td>For each group, number of participants (denominator) included in each analysis and whether the analysis was by original assigned groups</td>
</tr>
<tr>
<td>17a</td>
<td>Outcomes and estimation</td>
<td>For each primary and secondary outcome, results for each group, and the estimated effect size and its precision (such as 95% confidence interval)</td>
</tr>
<tr>
<td>17b</td>
<td>Outcomes and estimation</td>
<td>For binary outcomes, presentation of both absolute and relative effect sizes is recommended</td>
</tr>
<tr>
<td>18</td>
<td>Ancillary analyses</td>
<td>Results of any other analyses performed, including subgroup analyses and adjusted analyses, distinguishing pre-specified from exploratory</td>
</tr>
<tr>
<td>19</td>
<td>Harms</td>
<td>All important harms or unintended effects in each group</td>
</tr>
</tbody>
</table>

**Discussion**

<table>
<thead>
<tr>
<th>Item</th>
<th>Category</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>Limitations</td>
<td>Trial limitations, addressing sources of potential bias, imprecision, and, if relevant, multiplicity of analyses</td>
</tr>
<tr>
<td>21</td>
<td>Generalizability</td>
<td>Generalizability (external validity, applicability) of the trial findings</td>
</tr>
<tr>
<td>22</td>
<td>Interpretation</td>
<td>Interpretation consistent with results, balancing benefits and harms, and considering other relevant evidence</td>
</tr>
</tbody>
</table>

**Other information**

<table>
<thead>
<tr>
<th>Item</th>
<th>Category</th>
<th>Description</th>
</tr>
</thead>
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<tr>
<td>23</td>
<td>Registration</td>
<td>Registration number and name of trial registry</td>
</tr>
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<td>24</td>
<td>Protocol</td>
<td>Where the full trial protocol can be accessed, if available</td>
</tr>
<tr>
<td>25</td>
<td>Funding</td>
<td>Sources of funding and other support (such as supply of drugs), role of funders</td>
</tr>
</tbody>
</table>

Note. All items were coded in duplicate by two independent reviewers with 0 = item not fulfilled, 0.5 = item only partially fulfilled, 1 = item fulfilled, NA = not applicable to the study.
Appendix 2.5

Cochrane risk of bias assessment across studies (Higgins et al., 2011; Higgins & Green, 2005).
### Appendix 2.6

Cochrane risk of bias assessment for each study (Higgins et al., 2011; Higgins & Green, 2005).

(H = high risk, U = unclear risk, L = low risk, NA = not applicable)

<table>
<thead>
<tr>
<th>Study</th>
<th>Random seq. generation</th>
<th>All. concealment</th>
<th>Blinding (part./pers.)</th>
<th>Blinding (outcome)</th>
<th>Incomplete data</th>
<th>Selective reporting</th>
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<td>Ahn et al., 2016</td>
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<td>U</td>
<td>U</td>
<td>L</td>
<td>U</td>
</tr>
<tr>
<td>Allen et al., 2013</td>
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<td>L</td>
<td>U</td>
<td>U</td>
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<td>Black et al., 2015</td>
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<td>L</td>
<td>H</td>
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<td>U</td>
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<tr>
<td>Brindal et al., 2013</td>
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<td>U</td>
<td>L</td>
<td>H</td>
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<td>Kim et al., 2017</td>
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<td>Laing et al., 2014</td>
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<td>Lee et al., 2010</td>
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<td>L</td>
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<td>Ross &amp; Wing, 2016</td>
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<td>Spring et al., 2017</td>
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<td>Stephens et al., 2017</td>
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<td>Thomas &amp; Wing, 2013</td>
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<td>Torbjenson et al., 2014</td>
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</tbody>
</table>

**Note.** Criterion for assessment of “incomplete outcome data”: high = >25%, low = <25% or intention-to-treat analysis, unclear = no data provided.
Appendix 2.7

Behaviour Change Techniques (BCTs) for each study.

Note. Blue coloured squares represent the presence of the respective BCT cluster; green coloured squares the presence of a single BCT.
Appendix 2.8

Detailed description of included studies and analysed outcomes.

Legend: $^\dagger$ = groups were pooled and combined; $^*$ = groups were excluded from analysis; $^+$ = groups were analysed separately, $^2$ app available for download. For outcomes in bold separate analyses are reported. Outcomes in italic are pooled in the analyses of nutrition behaviours and nutrition-related health outcomes.

<table>
<thead>
<tr>
<th>Author</th>
<th>Design</th>
<th>Study groups</th>
<th>App</th>
<th>Sample size</th>
<th>Participants</th>
<th>Aim of the study</th>
<th>Intervention</th>
<th>Duration</th>
<th>Outcomes as reported in the primary study</th>
<th>Nutrition behaviours</th>
<th>Nutrition-related health outcomes</th>
<th>#Outcome</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ahn et al., 2016</td>
<td>Control group design</td>
<td>2 groups: (1) Web-based u-Health program (2) Control group</td>
<td>Diabetes Mellitus Dietary Management Guide, DMDMG</td>
<td>26</td>
<td>Diabetes patients (1) $M_{\text{age}} = 50.5$ ($SD = 17.1$); (2) $M_{\text{age}} = 49.7$ ($SD = 16.4$)</td>
<td>Development of a mobile nutritional management program for integration into the web-based program for diabetic patients.</td>
<td>App only</td>
<td>2 months (1 month intervention)</td>
<td>Anthropometric measures, nutrients, effectiveness of program</td>
<td>Caloric intake (kcal) Dietary pattern (study specific score), carbohydrates, lipids, protein, vitamin A, vitamin B, vitamin C, vitamin B1, vitamin B2, vitamin B6, niacin, pholic acid, CA, P, FE, NA, K</td>
<td>Body weight BMI</td>
<td>20</td>
</tr>
<tr>
<td>Author</td>
<td>Design</td>
<td>Study groups</td>
<td>App</td>
<td>Sample size</td>
<td>Participants</td>
<td>Aim of the study</td>
<td>Intervention</td>
<td>Duration</td>
<td>Outcomes as reported in the primary study</td>
<td>Nutritional behaviours</td>
<td>Nutrition-related health outcomes</td>
<td>#Outcome</td>
</tr>
<tr>
<td>--------</td>
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<td>------------------------------------------</td>
<td>----------------------</td>
<td>-----------------------------------</td>
<td>---------</td>
</tr>
<tr>
<td>Allen et al., 2013</td>
<td>RCT</td>
<td>4 groups: (1) Intensive counselling (2) Intensive counselling plus smartphone* (3) Less intensive counselling plus smartphone* (4) Smartphone*</td>
<td>LoseIt³</td>
<td>68 (43 after dropout)</td>
<td>Obese participants $M_{age} = 44.9$ ($SD = 11.1$); $M_{BMI} = 34.3$ ($SD = 3.9$)</td>
<td>Evaluation of feasibility, acceptability, and preliminary efficacy of theoretically-based behavioural interventions delivered by smartphone technology.</td>
<td>App + nutrition counselling</td>
<td>6 months (study and intervention)</td>
<td>Weight, BMI, waist circumference, Diet, physical activity</td>
<td>Caloric intake (kcal) Fruit/vegetable intake Sodium</td>
<td>Body weight BMI</td>
<td>5</td>
</tr>
<tr>
<td>Appel et al., 2014</td>
<td>Control group design</td>
<td>2 groups: (1) App group (2) Control group</td>
<td>LoseIt³</td>
<td>421 (118 after presurvey)</td>
<td>Ethnically diverse and low-income participants $M_{age} = 15.9$ ($SD = 1.3$); $M_{BMI} = 23.9$ ($SD = 4.9$)</td>
<td>Test an intervention for childhood obesity using a free smartphone app with the primary aim of assessing students’ knowledge of nutritional indicators, physical exercise and use of screen time.</td>
<td>App only</td>
<td>20 days (study and intervention)</td>
<td>Physical activity, screen time, type of food, height, weight, nutrition knowledge</td>
<td></td>
<td>BMI</td>
<td>1</td>
</tr>
<tr>
<td>Author</td>
<td>Design</td>
<td>Study groups</td>
<td>App</td>
<td>Sample size</td>
<td>Participants</td>
<td>Aim of the study</td>
<td>Intervention</td>
<td>Duration</td>
<td>Outcomes as reported in the primary study</td>
<td>Nutrition behaviours</td>
<td>Nutrition-related health outcomes</td>
<td>#Outcome</td>
</tr>
<tr>
<td>-----------------------------</td>
<td>--------</td>
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<td>---------------------</td>
<td>----------------------------------</td>
<td>----------</td>
</tr>
<tr>
<td>Balk-Møller et al., 2017</td>
<td>RCT</td>
<td>2 groups:</td>
<td>SoSu-life</td>
<td>566 (269 after dropout)</td>
<td>Nursing home employees; (1) $M_{grp} = 47$ ($SD = 10.0$); (2) $M_{grp} = 47$ ($SD = 9.9$)</td>
<td>Test a web- and mobile app-based tool ('SoSu-life') on employees in the social welfare and health care sector in Denmark.</td>
<td>App only</td>
<td>38 weeks (study and intervention)</td>
<td>Weight, Body fat, waist circumference, blood pressure, cholesterol, well-being</td>
<td>Body weight, Cholesterol</td>
<td>Body fat, waist circumference, systolic blood pressure, diastolic blood pressure</td>
<td>6</td>
</tr>
<tr>
<td>Block et al., 2015</td>
<td>RCT</td>
<td>2 groups:</td>
<td>Alive-PD³</td>
<td>339 (292 after dropout)</td>
<td>Prediabetic adults $M_{grp} = 55$ ($SD = 8.9$)</td>
<td>Evaluate the effectiveness of a fully automated algorithm-driven behavioural intervention for diabetes prevention.</td>
<td>App + weekly emails, individual web page, automated phone calls</td>
<td>12 months (study and intervention but with less intensive intervention in last 6 months)</td>
<td>Glucose, Weight, BMI, waist circumference, triglyceride/HDL ratio, Framingham diabetes risk score</td>
<td>Body weight, BMI</td>
<td>Waist circumference, fasting glucose, HbA1c, triglyceride/HDL ratio</td>
<td>6</td>
</tr>
<tr>
<td>Author</td>
<td>Design</td>
<td>Study groups</td>
<td>App</td>
<td>Sample size</td>
<td>Partici- pants</td>
<td>Aim of the study</td>
<td>Intervention</td>
<td>Duration</td>
<td>Outcomes as reported in the primary study</td>
<td>Nutrition behaviours</td>
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<tr>
<td>Brindal et al., 2013</td>
<td>RCT</td>
<td>2 groups: (1) MRP support app (2) Static app based on information in MRP</td>
<td>Meal Replacement Program, MRP</td>
<td>58 (44 after dropout)</td>
<td>Adult women with BMI &gt; 25 $M_{age} = 42$ (range: 19-63); $M_{weight} = 92.4$ kg ($SD = 14.7$); $M_{BMI} = 34$ (range: 26-43)</td>
<td>Development and evaluation of a weight-loss intervention delivered by an evidence-based smartphone app that supported individuals embarking on a diet.</td>
<td>App only</td>
<td>2 months (study and intervention)</td>
<td>User interaction, App evaluation, mood, motivation, weight, dietary compliance</td>
<td>Dietary pattern (Meal replacement)</td>
<td>Body weight</td>
<td>2</td>
</tr>
<tr>
<td>Brindal et al., 2016</td>
<td>RCT</td>
<td>2 groups: (1) MRP support app (2) Static app based on information in MRP</td>
<td>Meal Replacement Program, MRP</td>
<td>146 (84 after dropout)</td>
<td>Overweight and obese adults $M_{age} = 48.18$ ($SD = 11.75$)</td>
<td>Design and evaluate a weight-loss program, including a partial MRP, point-of-care testing and face-to-face and smartphone app support, appropriate for delivery in a community pharmacy setting.</td>
<td>App + MRP</td>
<td>6 months (3 months intervention)</td>
<td>Weight, blood pressure, glucose and blood lipids</td>
<td>Self-efficacy, physical activity, feedback</td>
<td>Body weight, Cholesterol</td>
<td>Systolic blood pressure, diastolic blood pressure, glucose, triglyceride, HDL, LDL</td>
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<tr>
<td>Author</td>
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<td>Study groups</td>
<td>App</td>
<td>Sample size</td>
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<td>Burke et al., 2017</td>
<td>RCT</td>
<td>3 groups:  (1) LoseIt smartphone app*  (2) App + feedback*  (3) App + feedback + in-persons group sessions*</td>
<td>LoseIt*</td>
<td>39 (29 after drop-out)</td>
<td>Obese or overweight adults $M_{age} = 44.84$ $(SD = 12.75)$; $M_{BMI} = 33.76$ $(SD = 4.28)$</td>
<td>Test the feasibility of providing 1-4 daily messages tailored to dietary recordings via smartphone.</td>
<td>App + feedback messages, group sessions</td>
<td>3 months (study and intervention)</td>
<td>Recruitment, retention, adherence, weight Blood pressure, self-efficacy</td>
<td>Body weight</td>
<td></td>
<td>1</td>
</tr>
<tr>
<td>Carter et al., 2013</td>
<td>RCT</td>
<td>3 groups:  (1) Mobile Website*  (2) Website*  (3) Diary group*</td>
<td>My Meal Mate (MMM)*</td>
<td>128 (79 after drop-out)</td>
<td>Overweight adults (1) $M_{age} = 41.2$ $(SD = 8.5)$; $M_{BMI} = 33.7$ $(SD = 4.2)$ (2) $M_{age} = 41.9$ $(SD = 10.6)$; $M_{BMI} = 34.5$ $(SD = 5.6)$ (3) $M_{age} = 42.5$ $(SD = 8.3)$; $M_{BMI} = 34.5$ $(SD = 5.7)$</td>
<td>Collect acceptability and feasibility outcomes of a self-monitoring weight management intervention delivered by a smartphone app.</td>
<td>App only</td>
<td>6 months (study and intervention)</td>
<td>Feasibility and acceptability Height, weight, BMI, body fat, demographics, physical activity, eating behaviour</td>
<td>Body weight BMI Body fat</td>
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<tr>
<td>Author</td>
<td>Design</td>
<td>Study groups</td>
<td>App&lt;sup&gt;1&lt;/sup&gt;</td>
<td>Sample size</td>
<td>Participants</td>
<td>Aim of the study</td>
<td>Intervention</td>
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<tr>
<td>Duncan et al., 2014</td>
<td>RCT</td>
<td>2 groups: (1) Print-based (2) IT-based</td>
<td>ManUp</td>
<td>301</td>
<td>Adult males (1) M&lt;sub&gt;avg&lt;/sub&gt; = 43.8 (SD = 0.6) (2) M&lt;sub&gt;avg&lt;/sub&gt; = 44.2 (SD = 0.4)</td>
<td>Examine the effectiveness of an IT-based intervention to improve physical activity, dietary behaviors, and health literacy compared to a print-based intervention.</td>
<td>App only</td>
<td>9 months (study and intervention)</td>
<td>Physical activity, dietary behaviour, health literacy, satisfaction, IT platform usage</td>
<td>Dietary pattern (study specific score)</td>
<td>High-fibre bread, low-fat milk consumption</td>
<td>3</td>
</tr>
<tr>
<td>Frøisland et al., 2012</td>
<td>Pre-post design</td>
<td>1 group testing two apps</td>
<td>Diambo, unnamed app</td>
<td>12</td>
<td>Adolescents, Diabetes Type 1 M&lt;sub&gt;avg&lt;/sub&gt; = 16.2 (SD = 1.7); M&lt;sub&gt;avg&lt;/sub&gt; = 23.3 (SD = 3.2)</td>
<td>Explore how mobile phone applications can be used in follow-up of adolescents with type 1 diabetes, and use the findings to development these applications further.</td>
<td>App + counselling and reflection</td>
<td>3 months (study and intervention)</td>
<td>HbA1C, glycaemic control, usability, knowledge tests</td>
<td></td>
<td></td>
<td>1</td>
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<tr>
<td>Fukuoka et al., 2015</td>
<td>RCT</td>
<td>2 groups: (1) Intervention (2) Control</td>
<td>Mobile Diabetes Prevention Program, mDPP</td>
<td>61</td>
<td>Adults with risk of Type 2 Diabetes M&lt;sub&gt;avg&lt;/sub&gt; = 55.3 (SE = 9); M&lt;sub&gt;avg&lt;/sub&gt; = 33.3 (SE = 6)</td>
<td>Examine the feasibility and efficacy of a diabetes prevention intervention combined with a mobile app and pedometer.</td>
<td>App + in-person sessions</td>
<td>5.5 months (5 months intervention)</td>
<td>Weight, BMI Hip circumference, blood pressure, lipids, glucose, physical activity, caloric, SSB, fat intake, social support, self-efficacy, depression</td>
<td>Caloric intake (kcal) Fat, saturated fat, SSB consumption</td>
<td>Body weight BMI Cholesterol</td>
<td>14</td>
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<tr>
<td>Author</td>
<td>Design</td>
<td>Study groups</td>
<td>App2</td>
<td>Sample size</td>
<td>Participants</td>
<td>Aim of the study</td>
<td>Intervention</td>
<td>Duration</td>
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<tr>
<td>Gilson et al., 2017</td>
<td>Pre-post design</td>
<td>1 group</td>
<td>Jawbone Up3</td>
<td>26 (19 after dropout)</td>
<td>Male Australian truck drivers $M_{age} = 44.4$ ($SD = 10$); $M_{BMI} = 31.2$ ($SD = 4.6$)</td>
<td>Examine the extent to which an m-Health financial incentive program facilitated physical activity and healthy dietary choices.</td>
<td>App + feedback, guidance and monetary reward</td>
<td>7 months (5 months intervention)</td>
<td>Physical activity</td>
<td>Fruit intake</td>
<td>Vegetable intake</td>
<td>4</td>
</tr>
<tr>
<td>Godino et al., 2016</td>
<td>RCT</td>
<td>2 groups: (1) SMART intervention (2) Control group</td>
<td>GoalGetter App, BeHealthy App, Trend Setter App</td>
<td>404 (355 after dropout)</td>
<td>Young adults $M_{age} = 22.7$ ($SD = 3.8$) (1) $M_{BMI} = 28.9$ ($SD = 2.8$) (2) $M_{BMI} = 29$ ($SD = 2.7$)</td>
<td>Assess the efficacy of a 2-year theory-based weight-loss intervention delivered via integrated user experiences.</td>
<td>App + Facebook, text messaging, emails, website, technology-mediated communication with a health coach</td>
<td>24 months</td>
<td>Weight</td>
<td>Body weight</td>
<td>BMI</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td>1 group</td>
<td>See Me Smoke-Free™</td>
<td>73 (66 after dropout)</td>
<td>Smoking women $M_{age} = 39.1$ ($SD = 13.1$)</td>
<td>Develop and test the feasibility and potential of the See Me Smoke-Free™ m-Health app to address smoking, diet, and physical activity among women smokers.</td>
<td>App only</td>
<td>3 months (30 days intervention)</td>
<td>Physical activity</td>
<td>Fruit intake</td>
<td>Vegetable intake</td>
<td>4</td>
</tr>
</tbody>
</table>

Outcomes included in the analyses:
- Physical activity
- Sedentary time
- Fruit intake
- Vegetable intake
- Saturated fat, sugar
- Body weight
- BMI
- Waist circumference
- Arm circumference
- Blood pressure
- Systolic blood pressure
- Diastolic blood pressure
- Heart rate

Note: The table and text were reformatted for clarity and readability.
<table>
<thead>
<tr>
<th>Author</th>
<th>Design</th>
<th>Study groups</th>
<th>App</th>
<th>Sample size</th>
<th>Participants</th>
<th>Aim of the study</th>
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<th>Duration</th>
<th>Outcomes as reported in the primary study</th>
<th>Nutrition behaviours</th>
<th>Nutrition-related health outcomes</th>
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</thead>
<tbody>
<tr>
<td>Hales et al., 2016</td>
<td>RCT</td>
<td>2 groups: (1) Social POD app; (2) Standard app</td>
<td>Social POD App</td>
<td>51 (42 after dropout)</td>
<td>Overweight adults; M_age = 46.2 (SD = 12.4); M_BMI = 34.7 (SD = 6.0)</td>
<td>Test the efficacy of a weight loss mobile app based on recommender systems to target social support and self-monitoring of diet, physical activity, and weight, compared to a commercially-available diet and physical activity tracking app.</td>
<td>App + podcasts</td>
<td>3 months (study and intervention)</td>
<td>Weight, BMI, caloric intake, expenditure, social support, self-efficacy, outcome expectations</td>
<td>Caloric intake (kcal)</td>
<td>Body weight BMI</td>
<td>3</td>
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<tr>
<td>Hebden et al., 2014</td>
<td>RCT</td>
<td>2 groups: (1) Intervention; (2) Control</td>
<td>m-Health program</td>
<td>51 (46 after dropout)</td>
<td>(1) M_age = 22.6 (SD = 5.4); M_BMI = 27.3 (2) M_age = 23.1 (SD = 3.7); M_BMI = 27.2</td>
<td>Measure the effect of a m-Health intervention program on body weight, BMI and specific lifestyle behaviours.</td>
<td>App + SMS, e-mails, internet forum, guidance of investigator</td>
<td>13 weeks (12 weeks intervention)</td>
<td>Weight, BMI, Sitting time, physical activity, SSB intake, energy-dense takeaway meals, fruit and vegetables</td>
<td>Fruit intake Vegetable intake</td>
<td>SSB consumption</td>
<td>5</td>
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<tr>
<td>Author</td>
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<td>Study groups</td>
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<td>Holmen et al., 2014</td>
<td>RCT</td>
<td>3 groups: (1) FTA (2) FTA + health counselling (3) Control group</td>
<td>Few Touch Application, FTA</td>
<td>151 (120 after drop-out)</td>
<td>Overweight adults age range: 18 - 35; BMI range: 24 - 32</td>
<td>Test whether the use of a mobile phone-based self-management system, with or without telephone health counselling, could improve glycated haemoglobin A1c level, self-management, and health-related quality of life.</td>
<td>App only</td>
<td>1 year (study and intervention)</td>
<td>HbA1c level</td>
<td>Self-management, lifestyle, dietary habits, physical activity, depressive symptoms, weight</td>
<td>Body weight HbA1c</td>
<td>2</td>
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<tr>
<td>Ipjian et al., 2017</td>
<td>RCT</td>
<td>2 groups: (1) MyFitnessPal App (2) Writing journal</td>
<td>MyFitnessPal</td>
<td>30</td>
<td>Adults $\bar{M}<em>{\text{BMI}} = 24.5$ ($SD = 4.9$) (1) $\bar{M}</em>{\text{BMI}} = 25.3$ ($SD = 4.9$) (2) $\bar{M}_{\text{BMI}} = 25.9$ ($SD = 3.7$)</td>
<td>Reducing sodium intake to determine whether a commercial health app is useful for promoting dietary change.</td>
<td>App only</td>
<td>1 month (study and intervention)</td>
<td>Sodium intake, dietary quality score, blood pressure, weight, body fat, waist circumference</td>
<td>Dietary pattern (Rapid Eating and Activity Assessment for Participants - short version, REAP-S), sodium</td>
<td>Body weight BMI</td>
<td>2</td>
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<tr>
<td>Jensen et al., 2016</td>
<td>Pre-post design</td>
<td>1 group in two different phases (3 months combined treatment followed by 3 months electronic treatment)</td>
<td>Daily Burn Tracker</td>
<td>16 (10 after drop-out)</td>
<td>Overweight or obese adolescents $\bar{M}_{\text{BMI}} = 14.3$ ($SD = 1.1$)</td>
<td>Examine the efficacy and acceptability of a smartphone assisted adolescent behavioural weight control intervention.</td>
<td>App + group and family weight loss program, text messages</td>
<td>1 year (2 intervention periods of 3 months each)</td>
<td>BMI, weight, satisfaction with intervention</td>
<td>Feasibility of intervention</td>
<td>Body weight BMI</td>
<td>2</td>
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<tr>
<td>Author</td>
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<tr>
<td>Johnston et al., 2013</td>
<td>RCT</td>
<td>2 groups: (1) Weight Watchers App (2) Self-help control group</td>
<td>Weight Watchers App</td>
<td>292 (257 after drop-out)</td>
<td>Obese or overweight adults $M_{age} = 46.5$ ($SD = 10.5$); $M_{BMI} = 33$ ($SD = 3.6$)</td>
<td>Examine weight loss between a community-based, intensive behavioural counselling program and a self-help condition.</td>
<td>App + weekly meetings, online tools</td>
<td>6 months (study and intervention)</td>
<td>Weight, BMI Attendance, mobile device application usage, use of access points</td>
<td></td>
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<tr>
<td>Kim et al., 2017</td>
<td>Online survey</td>
<td>1 group</td>
<td>Noom</td>
<td>384</td>
<td>Adults and adolescents using Noom $M_{age} = 34.4$ ($SD = 10.6$); $M_{BMI} = 30.6$ ($SD = 6.5$)</td>
<td>Examine the use of a weight loss app to elucidate how it can help individuals harness the power of self-efficacy and group support to enact behaviour change and accomplishment of health goals.</td>
<td>App only</td>
<td>One-time assessment but extracted data from 6 months</td>
<td>Self-efficacy, behavioural variables, weight, BMI</td>
<td></td>
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<tr>
<td>Laing et al., 2014</td>
<td>RCT</td>
<td>2 groups: (1) Usual primary care + app (2) Usual primary care</td>
<td>MyFitness Pal</td>
<td>212 (158 after drop-out)</td>
<td>Overweight or obese adults $M_{age} = 43.1$ ($SD = 14$) (1) $M_{BMI} = 33.3$ ($SD = 6.8$) (2) $M_{BMI} = 33.3$ ($SD = 7.2$)</td>
<td>Evaluate the impact of introducing patients to a popular, free smartphone app for weight loss in a primary care setting</td>
<td>App only</td>
<td>6 months (study and intervention)</td>
<td>Weight Blood pressure, physical activity, healthy diet, calorie goals, self-efficacy</td>
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<td>Dietary pattern (two study specific score)</td>
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<tr>
<td>Author</td>
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<tr>
<td>Lee et al., 2010</td>
<td>Case-control design</td>
<td>2 groups: (1) Intervention group (2) Informed control group</td>
<td>The SmartDiet</td>
<td>36</td>
<td>Volunteers from an obesity clinic; (1) $M_{\text{age}} = 28.2$; $M_{\text{BMI}} = 22.2$ (2) $M_{\text{age}} = 29.5$; $M_{\text{BMI}} = 22.3$</td>
<td>Evaluate the effectiveness of the mobile phone application with respect to acquiring dietary information, weight control, and user satisfaction.</td>
<td>App only</td>
<td>6 weeks (study and intervention)</td>
<td>Body composition, physical activity, regularity of eating, smoking, drinking</td>
<td></td>
<td>Body weight, BMI</td>
<td>3</td>
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<tr>
<td>Mc Carroll et al., 2015</td>
<td>Pre-post design</td>
<td>1 group</td>
<td>Loselt!</td>
<td>50</td>
<td>(35 after dropout) Endometrial and breast cancer survivors $M_{\text{age}} = 58.4$ ($SD = 10.3$); $M_{\text{BMI}} = 36.4$ ($SD = 8.1$)</td>
<td>Assess a one-month lifestyle intervention delivered via a web-and mobile-based weight-loss application using a healthcare-provider interface.</td>
<td>App + nutrition and weight goal set at baseline, phone calls, e-mail notifications</td>
<td>1 month (study and intervention)</td>
<td>Weight, BMI, waist circumference, Physical activity, caloric intake and nutritional content</td>
<td>Caloric intake (kcal), Carbohydrates, fat, protein, fibre</td>
<td></td>
<td>Body weight, BMI</td>
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<tr>
<td>Mummah et al., 2016</td>
<td>RCT</td>
<td>2 groups: (1) Intervention (2) Wait-list control condition</td>
<td>Vegethon</td>
<td>17</td>
<td>Overweight adults $M_{\text{age}} = 42$ ($SD = 7.3$); $M_{\text{BMI}} = 32$ ($SD = 3.5$)</td>
<td>Assess the initial efficacy and user acceptability of a theory-driven mobile app to increase vegetable consumption.</td>
<td>App only</td>
<td>3 months (intervention app at least 6 weeks)</td>
<td>Vegetable consumption</td>
<td>Vegetable intake (all vegetables, green leafy vegetables, cruciferous vegetables, dark yellow vegetables, tomatoes, other vegetables, beans/lentils)</td>
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<tr>
<td>Author</td>
<td>Design</td>
<td>Study groups</td>
<td>App</td>
<td>Sample size</td>
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<td>Aim of the study</td>
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<td>Outcomes included in the analyses</td>
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<tr>
<td>Partridge et al., 2015</td>
<td>RCT</td>
<td>2 groups: (1) Intervention group (2) Control group</td>
<td>TXT2BFit</td>
<td>248 (214 after dropout at 12 weeks)</td>
<td>(1) M_age = 28.1 (SD = 4.9); M_BMI = 27.3 (SD = 2.4) (2) M_age = 27.2 (SD = 4.9); M_BMI = 27.1 (SD = 2.7)</td>
<td>Design and assess the efficacy of a m-Health prevention program in preventing excess weight gain and improving dietary and physical activity behaviours in young adults at increased risk of obesity and unhealthy lifestyle choices.</td>
<td>App + coaching calls, text messages, e-mails</td>
<td>3 months (study and intervention)</td>
<td>Weight, BMI</td>
<td>Physical activity, fruit and vegetable intake, SSB, energy-dense takeout meals</td>
<td>Body weight BMI</td>
<td>2</td>
</tr>
<tr>
<td>Partridge et al., 2017</td>
<td>RCT</td>
<td>2 groups: (1) Intervention group (2) Control group</td>
<td>TXT2BFit</td>
<td>248 (202 after dropout at 9 month)</td>
<td>Young adults at risk of weight gain age range: 18 - 35; BMI range: 21 - 32</td>
<td>Assess the intervention effects on knowledge, self-efficacy and stage-of-change for four target lifestyle behaviours, and investigate the mediating effects of self-efficacy on those lifestyle behaviours in the weight gain prevention intervention.</td>
<td>App + coaching calls, text messages, e-mails, study website, booklet</td>
<td>9 months (3 months intervention)</td>
<td>Fruit and vegetable knowledge, self-efficacy, diet (stage of change for fruit, vegetables, SSB, take-away meals), physical activity</td>
<td>Fruit intake Vegetable intake</td>
<td>SSB, take-away meal consumption</td>
<td>4</td>
</tr>
<tr>
<td>Author</td>
<td>Design</td>
<td>Study groups</td>
<td>App¹</td>
<td>Sample size</td>
<td>Participants</td>
<td>Aim of the study</td>
<td>Intervention</td>
<td>Duration</td>
<td>Outcomes as reported in the primary study</td>
<td>Nutrition behaviours</td>
<td>Nutrition-related health outcomes</td>
<td>#Outcome</td>
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<tr>
<td>Rabbi et al., 2015</td>
<td>RCT</td>
<td>2 groups: (1) Intervention group with personalized suggestions (2) Control group</td>
<td>My Behaviour</td>
<td>18 (17 after drop-out)</td>
<td>Adults $M_{sex} = 28.3$ ($SD = 7.0$)</td>
<td>Technical feasibility on implementing an automated feedback system, the impact of the suggestions on user physical activity and eating behaviour, and user perceptions of the automatically generated suggestions.</td>
<td>App only</td>
<td>3 weeks (2 weeks intervention)</td>
<td>Dietary behaviour, physical activity</td>
<td>Caloric intake (kcal)</td>
<td></td>
<td>1</td>
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<tr>
<td>Recio-Rodriquez et al., 2016</td>
<td>RCT</td>
<td>2 groups: (1) App + counselling group (2) Counselling only group</td>
<td>unclear</td>
<td>833 (765 after drop-out)</td>
<td>(1) $M_{age} = 51.4$ ($SD = 12.1$); $M_{BMI} = 28.1$ ($SD = 5.1$) (2) $M_{age} = 52.3$ ($SD = 12$); $M_{BMI} = 27.6$ ($SD = 4.6$)</td>
<td>Evaluate the effect of adding an app to standard counselling on increased physical activity and adherence to the Mediterranean diet, 3 months after implementation.</td>
<td>App + counselling in physical activity and Mediterranean diet, one in-between visit</td>
<td>12 months (3 months intervention)</td>
<td>Physical activity, Mediterranean diet score; Blood pressure, waist circumference, BMI, laboratory parameters</td>
<td>Dietary pattern (Mediterranean diet according to MEDAS - Mediterranean Diet Adherence Screener)</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Author</td>
<td>Design</td>
<td>Study groups</td>
<td>App</td>
<td>Sample size</td>
<td>Participants</td>
<td>Aim of the study</td>
<td>Intervention</td>
<td>Duration</td>
<td>Outcomes as reported in the primary study</td>
<td>Nutrition behaviours</td>
<td>Nutrition-related health outcomes</td>
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<tr>
<td>Ross &amp; Wing, 2016</td>
<td>RCT</td>
<td>3 groups: (1) Standard tool (2) Technology-based tool* (3) Technology-based tool combined with phone-based intervention*</td>
<td>FitBit Smartphone App$^*$</td>
<td>80 (72 after drop-out)</td>
<td>Overweight and obese adults $M_{opt} = 51.1$ ($SD = 11.7$); $M_{BMI} = 33.0$ ($SD = 3.4$)</td>
<td>Examine efficacy of self-monitoring technology, with and without phone-based intervention, on 6-month weight loss in overweight and obese adults.</td>
<td>App + in person “weight loss 101” session</td>
<td>6 months (study and intervention)</td>
<td>Weight Adherence to self-monitoring</td>
<td>Body weight</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Spring et al., 2017</td>
<td>RCT</td>
<td>3 groups: (1) Self-guided* (2) Standard (3) Technology supported</td>
<td>ENGAG-ED</td>
<td>96 (83 after drop-out)</td>
<td>Overweight or obese adults $M_{opt} = 39.3$ ($SD = 11.7$); $M_{BMI} = 34.6$ ($SD = 3$)</td>
<td>Determine the effects on weight loss of three abbreviated behavioural weight loss interventions with and without coaching and mobile technology.</td>
<td>App + weight loss target, kcal goal, team competition, financial incentive, group sessions</td>
<td>12 months (6 months intervention)</td>
<td>Weight Behavioural adherence</td>
<td>Body weight</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Author</td>
<td>Design</td>
<td>Study groups</td>
<td>App</td>
<td>Sample size</td>
<td>Participants</td>
<td>Aim of the study</td>
<td>Intervention</td>
<td>Duration</td>
<td>Outcomes as reported in the primary study</td>
<td>Nutrition behaviours</td>
<td>Nutrition-related health outcomes</td>
<td>#Outcome</td>
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<tr>
<td>Steinert et al., 2016</td>
<td>Pre-post design</td>
<td>1 group</td>
<td>MyTherapy®</td>
<td>30</td>
<td>$\bar{M}<em>{\text{age}} = 68$ (range: 61-76); 15 females with $M</em>{\text{BMI}} = 27.7$ (range: 24-35); 15 males with $M_{\text{BMI}} = 27.3$ (range: 22.5-34)</td>
<td>Identify the benefit of self-monitoring with a smartphone application for adults.</td>
<td>App only</td>
<td>5 weeks (4 weeks intervention)</td>
<td>Recreational and physical activity, weight, water control, nutrition, medication intake</td>
<td>Fruit intake</td>
<td>Fish consumption</td>
<td>3</td>
</tr>
<tr>
<td>Stephens et al., 2017</td>
<td>RCT</td>
<td>2 groups: (1) Intervention group with app + health coach + counselling (2) Only counselling control group</td>
<td>LoseIt®</td>
<td>62 (59 after drop-out)</td>
<td>Young adults age range: 18 - 25; $M_{\text{BMI}} = 28.5$</td>
<td>Effectiveness of a behaviour-based smartphone application for weight loss, combined with text messaging from a health coach on weight, body mass index, and waist circumference in young adults in comparison with a control condition.</td>
<td>App + baseline counselling sessions, specific goal setting, text messages from health coach</td>
<td>3 months (study and intervention)</td>
<td>Weight, BMI, waist circumference Diet, physical activity, self-efficacy</td>
<td>Fruit intake</td>
<td>Vegetable intake Caloric intake (kcal) Carbohydrates, protein, fat, saturated fat, sugar, added sugar, fibre, sodium, dairy product consumption</td>
<td>15</td>
</tr>
</tbody>
</table>

**Outcome**
<table>
<thead>
<tr>
<th>Author</th>
<th>Design</th>
<th>Study groups</th>
<th>App</th>
<th>Sample size</th>
<th>Participants</th>
<th>Aim of the study</th>
<th>Intervention</th>
<th>Duration</th>
<th>Outcomes as reported in the primary study</th>
<th>Nutrition behaviours</th>
<th>Nutrition-related health outcomes</th>
<th>#Outcome</th>
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</thead>
<tbody>
<tr>
<td>Svetkey et al., 2015</td>
<td>RCT</td>
<td>3 groups:</td>
<td></td>
<td>365</td>
<td>Young overweight or obese adults $M_{app} = 29.4$ (SD = 4.3); $M_{bmi} = 35.2$ (SD = 7.8)</td>
<td>Determine the effect on weight of two mobile technology-based behavioural weight loss interventions in young adults.</td>
<td>App only</td>
<td>2 years (study and intervention)</td>
<td>Weight, Weight changes in sub-groups, Healthy Eating Index</td>
<td>Dietary pattern (Healthy Eating Index, HEI-2005)</td>
<td>Body weight</td>
<td>2</td>
</tr>
<tr>
<td>Thomas &amp; Wing, 2013</td>
<td>Pre-post design</td>
<td>1 group</td>
<td></td>
<td>20</td>
<td>Overweight or obese adults $M_{app} = 53.0$ (SD = 1.9); $M_{bmi} = 36.3$ (SE = 1.2)</td>
<td>Evaluate smartphones as a method of delivering key components of established and empirically validated behavioural weight loss treatment, with an emphasis on adherence to self-monitoring.</td>
<td>App + individual goal setting sessions, SMS, in-person weigh-ins, paper lessons</td>
<td>6 months (at least 3 months intervention with additional treatment at 6 months)</td>
<td>Weight, adherence to self-monitoring protocol, Satisfaction with program</td>
<td>Body weight</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Author</td>
<td>Design</td>
<td>Study groups</td>
<td>App</td>
<td>Sample size</td>
<td>Participants</td>
<td>Aim of the study</td>
<td>Intervention Duration</td>
<td>Outcomes as reported in the primary study</td>
<td>Nutrition behaviours</td>
<td>Nutrition-related health outcomes</td>
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<tr>
<td>Torbjørnsen et al., 2014</td>
<td>RCT</td>
<td>3 groups: (1) FTA intervention (2) FTA + health counselling intervention (3) Usual care control group</td>
<td>Few Touch Application, FTA</td>
<td>151 (129 after dropout)</td>
<td>Adults with type 2 diabetes $M_{min} = 57$ ($SD = 12$); $M_{max} = 31.7$ ($SD = 6.0$)</td>
<td>Evaluate whether the introduction of technology-supported self-management using the FTA diabetes diary, with or without health counselling, improved HbA1c levels, self-management, behavioural change, and quality of life.</td>
<td>App only 1 year (study and intervention, but only 4 months follow-up included in paper)</td>
<td>HbA1c</td>
<td>Self-management, behaviour change, health-related quality of life</td>
<td>1</td>
<td></td>
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<tr>
<td>Turner-McGreivy &amp; Tate, 2011</td>
<td>RCT</td>
<td>2 groups: (1) Podcast mobile group (2) Podcast</td>
<td>FatSecret’s Calorie Counter app (version 2010) + Twitter app</td>
<td>96 (86 after dropout)</td>
<td>Overweight adults age range: 18-60; $M_{min} = 32.6$ (range: 25-45)</td>
<td>Examine whether a combination of podcasting, mobile support communication, and mobile diet monitoring can assist people in weight loss.</td>
<td>App + Twitter, podcasts, messages from study coordinator 6 months (study and intervention)</td>
<td>Weight</td>
<td>Caloric intake (kcal)</td>
<td>4</td>
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<td></td>
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<td></td>
<td></td>
<td>Body weight</td>
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</table>
## App-Based Mobile Interventions

### Review

<table>
<thead>
<tr>
<th>Author</th>
<th>Design</th>
<th>Study groups</th>
<th>App2</th>
<th>Sample size</th>
<th>Participants</th>
<th>Aim of the study</th>
<th>Intervention</th>
<th>Duration</th>
<th>Outcomes as reported in the primary study</th>
<th>Nutrition behaviours</th>
<th>Nutrition-related health outcomes</th>
<th>#Outcome</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wharton et al., 2014</td>
<td>Control group design</td>
<td>3 groups: (1) App (2) Memo function* (3) Paper pencil*</td>
<td>LoseIt®</td>
<td>57 (47 after drop-out)</td>
<td>Adults aged 18-65 (1) <em>M</em> _app = 43.7 (SD = 3.5); <em>M</em> _max = 29.9 (SD = 0.9) (2) <em>M</em> _app = 41.5 (SD = 4.0); <em>M</em> _max = 31.0 (SD = 1.7) (3) <em>M</em> _app = 40.8 (SD = 3.8); <em>M</em> _max = 28.9 (SD = 1.0)</td>
<td>Test the use of a popular smartphone app for dietary self-monitoring and weight loss by comparing it with traditional diet counselling and entry methods.</td>
<td>App + nutrition counselling, messages</td>
<td>8 weeks (study and intervention)</td>
<td>Dietary intake, weight, BMI, attrition</td>
<td></td>
<td>Body weight</td>
<td>1</td>
</tr>
<tr>
<td>Widmer et al., 2015</td>
<td>Control group design</td>
<td>4 groups: (1) Entering CR (2) Finishing CR* (3) Entering CR using personal health assistant (PHA) (4) Finishing CR using personal health assistant*</td>
<td>Personal Health Assistant (PHA)</td>
<td>76 (72 after drop-out)</td>
<td>Clinic patients (1)&amp;(2) <em>M</em> _app = 70.4 (SD = 9.9); <em>M</em> _max = 30.6 (SD = 5.6) (3)&amp;(4) <em>M</em> _app = 60.2 (SD = 12.1); <em>M</em> _max = 29.2 (SD = 4.4)</td>
<td>Test a digital health intervention as an adjunct to cardiac rehabilitation (CR).</td>
<td>App + e-mail reminder</td>
<td>3 months (study and intervention)</td>
<td>Blood pressure, weight, blood parameters</td>
<td>Dietary pattern (study specific score)</td>
<td>Body weight, BMI, Cholesterol</td>
<td>systolic blood pressure, diastolic blood pressure, triglyceride, HDL, LDL, glucose</td>
</tr>
<tr>
<td>Author</td>
<td>Design</td>
<td>Study groups</td>
<td>App</td>
<td>Sample size</td>
<td>Participants</td>
<td>Aim of the study</td>
<td>Intervention</td>
<td>Duration</td>
<td>Outcomes as reported in the primary study</td>
<td>Nutrition behaviours</td>
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<tr>
<td>Willey &amp; Walsh, 2016</td>
<td>Quasi-experimental</td>
<td>1 group</td>
<td>YouPlus Health mobile coaching platform</td>
<td>10</td>
<td>Caucasian women $M_{age} = 43.5$ (range: 35-49); $M_{BMI} = 31.6$ (range: 27.2-36.4)</td>
<td>Evaluation of participants using the YouPlus Health mobile coaching platform.</td>
<td>App only</td>
<td>3 months (study and intervention)</td>
<td>Weight, waist circumference, blood pressure, lipids, glycohaemoglobin, maximum volume of oxygen consumption</td>
<td>Body weight Cholesterol</td>
<td>Waist circumference, systolic blood pressure, diastolic blood pressure, triglyceride, HDL, LDL, glycohaemoglobin</td>
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</tbody>
</table>
Appendix 2.9

Funnel plot for the all-encompassing data set with observed effect size Hedges’ $g$ on the horizontal axis plotted against the standard error.

Block et al., 2015
### Appendix 2.10

Meta-regression and moderation effect results.

<table>
<thead>
<tr>
<th>Moderator</th>
<th>Estimate</th>
<th>SE</th>
<th>p</th>
<th>CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Study design (RCT vs. no-RCT)</td>
<td>0.06</td>
<td>0.11</td>
<td>0.622</td>
<td>-0.17 - 0.28</td>
</tr>
<tr>
<td>Study quality</td>
<td>-0.18</td>
<td>0.12</td>
<td>0.120</td>
<td>-0.41 - 0.05</td>
</tr>
<tr>
<td>Sample size</td>
<td>-0.00</td>
<td>0.00</td>
<td>0.710</td>
<td>-0.00 - 0.00</td>
</tr>
<tr>
<td>Sample characteristic (clinical vs. non-clinical)</td>
<td>0.11</td>
<td>0.11</td>
<td>0.287</td>
<td>-0.10 - 0.32</td>
</tr>
<tr>
<td>Study sample (adolescents vs. adults)</td>
<td>0.12</td>
<td>0.24</td>
<td>0.602</td>
<td>-0.34 - 0.59</td>
</tr>
<tr>
<td>Study duration</td>
<td>-0.00</td>
<td>0.00</td>
<td>0.163</td>
<td>-0.01 - 0.00</td>
</tr>
<tr>
<td>Intervention duration</td>
<td>-0.00</td>
<td>0.00</td>
<td>0.304</td>
<td>-0.01 - 0.00</td>
</tr>
<tr>
<td>Drop-out rate (%)</td>
<td>-0.00</td>
<td>0.00</td>
<td>0.875</td>
<td>-0.01 - 0.01</td>
</tr>
<tr>
<td>Number of included outcomes</td>
<td>-0.01</td>
<td>0.01</td>
<td>0.467</td>
<td>-0.03 - 0.01</td>
</tr>
<tr>
<td>Type of app (commercial vs. research)</td>
<td>-0.07</td>
<td>0.10</td>
<td>0.457</td>
<td>-0.26 - 0.12</td>
</tr>
<tr>
<td>Treatment component in addition to app (app only vs. app+)</td>
<td>0.06</td>
<td>0.11</td>
<td>0.606</td>
<td>-0.16 - 0.27</td>
</tr>
<tr>
<td>Number of BCTs</td>
<td>-0.01</td>
<td>0.02</td>
<td>0.564</td>
<td>-0.06 - 0.03</td>
</tr>
</tbody>
</table>
**Appendix 2.11**

Effect sizes (Cohen’s $d$) for all analysis levels and outcomes.

<table>
<thead>
<tr>
<th>Analysis Level</th>
<th>Outcome</th>
<th>Effect Size</th>
<th>$p$ Value</th>
<th>$k$</th>
<th>Outcome Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>All-encomp. data set</td>
<td></td>
<td>$d = 0.33 (0.22-0.49)$</td>
<td>$&lt; 0.001$</td>
<td>41</td>
<td>373</td>
</tr>
<tr>
<td>Between within comparisons</td>
<td></td>
<td>$d = 0.22 (0.08-0.36)$</td>
<td>$= 0.002$</td>
<td>28</td>
<td>190</td>
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<tr>
<td>Within comparisons</td>
<td></td>
<td>$d = 0.48 (0.30-0.66)$</td>
<td>$&lt; 0.001$</td>
<td>24</td>
<td>183</td>
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<tr>
<td>Short-term</td>
<td></td>
<td>$d = 0.28 (0.12-0.44)$</td>
<td>$= 0.001$</td>
<td>13</td>
<td>57</td>
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<tr>
<td>Intermediate</td>
<td></td>
<td>$d = 0.28 (0.16-0.40)$</td>
<td>$= 0.001$</td>
<td>12</td>
<td>57</td>
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<tr>
<td>Long-term</td>
<td></td>
<td>$d = 0.08 (-0.10-0.26)$</td>
<td>$= 0.404$</td>
<td>9</td>
<td>31</td>
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</table>

**Adjusted data set**

<table>
<thead>
<tr>
<th>Outcome</th>
<th>Effect Size</th>
<th>$p$ Value</th>
<th>$k$</th>
<th>Outcome Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nutrition behaviours (primary outcome)</td>
<td></td>
<td>$d = 0.19 (0.05-0.32)$</td>
<td>$= 0.004$</td>
<td>24</td>
</tr>
<tr>
<td>Nutrition-related health outcomes (secondary outcome)</td>
<td></td>
<td>$d = 0.24 (0.11-0.36)$</td>
<td>$= 0.001$</td>
<td>24</td>
</tr>
</tbody>
</table>

| Body weight |  | $d = 0.27 (0.13-0.41)$ | $= 0.001$ | 31 | 39 |
| Obesity indices |  | $d = 0.31 (0.15-0.46)$ | $= 0.001$ | 32 | 76 |
| Blood pressure |  | $d = 0.21 (0.01-0.42)$ | $= 0.044$ | 25 | 86 |
| Blood lipids |  | $d = 0.16 (0.03-0.28)$ | $= 0.018$ | 5 | 22 |
| Blood sugar |  | $d = 0.18 (-0.27-0.62)$ | $= 0.43$ | 7 | 10 |
Appendix 2.12

Effect sizes (Hedges’ $g$) for all analysis levels and outcomes.

### All-encompassing data set

- **Short-term**
  - $g = 0.27 (0.12-0.43)$
  - $p = 0.001$
  - $k = 13$
  - outcome $n = 57$
- **Intermediate**
  - $g = 0.28 (0.15-0.40)$
  - $p = 0.001$
  - $k = 29$
  - outcome $n = 136$
- **Long-term**
  - $g = 0.38 (0.10-0.65)$
  - $p = 0.001$
  - $k = 9$
  - outcome $n = 31$

### Adjusted data set

- **Follow-up intervals**
  - **Short-term**
    - $g = 0.19 (0.06-0.32)$
    - $p = 0.004$
    - $k = 21$
    - outcome $n = 24$
- **Nutrition-related health outcomes**
  - **Short-term**
    - $g = 0.23 (0.12-0.36)$
    - $p < 0.001$
    - $k = 34$
    - outcome $n = 42$
- **Blood pressure**
  - $g = 0.21 (0.01-0.42)$
  - $p = 0.043$
  - $k = 7$
  - outcome $n = 19$
- **Blood lipids**
  - $g = 0.15 (0.03-0.28)$
  - $p = 0.018$
  - $k = 5$
  - outcome $n = 22$
- **Blood sugar**
  - $g = 0.18 (0.06-0.39)$
  - $p = 0.429$
  - $k = 7$
  - outcome $n = 10$
- **BMI**
  - $g = 0.37 (0.18-0.55)$
  - $p < 0.001$
  - $k = 17$
  - outcome $n = 21$
- **Obesity indices**
  - $g = 0.30 (0.15-0.45)$
  - $p < 0.001$
  - $k = 32$
  - outcome $n = 76$

- **Caloric intake**
  - $g = 0.17 (0.08-0.43)$
  - $p = 0.001$
  - $k = 11$
  - outcome $n = 25$
- **Intermediate**
  - $g = 0.32 (0.15-0.50)$
  - $p < 0.001$
  - $k = 8$
  - outcome $n = 27$
- **BMI**
  - $g = 0.37 (0.18-0.55)$
  - $p < 0.001$
  - $k = 17$
  - outcome $n = 21$

- **Body weight**
  - $g = 0.27 (0.15-0.41)$
  - $p < 0.001$
  - $k = 31$
  - outcome $n = 29$

---

Outcome n = 373 (between and within comparisons: $g = 0.22 (0.08-0.36)$, $p = 0.002$, $k = 28$, outcome $n = 190$)

Within comparisons $g = 0.47 (0.29-0.65)$, $p < 0.001$, $k = 34$, outcome $n = 183$
Appendix 2.13

Forest plots for outcomes.

I. Nutrition behaviours

**Figure 2.13a.** Forest plot showing the effects of app-based mobile interventions on caloric intake ($k = 8$, outcome $n = 9$; adjusted data set).

**Figure 2.13b.** Forest plot showing the effects of app-based mobile interventions on fruit/vegetable intake ($k = 8$, outcome $n = 27$; adjusted data set).
II. Nutrition-related health outcomes

![Forest plot showing the effects of app-based mobile interventions on obesity indices (k = 32, outcome n = 76; adjusted data set).](image)

**Figure 2.13c.** Forest plot showing the effects of app-based mobile interventions on obesity indices (k = 32, outcome n = 76; adjusted data set).

![Forest plot showing the effects of app-based mobile interventions on body weight (k = 31, outcome n = 39; adjusted data set).](image)

**Figure 2.13d.** Forest plot showing the effects of app-based mobile interventions on body weight (k = 31, outcome n = 39; adjusted data set).
Figure 2.13e. Forest plot showing the effects of app-based mobile interventions on BMI ($k = 17$, outcome $n = 21$; adjusted data set).
**Figure 2.13f.** Forest plot showing the effects of app-based mobile interventions on blood pressure ($k = 7$, outcome $n = 19$; adjusted data set).

**Figure 2.13g.** Forest plot showing the effects of app-based mobile interventions on blood lipids ($k = 5$, outcome $n = 22$; adjusted data set).
Figure 2.13h. Forest plot showing the effects of app-based mobile interventions on cholesterol ($k = 5$, outcome $n = 7$; adjusted data set).

Figure 2.13i. Forest plot showing the effects of app-based mobile interventions on blood sugar ($k = 7$, outcome $n = 10$; adjusted data set).
Appendix 2.14

Weighted mean differences for BMI and body weight.

Table 2.14a

Weighted mean differences for BMI (kg/m²) for the intervention group (k = 13).

<table>
<thead>
<tr>
<th>Study</th>
<th>Difference (BMI Points)</th>
<th>Weights</th>
<th>Weighted Mean Difference (BMI Points)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ahn et al., 2016</td>
<td>0.21</td>
<td>3.50</td>
<td>3.71</td>
</tr>
<tr>
<td>Allen et al., 2013</td>
<td>-1.22</td>
<td>4.11</td>
<td>-5.01</td>
</tr>
<tr>
<td>Appel et al., 2014</td>
<td>0.08</td>
<td>6.27</td>
<td>0.50</td>
</tr>
<tr>
<td>Carter et al., 2013</td>
<td>-1.60</td>
<td>6.89</td>
<td>-11.02</td>
</tr>
<tr>
<td>Fukuoka et al., 2015</td>
<td>-2.00</td>
<td>4.39</td>
<td>-8.78</td>
</tr>
<tr>
<td>Hales et al., 2016</td>
<td>-1.41</td>
<td>6.47</td>
<td>-9.09</td>
</tr>
<tr>
<td>Hebden et al., 2014</td>
<td>-0.58</td>
<td>4.96</td>
<td>-2.88</td>
</tr>
<tr>
<td>Kim et al., 2017</td>
<td>-1.05</td>
<td>8.54</td>
<td>-8.97</td>
</tr>
<tr>
<td>Lee et al., 2010</td>
<td>-0.80</td>
<td>5.22</td>
<td>-4.18</td>
</tr>
<tr>
<td>McCarroll et al., 2015</td>
<td>-0.80</td>
<td>5.92</td>
<td>-4.74</td>
</tr>
<tr>
<td>Partridge et al., 2015</td>
<td>-0.90</td>
<td>7.55</td>
<td>-6.80</td>
</tr>
<tr>
<td>Stephens et al., 2017</td>
<td>-0.63</td>
<td>4.21</td>
<td>-2.63</td>
</tr>
<tr>
<td>Widmer et al., 2015</td>
<td>-1.20</td>
<td>4.23</td>
<td>-5.08</td>
</tr>
</tbody>
</table>

Mean          -0.92          -0.90

Note. Includes intervention studies specifying absolute mean difference in BMI points (kg/m²) for the intervention group. Out of 17 studies reporting BMI changes (see Figure 2.13e), one was excluded due to outlier values (G. Block et al., 2015) and three did not report within BMI changes (Godino et al., 2016, Jensen et al., 2016 and Johnston et al., 2013), and thus, they were not included.
Table 2.14b

Weighted mean differences for body weight in kilograms for the intervention group ($k = 29$).

<table>
<thead>
<tr>
<th>Study</th>
<th>Difference (kg)</th>
<th>Weights</th>
<th>Weighted Mean Difference (kg)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ahn et al., 2016</td>
<td>0.64</td>
<td>1.95</td>
<td>1.25</td>
</tr>
<tr>
<td>Allen et al., 2013</td>
<td>-3.56</td>
<td>2.27</td>
<td>-8.08</td>
</tr>
<tr>
<td>Balk-Moller et al., 2017</td>
<td>-1.24</td>
<td>4.15</td>
<td>-5.15</td>
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<tr>
<td>Brindal et al., 2016</td>
<td>-5.88</td>
<td>4.02</td>
<td>-23.64</td>
</tr>
<tr>
<td>Burke et al., 2017</td>
<td>-2.79</td>
<td>3.59</td>
<td>-10.02</td>
</tr>
<tr>
<td>Carter et al., 2013</td>
<td>-4.60</td>
<td>3.70</td>
<td>-17.02</td>
</tr>
<tr>
<td>Fukuoka et al., 2015</td>
<td>-5.70</td>
<td>2.42</td>
<td>-13.79</td>
</tr>
<tr>
<td>Godino et al., 2016</td>
<td>-0.52</td>
<td>4.32</td>
<td>-2.27</td>
</tr>
<tr>
<td>Gordon et al., 2017</td>
<td>-0.20</td>
<td>3.76</td>
<td>-0.77</td>
</tr>
<tr>
<td>Hales et al., 2016</td>
<td>-3.75</td>
<td>3.49</td>
<td>-13.09</td>
</tr>
<tr>
<td>Hebden et al., 2014</td>
<td>-1.60</td>
<td>2.72</td>
<td>-4.35</td>
</tr>
<tr>
<td>Holmen et al., 2014</td>
<td>-1.30</td>
<td>3.03</td>
<td>-3.94</td>
</tr>
<tr>
<td>Jensen et al., 2016</td>
<td>0.09</td>
<td>2.35</td>
<td>0.20</td>
</tr>
<tr>
<td>Johnston et al., 2013</td>
<td>-4.60</td>
<td>4.07</td>
<td>-18.72</td>
</tr>
<tr>
<td>Kim et al., 2017</td>
<td>-2.98</td>
<td>4.50</td>
<td>-13.41</td>
</tr>
<tr>
<td>Laing et al., 2014</td>
<td>-0.03</td>
<td>3.93</td>
<td>-0.12</td>
</tr>
<tr>
<td>Lee et al., 2010</td>
<td>-1.90</td>
<td>2.84</td>
<td>-5.40</td>
</tr>
<tr>
<td>McCarroll et al., 2015</td>
<td>-2.30</td>
<td>3.21</td>
<td>-7.38</td>
</tr>
<tr>
<td>Partridge et al., 2015</td>
<td>-1.90</td>
<td>4.02</td>
<td>-7.64</td>
</tr>
<tr>
<td>Ross &amp; Wing, 2016</td>
<td>-5.22</td>
<td>3.01</td>
<td>-15.71</td>
</tr>
<tr>
<td>Spring et al., 2017</td>
<td>-3.97</td>
<td>3.23</td>
<td>-12.81</td>
</tr>
<tr>
<td>Steinert et al., 2016</td>
<td>0.50</td>
<td>3.10</td>
<td>1.55</td>
</tr>
<tr>
<td>Stephens et al., 2017</td>
<td>-1.80</td>
<td>2.32</td>
<td>-4.18</td>
</tr>
<tr>
<td>Svetkey et al., 2015</td>
<td>-1.11</td>
<td>4.15</td>
<td>-4.62</td>
</tr>
<tr>
<td>Thomas &amp; Wing, 2013</td>
<td>-9.65</td>
<td>3.03</td>
<td>-29.24</td>
</tr>
<tr>
<td>Turner-McGr. &amp; Tate, 2011</td>
<td>-2.50</td>
<td>3.35</td>
<td>-8.38</td>
</tr>
<tr>
<td>Wharton et al., 2014</td>
<td>-1.59</td>
<td>2.57</td>
<td>-4.09</td>
</tr>
<tr>
<td>Widmer et al., 2015</td>
<td>-4.00</td>
<td>2.32</td>
<td>-9.28</td>
</tr>
<tr>
<td>Willey &amp; Walsh, 2016</td>
<td>-6.12</td>
<td>1.63</td>
<td>-9.98</td>
</tr>
</tbody>
</table>

Mean: -2.74 - 2.69

Note. Includes intervention studies specifying absolute mean difference in body weight in kg (or lbs) for the intervention group. Out of the 31 studies reporting body weight changes (see Figure 2.13d), one was using a different metric (Brindal et al., 2013), and one was excluded due to outlier values (G. Block et al., 2015) and thus, they were not included.
3

Eating Motives

Why We Eat What We Eat: Dispositional and In-the-Moment Eating Motives

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University of Konstanz

3. Eating Motives

3.1 Abstract

Background: Eating motives are diverse, ranging from hunger to affect regulation. Current psychometric measures can capture multiple eating motives, but rely on dispositional rather than idiographic approaches, neglecting the moment-to-moment variability of eating motives that are associated with the situational fluctuations of daily life.

Objective: To compare 15 basic eating motives measured by a single-time-point dispositional assessment (trait) with an in-the-moment assessment of the same motives (state) in order to examine differences between why people think they eat and why they eat in the moment of consumption.

Methods: Eating motives were assessed in 35 participants using two methodological approaches: (1) a dispositional single-time point assessment, (2) an in-the-moment mobile assessment across eight days ($N = 888$ meals). The resulting eating motive profiles were compared according to different indices of profile similarity. Moreover, a visualized person x motive data matrix was created to analyze and visualize between- and within-person data.

Results: An omnibus index of profile similarity yielded a good overall similarity between the trait and state eating motive profiles across participants, with $\text{ICC}_{de} = 0.52$ ($p < .001$). However, while the two approaches revealed a comparable rank order ($r = 0.65$, $p<.001$), trait motives overestimated 12 of 15 state motives ($p<.001$, $d = 1.97$). Large differences ($d > 0.8$) between trait and state eating motives were found for price, sociability, need and hunger, traditional eating, habit, and natural concerns. Further, the person x motive data matrix revealed substantial inter-individual differences in intra-individual motive profiles.

Conclusions: For a comprehensive understanding of why we eat what we eat, dispositional assessments need to be extended by comprehensive in-the-moment mobile assessments. Targeting differences between why people think they eat and why they actually eat in the moment might hold great promise for tailored inventions for behavior change.
3.2 Introduction

3.2.1 Background

Food is almost ubiquitous in our everyday life, and ‘eating’ is one of the simplest yet most complex behaviors (Fischler, 1980; Rozin, 1996, 2007), involving up to 200 decisions a day (Wansink & Sobal, 2007). The motives for and functions of eating in everyday life play a crucial role in promoting healthy eating behaviours (Adriaanse et al., 2009). A deeper understanding of the underlying mechanisms and causes of human food choices is indispensable for designing and facilitating effective primary interventions to counteract the obesity epidemic (World Health Organization, 2017) and its associated health risks (GBD 2015 Obesity Collaborators, 2017; The Global BMI Mortality Collaboration, 2016; NCD Risk Factor Collaboration, 2016). The questions ‘what we eat’ and also ‘why we eat, what we eat’ are therefore of great importance for promoting normal eating and preventing the development of obesity and eating disorders.

Everyday human eating behaviors are regulated by numerous motives (Renner et al., 2012; Sproesser, Ruby, et al., 2018) that range from physiological factors (Schupp & Renner, 2011; Tylka, 2006), psychological factors (such as positive or negative emotional states, e.g., (Macht & Simons, 2000; Schüz, Bower, & Ferguson, 2015; Sproesser, Strohbach, Schupp, & Renner, 2011; Tomiyama, Mann, & Comer, 2009) and social reasons (Cruwys, Bevelander, & Hermans, 2015; Higgs & Thomas, 2016; Stok, Mollen, Verkooijen, & Renner, 2018), to various situational factors such as food’s smell or appearance (Pollard, Kirk, & Cade, 2002; Renner, Sproesser, Stok, & Schupp, 2016; Schüz, Schüz, et al., 2015; Van Strien et al., 1986). Thus, in addition to hunger, there are other compelling reasons for choosing and eating certain food items.

Since eating motives are so multidimensional, assessing eating motives is a major challenge. Most psychometric measures focus on specific motives, such as the Motivation to Eat Scale, which assesses four core motives including pleasure, coping with negative affect, being social, and complying with others’ expectations (Jackson et al., 2003), or the Dutch Eating Behavior Questionnaire (DEBQ; Van Strien et al., 1986), which includes eating in response to negative emotions and in response to external sensory cues as two core motivations for eating. A more comprehensive conceptualization of eating motives is the
Food Choice Questionnaire (FCQ) developed by Steptoe et al. (1995), which encompasses nine different food choice motives for everyday life (cf., Eertmans, Victoir, Notelaers, Vansant, & Van den Bergh, 2006; Fotopoulos, Krystallis, Vassallo, & Pagiaslis, 2009; Januszewska, Pieniak, & Verbeke, 2011 for factorial validity across countries). In two samples, Steptoe et al. (1995) showed that the taste, appearance, and smell of food were rated as the most important motives for food choices, followed closely by healthiness, affordability, and availability.

However, since the FCQ did not include important motives such as social or physiological motives, The Eating Motivation Survey (TEMS) was developed to include a more extensive set of 15 ‘basic’ eating motives (Renner et al., 2012; Sproesser, Ruby, et al., 2018). These 15 motives comprise eating because of taste, habit, hunger, health concerns, convenience, pleasure, tradition, natural concerns, price considerations, visual appeal, sociability, weight control concerns, regulating negative affect, and concerns about social norms and social image. The 15 TEMS motives have been consistently found across different groups (such as women as compared with men, young as compared with older people, and normal- as compared with overweight people; Pechey, Monsivais, Ng, & Marteau, 2015; Renner et al., 2012), different contexts (such as work environments; Sonnentag, Pundt, & Venz, 2016), and countries (including Germany, USA, India, and Brazil; Moraes & Alvarenga, 2017; Sproesser, Ruby, et al., 2018).

Although current psychometric measures capture multiple motives, they commonly assess eating motives as time and situational invariant dispositions, asking for ‘typical’ reasons, e.g. why respondents usually eat what they eat (Renner et al., 2012; Steptoe et al., 1995). This single time-point method has key advantages due to its efficient and cost-effective way of data collection, but also has conceptual and methodological implications (Streiner, Norman, & Cairney, 2015). Theoretically, participants need to recall eating motives for each past eating event to derive a judgment about their typical eating motives. Considering the daily multitude of eating occasions, people are unlikely to accurately recall all their relevant reasons for eating, and so must reconstruct their eating motives (Fahrenberg et al., 2007; Garbinsky et al., 2014; Jezior et al., 1990; Redelmeier & Kahneman, 1996; Robinson, 2014; Robinson et al., 2011). Even when people manage to do this accurately, they still need to aggregate the different reasons across multiple eating occasions to infer their ‘typical’ reasons (Schwarz & Oyserman, 2001). Self to peer comparisons of eating motives
(Sproesser, Klusmann, Schupp, & Renner, 2017) have shown initial evidence that people might have biased conceptions of their dispositional eating motives. Hence, current measures for assessing eating motives may be substantially affected by memory and aggregation biases (Schwarz & Oyserman, 2001; Stone et al., 2007).

Moreover, assessments of eating motives rely on general rather than idiographic approaches, neglecting the moment-to-moment variability of the psychological phenomena associated with situational fluctuations in daily life (Shiffman et al., 2008). Differential eating motive profiles can therefore be described, for example that health and natural concerns are more important for person A than for person B (inter-individual differences), but these do not capture the intra-individual dynamics of eating motives occurring across time and situations within either person (intra-individual differences). Since daily eating situations can differ greatly, for example depending on time and place (Schüz, Bower, et al., 2015; Villinger et al., 2017; Wahl, Villinger, Sproesser, et al., 2017) and food choices show only small, albeit significant associations with personality traits (C. Keller & Siegrist, 2015), eating motives may also fluctuate within individuals. This raises the questions of the degree to which dispositional eating motives (akin to traits) reflect in-the-moment eating motives (akin to states), and whether greater variability exists at the motive or person level.

3.2.2 The Present Study

To answer these questions, the present study assessed 15 eating motives based on TEMS (Renner et al., 2012) that were realized in a single-time point dispositional assessment (later referred to as trait motives) and a one-week in-the-moment mobile assessment (later referred to as state motives) to record eating motives in both real-life and real-time (T. S. Conner & Mehl, 2015; Ebner-Priemer & Trull, 2009; Shiffman et al., 2008; Trull & Ebner-Priemer, 2013, 2014).

Profile similarity indices are used to establish whether and to what degree the 15 trait eating motives concur with the 15 state motives (Furr, 2009, 2010). The omnibus index reflects a proxy of the overall fit between the trait and state profiles. Furthermore, profiles can be similar in respect of three major characteristics: their shape, scatter, and elevation (see Figure 3.3). A large shape similarity indicates that the same motives score on average high (or low) within the trait and state profile. A large scatter similarity indicates that the
variability between the two eating motive profiles is relatively comparable. A high elevation similarity indicates that the average of the 15 motives is similar between the trait and state measure (for more details, see Furr, 2009, 2010). These similarity indices can be applied on different levels of analyses to assess inter- and intra-individual differences in profile similarity, including the between-person, between-motive and the within-person level.

To analyze and visualize the high-dimensional data and the different levels of data aggregation, we developed a new visualization tool called the ‘SMART-Profile-Explorer’. Using a ‘person x motive’ matrix format, the different profile similarity indices between trait and state eating motives were calculated and displayed separately for each individual and eating motive. To make the data and similarity indices available to other scientists (Lindsay, 2017) the full person x motive matrix created by the SMART-Profile-Explorer can be accessed online and can be used interactively to sort, filter and visualize the present data. Advances in technology play a large role in making such an open-sharing and interactive approach possible and the development of the SMART-Profile-Explorer aims at a comprehensive visualization of high-dimensional data to facilitate communication and data sharing.

3.3 Methods

3.3.1 Design and Procedure

The present study was part of the research project SmartAct, funded by the German Bundesministerium für Bildung und Forschung (BMBF). The study adhered to the guidelines of the German Psychological Society (Deutsche Gesellschaft für Psychologie) and the Declaration of Helsinki. The study protocol was approved by the University of Konstanz’s Institutional Review Board, and is in accordance with ethical guidelines and regulations. All participants gave written informed consent prior to participation.

Participants were recruited through leaflets distributed at the University of Konstanz and postings on Facebook groups. Participants were invited to the laboratory for individual introductory sessions. At the baseline session, participants completed a questionnaire assessing 15 dispositional (trait) eating motives based on a single-item version of TEMS (Renner et al., 2012) and demographic variables. We used the mobile application (app) SMARTFOOD, which was developed as part of the research project SmartAct (for more details, see Butscher et al., 2016), to record these motives in the moment of consumption.
Eating Motives

The participants were provided and familiarized with the smartphones (ASUS Padphone Infinity, Android 5.0.2) and research app during the introductory session. They were asked to record all eating events for eight consecutive days using the SMARTFOOD app (Figure 3.1). Specifically, they were asked to record the meal type (Figure 3.1, left), to take a picture of their meal (Figure 3.1, second from left), and to classify what they ate using a drop-down menu (Figure 3.1, third from left). Additional courses and leftovers were also recorded by taking pictures. In addition, participants rated 15 reasons why they ate what they ate based on the brief TEMS (Figure 3.1, right). As compensation, participants could choose between receiving 25€ or course credits (3 hours).

Figure 3.1. Mobile assessment of eating behavior and 15 eating motives (TEMS; see also Renner et al., 2012) using the app SMARTFOOD.

3.3.2 Participants and Eating Occasions

In total, 35 individuals participated in the study (88.6% female), with a mean age of 25.49 years ($SD = 5.70$; range 19 to 41 years) and an average BMI of 22.51 kg/m² ($SD = 5.51$; range 15.43 to 42.87 kg/m²). No participant dropped out. In total, 888 eating occasions were recorded during the mobile assessment. By using a participant-identified approach (see Leech, Worsley, Timperio, & McNaughton, 2015; Wahl, Villinger, Sproesser, et al., 2017), 231 (25.8%) eating occasions were classified as breakfast, 194 (21.8%) as lunch, 25 (2.8%) as afternoon tea time, 209 (23.5%) as snacks, and 229 (25.8%) as dinner.
3.3.3 Measures

The 15 eating motives were surveyed using a single-item version of the TEMS (Renner et al., 2012), in which a single item represented each of the motives, including liking, habits, need and hunger, health, convenience, pleasure, traditional eating, natural concerns, sociability, price, visual appeal, weight control, affect regulation, social norms, and social image (see Appendix 3.1). In the single-time point dispositional assessment (trait) and at every time participants logged a meal or snack (state assessment), they were asked to answer the question ‘I eat what I eat because of…’ by rating each of the 15 motives on a Likert scale ranging from [1] ‘strongly disagree’ to [4] ‘strongly agree’.

3.3.4 Analytical Procedure

To statistically compare trait to state eating motives, repeatedly assessed state motives were averaged across all eating occasions. Profile similarity was analyzed according to four different similarity indices: overall profile similarity by double-entry intraclass correlations ($ICC_{de}$), shape similarity ($r$) by Pearson correlations, scatter similarity ($Var_d$) by raw differences between profile variances, and elevation similarity ($M_d$) by raw differences between profile means (Furr, 2009, 2010). Findings were analyzed by paired t-tests and Pearson correlation analysis for each motive. Effect sizes were classified by Cohen’s $d$ (Cohen, 1988). All analyses were conducted with SPSS (Version 24). Furthermore, the SMART-Profile-Explorer was used in order to visualize and compare the resulting trait and state eating motive profiles at the different levels of data analyses. An online version of the SMART-Profile-Explorer is available at http://subspace.dbvis.de/smart-profile-explorer-v1.0/ (Log-in: parma. Password: !parma!).
3.4 Results

3.4.1 State and Trait Eating Motives: The Visualized Person x Motive Data Matrix

Each participant and eating motive were visualized in a matrix using the SMART-Profile-Explorer\(^1\). The visualized person x motive data matrix encompasses three dimensions: (1) the between-person level, displaying aggregated state and trait motives across participants and motives, (2) the between-motive level, for comparing pairs of trait and state motives within each of the 15 motives across all participants (vertical comparison), and (3) the within-person level, allowing a comparison of the 15 trait and state eating motives within a single participant (horizontal comparison). The three profile similarity indices were calculated, respectively, and averaged means of the 15 trait and state eating motives are additionally displayed as the last lines of the matrix. The visualized data matrix is illustrated in Figure 3.2 and fully displayed in Figure 3.4. Statistical indices and individual state and trait motive profiles are additionally summarized in Appendix 3.2–3.4.

Within the visualized person x motive data matrix, for the group and for each participant, the first left column shows the individual trait (blue line) and state eating motive profile (orange line). The second column depicts the average trait (blue dash) and state (orange dash) values aggregated across the 15 eating motives for the group and each participant, respectively. Columns 3-17 display the 15 trait (blue dash) and 15 state (orange dash) eating motives separately. Values within each data box can range from 1 (dash at the bottom) indicating a low value for the respective motive to 4 (dash at the ceiling) indicating a high value for the motive. The difference between the trait and state motive values is further visualized by the size of a colored square between the trait and state motives. The greater the difference is the larger the colored square is, while the depth of the square’s color is determined by how pronounced the motive is. In addition, the white-grey background of the motive data boxes changes to visualize the observed variability of each state eating motive. A darker shading indicates a greater variance across the longitudinal in-the-moment assessment for the state motive and, hence, a greater within-person motive fluctuation across time. In addition, columns 18-21 display the four similarity indices shape (\(\hat{\eta}\)), elevation (\(M_\Delta\)), scatter (\(Var_\Delta\)), and the overall similarity index (\(ICC_{de}\)), with lighter colors indicating a high similarity value and darker colors indicating a low similarity value on the respective index.
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**Figure 3.2.** Illustration of the visualized person x motive data matrix and similarity indices for the 15 trait (blue) and state (orange) eating motive profiles. The first line displays data for the ‘average participant’ (between-person level). The second line displays data for participant 35 (within-person level). Note. D = Difference score (trait value – state value).

Illustrating the visualized data matrix exemplarily (see Figure 3.2) shows that participant 35 scored high on the overall similarity with $ICC_{de} = 0.8$. More specifically, the separate indices revealed $r = 0.9$ for shape similarity as well as $M_D = 0.4$ for elevation and $Var_D = 0.4$ for scatter similarity. Focusing on the single eating motive *natural concerns*, participant 35 scored higher in the trait ($M_{trait} = 4.00$, blue dash) than in the state assessment ($M_{state} = 2.40$, orange dash). This difference of 1.60 is further visualized by the colored square. Since participant 35’s trait motive for *natural concerns* was more pronounced than the state motive, the square is colored in blue. The comparatively dark grey background color of the data box indicates a high observed state variance across the in-the-moment assessment of *natural concern* with $Var = 1.49$ (see also Appendix 3.4 for more details).

### 3.4.2 State and Trait Eating Motives: The Between-Person Level

Figure 3.3 illustrates the averaged profiles of the 15 trait and state eating motives. The omnibus index of profile similarity yielded a good overall similarity between the trait and state eating motive profiles across participants with $ICC_{de} = 0.52$ ($p < .001$). Thus, 27 percent of the observed variance in state eating motive profiles is explained by respective trait motive profiles.
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Figure 3.3. Average (typical) profile of the 15 trait (blue) and state (orange) eating motives with ICC$_{de}$ = 0.52, $p < .001$. Note. Rating ranged from [1] ‘strongly disagree’ to [4] ‘strongly agree’. Motives are arranged according to their rank order observed for the TEMS (Renner et al., 2012).

The shape of the averaged trait and state motive profiles coincides with $r = 0.65, p < .001$, indicating a comparable rank order across participants. However, trait and state motive profiles differed substantially in respect to the observed elevation ($M_D = 0.53$). Trait motives were rated higher on average than state motives, $M_{trait} = 2.41, SD = 0.31; M_{state} = 1.88, SD = 0.23; t(34) = 9.02, p < .001, d = 1.97$. In terms of scatter similarity, the average ratings ranged from 1.20 to 3.77 for trait and from 1.09 to 3.12 for state motives, indicating comparable scatters for both assessment methods. The average scatter index yielded a raw variance difference of $Var_D = 0.33$.

3.4.3 State and Trait Eating Motives: The Between-Motive Level

Twelve out of 15 eating motives were rated significantly higher on average when assessed as trait motives as compared to state motives, indicating a consistent pattern of results with the found overall elevation differences (see Figure 3.4 and Appendix 3.2). Large differences between trait and state eating motives ($d > 0.8$) were found for price, sociability, need and hunger, traditional eating, habit, and natural concerns. Moderate mean level differences ($d > 0.5$) emerged for weight control, affect regulation, health, pleasure, and liking, while a small effect size ($d > 0.3$) emerged for social norms. Despite these elevation differences, positive correlations were found for nine out of 15 eating motives, indicating that participants
who had a higher trait eating motive also tended to exhibit higher average state scores for the respective eating motive (see Appendix 3.2). The highest correlations between state and trait eating motive \( (r \geq 0.50) \) were found for visual appeal, weight control, affect regulation, natural concern, and price. State-trait correlations within the medium effect size range \( (r \geq 0.30) \) were observed for pleasure, sociability, convenience, and health. Comparing the variability for each pair of trait and state eating motives showed that some motives such as sociability, weight control, traditional eating, and affect regulation showed large variances in the trait \( (\text{Var} \geq 0.64) \) but low variances \( (\text{Var} \leq 0.19) \) in the state assessment. Inversely, motives such as visual appeal, pleasure, convenience, health, and natural concerns showed large variances \( (\text{Var} \geq 0.67) \) in both the trait assessment and the state assessment \( (\text{Var} \geq 0.41) \), indicating relatively high situational and/or between-person fluctuations.

### 3.4.4 State and Trait Eating Motives: The Within-Person Level

In Figure 3.4, participants are arranged according to their overall profile similarity \( (\text{ICC}_{de}) \), with participant 35 displaying the highest and participant 22 the lowest profile similarity. This omnibus index yielded a high overall similarity for seven of the 35 participants, with \( \text{ICC}_{de} \geq .80, p < .001 \) (see also Appendix 3.4). Thus, at least 64% of the observed variance in the state profile was explained by the respective trait profile. In addition, 15 participants showed a substantial profile similarity with at least 25% of the observed state variance explained by the trait variance \( (\text{ICC}_{de} \geq .50, p < .001) \). However, the remaining 13 participants showed only a low overall similarity between state and trait eating motive profiles, with less than 25% of the variance explained. The shape of the individual trait and state motive profiles coincides with \( r \geq 0.80 \) for 13 participants, indicating a highly similar rank order of the 15 eating motives within these participants. Furthermore, 16 participants showed a substantial rank order similarity with \( r \geq 0.60 \), and six participants showed a comparable low shape similarity with \( r \leq 0.40 \). Trait and state eating motive profiles differed substantially within participants for the observed elevation. At both group and individual levels, trait motives were rated higher on average than state motives. Specifically, 20 of the 35 participants scored half a point higher on the 4-point rating scale in the trait compared to the state assessment, whereas only two participants rated the state motives (slightly) higher than the trait motives. Comparing the variability between state and trait eating motives by using the index scatter shows substantial inter-individual differences in intra-individual trait-
state similarity. Eleven participants showed an average overall raw variance difference of $\text{Var}_D \geq 0.5$, indicating a substantial scatter difference between state and trait motives within these participants. Conversely, 13 participants showed a difference in variance of 0.2 or lower.

In addition, comparing the four similarity indices at the intra-individual level shows marked inter-individual differences. For example, the eating motive profiles of participants 35 and 13 yielded the same overall similarity ($\text{ICC}_{se} = 0.80$), but their elevation and scatter values still differed. Comparing their motive profiles shows that the differences were located at different state-trait motive pairs. While participant 35 overestimated the importance of *natural concerns* when asked about the ‘usual’ relevance for choosing food as compared to the relevance in the concrete eating situation, participant 13 showed an overestimation for the importance of *price* for his or her daily food choices. Hence, zooming in at the motive and person level revealed distinct individual similarity patterns leading to considerable differences in similarity between eating motives, as well as between and within individuals.
Figure 3.4. Visualized full person x motive data matrix. Participants are arranged in descending order according to the overall motive profile similarity ($ICC_{de}$) from high (top) to low (bottom).

Note. An online version of the SMART - Profile - Explorer is available at http://subspace.dbvis.de/smart-profile-explorer-v1.0/
Log-in: parma
Password: !parma!
3.5 Discussion

3.5.1 Principal Results

The present study aimed to compare dispositional and in-the-moment assessed eating motives at between-person, between-motive, and within-person levels. For this purpose, eating motives were measured by both a single-time-point dispositional assessment and a repeated in-the-moment assessment, and analyzed according to four different indices of profile similarity.

Examining the aggregated data across eating occasions and participants, we found that longitudinally in-the-moment assessed eating motives generally mirrored eating motives assessed through the classical cross-sectional approach. Specifically, at the between-person level, the similarity indices including overall similarity, shape, and scatter indicated a comparable rank order between motives and a comparable variance pattern. A positive relationship was also found at the between-motive level between trait and state motives, indicating that individuals who scored higher on a trait motive also scored higher on the respective state motive.

However, the similarity index elevation indicated substantial mean differences between trait and state motives. Compared to the state assessment, the trait assessment significantly overestimated 12 out of 15 eating motives. Interestingly, not only core motives such as need and hunger, price, habit, sociability but also motives such as natural concerns or traditional eating were rated far more importantly when people indicated why they typical eat than when asked in the moment of consumption. Likewise, motives such as health, weight concerns or affect regulation were overestimated in the trait assessment. Mean levels for state and trait motives only concurred for the motives convenience, visual appeal, and social image. Convenience and visual appeal were both important reasons for eating and the high mean values in the state and trait assessment indicate that they are generic motives, influencing eating on most occasions, across participants, and in a wide range of different contexts. Conversely, the low observed mean values for social image concerns in both assessments suggest that these concerns are limited to specific eating situations. This is in line with research on impression management, which suggests that eating behavior can serve a role of showing oneself to be a particular type of person in certain social situations (König, Giese,
Stok, & Renner, 2017; Pliner & Chaiken, 1990; Vartanian, Herman, & Polivy, 2007). For example, women are more inclined to try to create an impression of femininity by restricting food intake when situational variables such as eating with a male they do not know increase the desirability of presenting a feminine social identity (Pliner & Chaiken, 1990).

3.5.2 Implications of the Present Findings

The observed overestimation of the influence of motives in the moment of consumption through dispositional assessments might reflect different methodological issues affecting single-measurement of trait motives and longitudinal assessment of state motives, heterogeneous mechanisms and causes, or the complexity and multidimensionality of eating behavior in day-to-day life (Stok et al., 2017; Symmank et al., 2017). One might argue that people tend to view themselves favorably, and therefore overestimate the typical eating motives that they see as desirable. A recent study showed that the 15 eating motives differ in their perceived desirability (Sproesser et al., 2017), with hunger, health, and liking being perceived as highly desirable motives, whereas social image, social norms and affect regulation are seen as particularly undesirable. For desirable motives, participants rated their own motives as higher than their peers’, while the opposite pattern emerged for undesirable motives, indicating unrealistic optimism in eating motives (Sproesser et al., 2017). In the present study, trait eating motives were generally more pronounced than state motives, including desirable (e.g. need & hunger) and undesirable ones (e.g. affect regulation). Hence, social desirability concerns are unlikely to explain the observed pattern of results. Admittedly, to derive a judgment about their typical eating motives, people need to recall and aggregate the different reasons across multiple eating occasions. Numerous studies have shown that people often use heuristics to form judgments about their behavior and characteristics (Gigerenzer & Gaissmaier, 2011; Gigerenzer, Hertwig, & Pachur, 2011; Scheibehenne, Miesler, & Todd, 2007). In particular, participants might have used the representativeness heuristic as a mental shortcut to evaluate their typical eating motives, which might have caused the observed overestimations. In addition, measurement issues may have inflated the magnitude of trait motives or deflated the magnitude of state motives. For example, response biases to the mobile assessment scales such as under-reporting of momentary experiences of eating motives across assessments might have contributed to the lower mean levels. Further, enduring trait motives could shape the actual eating behavior
and as a consequence limit the occurrence of specific state eating motives. For example, an individual with a pronounced weight control motive at the trait level might avoid tempting food choices altogether (e.g. sweets, snacks) and therefore, she or he is less likely to report state weight control motives. Although avoidance of food items or eating situations might be caused by motives such as weight control, tradition, or social norms, in most cases, people probably opt for alternatives (e.g. an apple instead of chocolate) and thus, trait and state motives would covary.

Analyses on the within-person level showed pronounced inter-individual differences in intra-individual patterns between trait and state motives. Some participants seemed to have a very good notion of why they eat, since their trait and actual experienced motives covary to a high degree. For example, while participant 35 gave highly accurate estimations, except that she or he overestimated how much concerns about sustainability actually guided her or his eating in real life. Conversely, other participants (e.g. participant 22) showed a small overlap between state and trait motives. Hence, the concurrence between what they think about why they typically eat and why they actually eat is only marginal.

This interplay between inter- and intra-individual differences can only emerge from a comprehensive analysis that incorporates different aggregation levels, rather than focusing on overall means and between-person effects. The implemented visualized person x motive data matrix fosters this approach by facilitating an analysis that is close to the raw data. This approach aims to not only increase data transparency in terms of open data appeals (Lindsay, 2017), but also to illustrate underlying patterns and dynamics of eating motives. Focusing not just on between-person but also on within-person variability is crucial for gaining more detailed insights into psychological processes and counteracting the ‘threat to the conceptual integrity’ of psychological research elicited through a mismatch between theory and research practice (Voelkle, Brose, Schmiedek, & Lindenberger, 2014). We are convinced that a deeper understanding of human food choice behavior can only be achieved by integrating between- and within-person effects, and combining findings at the motive and person level.

To additionally consider real-life situational fluctuations in eating behaviors (Inauen, Shrout, Bolger, Stadler, & Scholz, 2016; Schüz, Bower, et al., 2015; Villinger et al., 2017) and prevent retrospective recall biases (Mitchell, Thompson, Peterson, & Cronk, 1997; Redelmeier & Kahneman, 1996; Wirtz, Kruger, Scollon, & Diener, 2003) an in-the-moment
approach was used to assess state eating motives. While it is admittedly true that in-the-moment approaches offer advantages over conventional single-time-point methods, especially in terms of their ecological validity (Shiffman et al., 2008; Stone et al., 1998; Trull & Ebner-Priemer, 2013), mobile assessments are also accompanied by increased expenditure for both participants and researchers. Especially in the case of eating, participants must log every eating occasion over a prolonged period to generate representative data, which in turn leads to methodological and statistical challenges for researchers (Hamaker & Wichers, 2017).

These cost-benefit-considerations also legitimate questioning whether repeatedly assessing eating motives in-the-moment provides sufficiently different findings compared to a single-time-point dispositional assessment to make them worthwhile. Previous studies in other research domains provide scarce and equivocal evidence for the correspondence of in-the-moment assessments with retrospective or dispositional measures (Cupach & Spitzberg, 1983; Jamison, Raymond, Slawsby, Mc Hugo, & Baird, 2006; Shiffman et al., 1997; Solhan, Trull, Jahng, & Wood, 2009), and cannot provide satisfying answers to this question. In the field of eating motives, the ecological validity of a single-time-point assessment of the DEBQ was supported by a two-week in-the-moment assessment of eating episodes and intrapersonal contextual factors (T. B. Mason et al., 2017). However, different assessment approaches of eating motives were not considered.

3.5.3 Strengths and Limitations

To our knowledge, the present study is the first that directly compares a dispositional assessment of eating motives to an in-the-moment assessment of the same motives in the same individuals to derive conceptual conclusions. Furthermore, the present findings are indicative for planning and designing effective health interventions. To promote healthy eating behavior and counteract the associated health risks of the rising obesity epidemic (Alberti, Zimmet, & Shaw, 2005; Di Chiara, Argano, Corrao, Scaglione, & Licata, 2012; Must et al., 1999), the interplay between person, situation and eating motive needs to be considered to improve intervention effectiveness by identifying critical cues, moments, and target groups.
Although the present findings expand the current state of research and provide important implications for health interventions, they must be viewed in consideration of two main limitations that should be accounted for in future research. While the sample size is comparable to other studies in eating research (Schüz, Bower, et al., 2015; Schüz, Schüz, et al., 2015; Stein & Corte, 2003; Zepeda & Deal, 2008), it is small, and the participants were predominantly white, female and highly educated. Moreover, future research is needed to investigate preceding situations that might also determine eating behavior, such as buying, choosing, or preparing food, to draw reliable conclusions and shed further light on explanations for the differences found between dispositional and in-the-moment eating motives.

3.5.4 Conclusion

In general, the present study found a substantial overlap between dispositional and in-the-moment assessed eating motives. However, elevation markedly differ between the two assessment approaches and the majority of eating motives are overestimated in dispositional assessments. A more detailed analysis of the interplay between person and motive revealed inter-individual differences in intra-individual similarity patterns. Hence, for a comprehensive understanding of why we eat what we eat, dispositional assessments need not only to be extended by comprehensive in-the-moment assessments but also to be analyzed at the between- and within-person level. Capturing these individual dynamics in eating motives is crucial in order to develop tailored dietary interventions to intervene in the critical moments of situations that determine eating behavior.
3.6 Acknowledgements

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Author’s contributions

B.R. and H.S. developed the study concept. All authors participated in the generation of the study design. D.W. conducted data analyses and M.B. developed and implemented the visualization tool for the data with input from D.W., K.V., and B.R. The manuscript draft was prepared by D.W. and B.R, and finalized with comments from H.S., K.V., L.K., K.Z., and G.S. All authors approved the final version of the manuscript for submission.

Conflicts of Interest

None declared.
### 3.7 Appendix

**Appendix 3.1**

Single-item version of The Eating Motivation Survey (TEMS; Renner et al., 2012).

<table>
<thead>
<tr>
<th>Ernährungsmotiv (original version)</th>
<th>Eating Motive (translated version)</th>
<th>trifft nicht zu</th>
<th>trifft voll zu</th>
</tr>
</thead>
<tbody>
<tr>
<td>„Warum haben Sie das gegessen?“ (state)</td>
<td>„Warum essen Sie das was Sie essen?“ (trait)</td>
<td>„I eat what I eat…“ (state)</td>
<td>„I eat what I eat…“ (trait)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Appetit</th>
<th>Liking</th>
<th>Gewohnheit</th>
<th>Habits</th>
<th>Hunger</th>
<th>Need and Hunger</th>
<th>Gesundheit</th>
<th>Health</th>
<th>Einfachheit</th>
<th>Convenience</th>
<th>Genuss</th>
<th>Pleasure</th>
<th>Tradition</th>
<th>Traditional Eating</th>
<th>Natürlichkeit</th>
<th>Natural Concerns</th>
<th>Gemeinschaft</th>
<th>Sociability</th>
<th>Preis</th>
<th>Price</th>
<th>Präsentation</th>
<th>Visual Appeal</th>
<th>Gewichtskontrolle</th>
<th>Weight Control</th>
<th>Affeektregulation</th>
<th>Affect Regulation</th>
<th>Soziale Normen</th>
<th>Social Norms</th>
<th>Soziales Image</th>
<th>Social Image</th>
</tr>
</thead>
<tbody>
<tr>
<td>„um mir eine Freude zu machen“</td>
<td>„because I like it“</td>
<td>„aus Gewohnheit“</td>
<td>„because I usually eat it“</td>
<td>„Hunger“</td>
<td>„because I’m hungry“</td>
<td>„aus gesundheitlichen Gründen“</td>
<td>„because it’s healthy“</td>
<td>„geringer Aufwand“</td>
<td>„because it’s convenient“</td>
<td>„um mir eine Freude zu machen“</td>
<td>„to indulge myself“</td>
<td>„aus traditionellen Gründen (z.B. Fest)“</td>
<td>„because it’s a tradition (e.g. special occasion)“</td>
<td>„aus ethischen Gründen (z.B. fairer Handel)“</td>
<td>„for ethical reasons (e.g. fair trade)“</td>
<td>„weil es gesellig ist“</td>
<td>„to be sociable“</td>
<td>„aus preislichen Gründen“</td>
<td>„because it is inexpensive“</td>
<td>„weil es mich angesprochen hat“</td>
<td>„because it spontaneously appeals to me“</td>
<td>„zur Gewichtskontrolle“</td>
<td>„because I watch my weight“</td>
<td>„aufgrund von negativen Emotionen (z.B. Frust)“</td>
<td>„to help me feel better (e.g. when frustrated)“</td>
<td>„weil es von mir erwartet wurde“</td>
<td>„because others expected me to eat it“</td>
<td>„weil andere das gut finden“</td>
<td>„because others like it“</td>
</tr>
</tbody>
</table>
### Appendix 3.2

Statistical characteristics of trait and state eating motives at the between-motive level.

<table>
<thead>
<tr>
<th></th>
<th>Trait Mean</th>
<th>State Mean</th>
<th>$M_0$ (SD)</th>
<th>95% CI</th>
<th>t</th>
<th>df</th>
<th>p</th>
<th>Cohen's $d$</th>
<th>r</th>
</tr>
</thead>
<tbody>
<tr>
<td>Liking</td>
<td>3.50 (0.56)</td>
<td>3.12 (0.52)</td>
<td>0.39 (0.74)</td>
<td>0.13 - 0.65</td>
<td>3.08</td>
<td>33</td>
<td>.004</td>
<td>0.34</td>
<td>.079 ns</td>
</tr>
<tr>
<td>Habit</td>
<td>2.77 (0.88)</td>
<td>1.84 (0.58)</td>
<td>0.93 (0.90)</td>
<td>0.62 - 1.24</td>
<td>6.11</td>
<td>34</td>
<td>.000</td>
<td>1.23</td>
<td>.292 ns</td>
</tr>
<tr>
<td>Need and Hunger</td>
<td>3.77 (0.43)</td>
<td>3.08 (0.46)</td>
<td>0.69 (0.62)</td>
<td>0.48 - 0.90</td>
<td>6.61</td>
<td>34</td>
<td>.000</td>
<td>1.35</td>
<td>.027 ns</td>
</tr>
<tr>
<td>Health</td>
<td>2.31 (0.96)</td>
<td>1.83 (0.64)</td>
<td>0.48 (0.95)</td>
<td>0.16 - 0.81</td>
<td>3.01</td>
<td>34</td>
<td>.005</td>
<td>0.58</td>
<td>.354*</td>
</tr>
<tr>
<td>Convenience</td>
<td>2.49 (0.82)</td>
<td>2.54 (0.69)</td>
<td>-0.05 (0.85)</td>
<td>-0.34 - 0.24</td>
<td>-0.36</td>
<td>34</td>
<td>.724</td>
<td>-0.07</td>
<td>.376*</td>
</tr>
<tr>
<td>Pleasure</td>
<td>2.94 (0.92)</td>
<td>2.58 (0.71)</td>
<td>0.36 (0.84)</td>
<td>0.07 - 0.66</td>
<td>2.53</td>
<td>33</td>
<td>.016</td>
<td>0.44</td>
<td>.493**</td>
</tr>
<tr>
<td>Traditional Eating</td>
<td>1.80 (0.80)</td>
<td>1.08 (0.19)</td>
<td>0.72 (0.83)</td>
<td>0.43 - 1.01</td>
<td>5.09</td>
<td>34</td>
<td>.000</td>
<td>1.28</td>
<td>-.102 ns</td>
</tr>
<tr>
<td>Natural Concerns</td>
<td>2.35 (1.10)</td>
<td>1.38 (0.69)</td>
<td>1.00 (0.90)</td>
<td>0.69 - 1.32</td>
<td>6.50</td>
<td>33</td>
<td>.000</td>
<td>1.03</td>
<td>.575***</td>
</tr>
<tr>
<td>Sociability</td>
<td>2.46 (0.92)</td>
<td>1.49 (0.39)</td>
<td>0.97 (0.84)</td>
<td>0.68 - 1.25</td>
<td>6.81</td>
<td>34</td>
<td>.000</td>
<td>1.25</td>
<td>.408*</td>
</tr>
<tr>
<td>Price</td>
<td>2.66 (0.84)</td>
<td>1.58 (0.59)</td>
<td>1.08 (0.74)</td>
<td>0.83 - 1.33</td>
<td>8.69</td>
<td>34</td>
<td>.000</td>
<td>1.45</td>
<td>.515**</td>
</tr>
<tr>
<td>Visual Appeal</td>
<td>2.97 (0.82)</td>
<td>2.97 (0.64)</td>
<td>-0.00 (0.65)</td>
<td>-0.22 - 0.22</td>
<td>-0.02</td>
<td>34</td>
<td>.981</td>
<td>-0.00</td>
<td>.635***</td>
</tr>
<tr>
<td>Weight Control</td>
<td>1.94 (0.94)</td>
<td>1.33 (0.44)</td>
<td>0.61 (0.74)</td>
<td>0.35 - 0.87</td>
<td>4.85</td>
<td>34</td>
<td>.000</td>
<td>0.70</td>
<td>.631***</td>
</tr>
<tr>
<td>Affect Regulation</td>
<td>1.71 (0.89)</td>
<td>1.15 (0.24)</td>
<td>0.56 (0.77)</td>
<td>0.30 - 0.83</td>
<td>4.31</td>
<td>34</td>
<td>.000</td>
<td>0.65</td>
<td>.606***</td>
</tr>
<tr>
<td>Social Norms</td>
<td>1.37 (0.65)</td>
<td>1.13 (0.18)</td>
<td>0.25 (0.63)</td>
<td>0.03 - 0.46</td>
<td>2.30</td>
<td>34</td>
<td>.028</td>
<td>0.48</td>
<td>.226 ns</td>
</tr>
<tr>
<td>Social Image</td>
<td>1.20 (0.47)</td>
<td>1.09 (0.19)</td>
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*Note.* Rating of eating motives ranged from 1 ‘strongly disagree’ to 4 ‘strongly agree’. *** $p < .001$, ** $p < .01$, * $p < .05$
Appendix 3.3

Profiles of the 15 eating motives for each individual with blue lines representing trait motives and orange lines state motives.
Appendix 3.4

Profile similarity indices for trait and state eating motives at the within-person level.

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<tr>
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<th>State</th>
<th>Trait</th>
<th>State</th>
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<th>Var</th>
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</table>

Note. Similarity refers to the comparison of trait and state assessed eating motives.

*** p<.001, **p<.01, *p<.05
Eating Happiness

Healthy Food Choices Are Happy Food Choices: Evidence from a Real Life Sample Using Smartphone Based Assessments

Deborah R. Wahl*, Karoline Villinger*, Laura M. König, Katrin Ziesemer, Harald, T. Schupp, & Britta Renner
*both authors contributed equally to this work

University of Konstanz

4. Eating Happiness

4.1 Abstract

Research suggests that “healthy” food choices such as eating fruits and vegetables have not only physical but also mental health benefits and might be a long-term investment in future well-being. This view contrasts with the belief that high-caloric foods taste better, make us happy, and alleviate a negative mood. To provide a more comprehensive assessment of food choice and well-being, we investigated in-the-moment eating happiness by assessing complete, real life dietary behaviour across eight days using smartphone-based ecological momentary assessment. Three main findings emerged: First, of 14 different main food categories, vegetables consumption contributed the largest share to eating happiness measured across eight days. Second, sweets on average provided comparable induced eating happiness to “healthy” food choices such as fruits or vegetables. Third, dinner elicited comparable eating happiness to snacking. These findings are discussed within the “food as health” and “food as well-being” perspectives on eating behaviour.
4.2 Introduction

When it comes to eating, researchers, the media, and policy makers mainly focus on negative aspects of eating behaviour, like restricting certain foods, counting calories, and dieting. Likewise, health intervention efforts, including primary prevention campaigns, typically encourage consumers to trade off the expected enjoyment of hedonic and comfort foods against health benefits (Cornil & Chandon, 2016). However, research has shown that diets and restrained eating are often counterproductive and may even enhance the risk of long-term weight gain and eating disorders (Mann et al., 2007; Van Strien, Herman, & Verheijden, 2014). A promising new perspective entails a shift from food as pure nourishment towards a more positive and well-being centred perspective of human eating behaviour (L. G. Block et al., 2011; Cornil & Chandon, 2016; Renner et al., 2012). In this context, L. G. Block et al. (2011) have advocated a paradigm shift from “food as health” to “food as well-being” (p. 848).

Supporting this perspective of “food as well-being”, recent research suggests that “healthy” food choices, such as eating more fruits and vegetables, have not only physical but also mental health benefits (T. S. Conner et al., 2017; Rooney et al., 2013) and might be a long-term investment in future well-being (Mujcic & Oswald, 2016). For example, in a nationally representative panel survey of over 12,000 adults from Australia, Mujcic and Oswald (2016) showed that fruit and vegetable consumption predicted increases in happiness, life satisfaction, and well-being over two years. Similarly, using lagged analyses, White et al. (2013) showed that fruit and vegetable consumption predicted improvements in positive affect on the subsequent day but not vice versa. Also, cross-sectional evidence reported by Blanchflower et al. (2013) shows that eating fruits and vegetables is positively associated with well-being after adjusting for demographic variables including age, sex, or race (Grant, Wardle, & Steptoe, 2009). Of note, previous research includes a wide range of time lags between actual eating occasion and well-being assessment, ranging from 24 hours (T. S. Conner, Brookie, Richardson, & Polak, 2015; White et al., 2013) to 14 days (T. S. Conner et al., 2017), to 24 months (Mujcic & Oswald, 2016). Thus, the findings support the notion that fruit and vegetable consumption has beneficial effects on different
indicators of well-being, such as happiness or general life satisfaction, across a broad range of time spans.

The contention that healthy food choices such as a higher fruit and vegetable consumption is associated with greater happiness and well-being clearly contrasts with the common belief that in particular high-fat, high-sugar, or high-caloric foods taste better and make us happy while we are eating them. When it comes to eating, people usually have a spontaneous “unhealthy = tasty” association (Raghunathan et al., 2006) and assume that chocolate is a better mood booster than an apple. According to this in-the-moment well-being perspective, consumers have to trade off the expected enjoyment of eating against the health costs of eating unhealthy foods (L. G. Block et al., 2011; Cornil & Chandon, 2016).

A wealth of research shows that the experience of negative emotions and stress leads to increased consumption in a substantial number of individuals (“emotional eating”) of unhealthy food (“comfort food”; Evers, Stok, & de Ridder, 2010; Sproesser, Schupp, & Renner, 2013; Taut, Renner, & Baban, 2012; Wansink, Cheney, & Chan, 2003). However, this research stream focuses on emotional eating to “smooth” unpleasant experiences in response to stress or negative mood states, and the mood-boosting effect of eating is typically not assessed (Tomiyama, Finch, & Cummings, 2015). One of the few studies testing the effectiveness of comfort food in improving mood showed that the consumption of “unhealthy” comfort food had a mood boosting effect after a negative mood induction but not to a greater extent than non-comfort or neutral food (Wagner et al., 2014). Hence, even though people may believe that snacking on “unhealthy” foods like ice cream or chocolate provides greater pleasure and psychological benefits, the consumption of “unhealthy” foods might not actually be more psychologically beneficial than other foods.

However, both streams of research have either focused on a single food category (fruit and vegetable consumption), a single type of meal (snacking), or a single eating occasion (after negative/neutral mood induction). Accordingly, it is unknown whether the boosting effect of eating is specific to certain types of food choices and categories or whether eating has a more general boosting effect that is observable after the consumption of both “healthy” and “unhealthy” foods and across eating occasions. Accordingly, in the present study, we investigated the psychological benefits of eating that varied by food categories and meal types by assessing complete dietary behaviour across eight days in real life.
Furthermore, previous research on the impact of eating on well-being tended to rely on retrospective assessments such as food frequency questionnaires (Blanchflower et al., 2013; Mujcic & Oswald, 2016) and written food diaries (White et al., 2013). Such retrospective self-report methods rely on the challenging task of accurately estimating average intake or remembering individual eating episodes and may lead to under-reporting food intake, particularly unhealthy food choices such as snacks (Rooney et al., 2013; Schüz, Bower, et al., 2015). To avoid memory and bias problems in the present study we used ecological momentary assessment (EMA; Shiffman, 2014) to obtain ecologically valid and comprehensive real life data on eating behaviour and happiness as experienced in-the-moment.

In the present study, we examined the eating happiness and satisfaction experienced in-the-moment, in real time and in real life, using a smartphone based EMA approach. Specifically, healthy participants were asked to record each eating occasion, including main meals and snacks, for eight consecutive days and rate how tasty their meal/snack was, how much they enjoyed it, and how pleased they were with their meal/snack immediately after each eating episode. This intense recording of every eating episode allows assessing eating behaviour on the level of different meal types and food categories to compare experienced eating happiness across meals and categories. Following the two different research streams, we expected on a food category level that not only “unhealthy” foods like sweets would be associated with high experienced eating happiness but also “healthy” food choices such as fruits and vegetables. On a meal type level, we hypothesised that the happiness of meals differs as a function of meal type. According to previous contention, snacking in particular should be accompanied by greater happiness.

4.3 Methods

The study conformed with the Declaration of Helsinki. All study protocols were approved by University of Konstanz’s Institutional Review Board and were conducted in accordance with guidelines and regulations. Upon arrival, all participants signed a written informed consent.
4.3.1 Participants

Thirty-eight participants (28 females: average age = 24.47, $SD = 5.88$, range = 18-48 years) from the University of Konstanz assessed their eating behaviour in close to real time and in their natural environment using an event-based ambulatory assessment method (EMA). No participant dropped out or had to be excluded. Thirty-three participants were students, with 52.6% studying psychology. As compensation, participants could choose between taking part in a lottery (4 x 25€) or receiving course credits (2 hours).

4.3.2 Procedure

Participants were recruited through leaflets distributed at the university and postings on Facebook groups. Prior to participation, all participants gave written informed consent. Participants were invited to the laboratory for individual introductory sessions. During this first session, participants installed the application movisensXS (version 0.8.4203) on their own smartphones and downloaded the study survey (movisensXS Library v4065). In addition, they completed a short baseline questionnaire, including demographic variables like age, gender, education, and eating principles. Participants were instructed to log every eating occasion immediately before eating by using the smartphone to indicate the type of meal, take pictures of the food, and describe its main components using a free input field. Fluid intake was not assessed. Participants were asked to record their food intake on eight consecutive days. After finishing the study, participants were invited back to the laboratory for individual final interviews.

4.3.3 Measures

Immediately before eating participants were asked to indicate the type of meal with the following five options: breakfast, lunch, afternoon tea, dinner, snack. In Germany, “afternoon tea” is called “Kaffee & Kuchen” which directly translates as “coffee & cake”. It is similar to the idea of a traditional “afternoon tea” meal in UK. Specifically, in Germany, people have “Kaffee & Kuchen” in the afternoon (between 4-5 pm) and typically coffee (or tea) is served with some cake or cookies. Dinner in Germany is a main meal with mainly savoury food.
After each meal, participants were asked to rate their meal on three dimensions. They rated (1) how much they enjoyed the meal, (2) how pleased they were with their meal, and (3) how tasty their meal was. Ratings were given on a scale of one to 100. For reliability analysis, Cronbach’s Alpha was calculated to assess the internal consistency of the three items. Overall Cronbach’s alpha was calculated with $\alpha = .87$. In addition, the average of the 38 Cronbach’s alpha scores calculated at the person level also yielded a satisfactory value with $\alpha = .83$ ($SD = .24$). Thirty-two of 38 participants showed a Cronbach’s alpha value above .70 (range = .42 - .97). An overall score of experienced happiness of eating was computed using the average of the three questions concerning the meals’ enjoyment, pleasure, and tastiness.

4.3.4 Analytical Procedure

The food pictures and descriptions of their main components provided by the participants were subsequently coded by independent and trained raters. Following a standardised manual, additional components displayed in the picture were added to the description by the raters. All consumed foods were categorised into 14 different food categories (see Table 4.1) derived from the food classification system designed by the German Nutrition Society (DGE) and based on the existing food categories of the German Nutrient Database (Max Rubner Institut). Liquid intake and preparation method were not assessed. Therefore, fats and additional recipe ingredients were not included in further analyses, because they do not represent main elements of food intake. Further, salty extras were added to the categorisation.

No participant dropped out or had to be excluded due to high missing rates. Missing values were below 5% for all variables. The compliance rate at the meal level cannot be directly assessed since the numbers of meals and snacks can vary between as well as within persons (between days). As a rough compliance estimate, the numbers of meals that are expected from a “normative” perspective during the eight observation days can be used as a comparison standard (8 x breakfast, 8 x lunch, 8 x dinner = 24 meals). On average, the participants reported $M = 6.3$ breakfasts ($SD = 2.3$), $M = 5.3$ lunches ($SD = 1.8$), and $M = 6.5$ dinners ($SD = 2.0$). In comparison to the “normative” expected 24 meals, these numbers indicate a good compliance (approx. 75%) with a tendency to miss six meals during the study period (approx. 25%). However, the “normative” expected 24 meals for the study
period might be too high since participants might also have skipped meals (e.g. breakfast). Also, the present compliance rates are comparable to other studies. For example, Elliston et al. (2017) recorded 3.3 meal/snack reports per day in an Australian adult sample and Casperson et al. (2015) recorded 2.2 meal reports per day in a sample of adolescents. In the present study, on average, $M = 3.4$ ($SD = 1.35$) meals or snacks were reported per day. These data indicate overall a satisfactory compliance rate and did not indicate selective reporting of certain food items.

To graphically visualise data, Tableau (version 10.1) was used and for further statistical analyses, IBM SPSS Statistics (version 24 for Windows).

4.3.5 Data Availability

The dataset generated and analysed during the current study is available from the corresponding authors on reasonable request.

4.4 Results

4.4.1 Eating Episodes

Overall, during the study period, a total of 1,044 completed eating episodes were reported (see also Table 4.1). On average, participants rated their eating happiness with $M = 77.59$ which suggests that overall eating occasions were generally positive. However, experienced eating happiness also varied considerably between eating occasions as indicated by a range from 7.00 to 100.00 and a standard deviation of $SD = 16.41$. 
Table 4.1

Descriptive statistics for eating happiness by meal type and food category.

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<td>100.00</td>
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<td>100.00</td>
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<td>Afternoon tea</td>
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<td>39.00</td>
<td>100.00</td>
<td>5.49 (13.81)</td>
</tr>
<tr>
<td>Dinner</td>
<td>245</td>
<td>81.47 (14.73)</td>
<td>19,959</td>
<td>11.00</td>
<td>100.00</td>
<td>4.09 (13.4)</td>
</tr>
<tr>
<td>Snack</td>
<td>332</td>
<td>79.45 (14.94)</td>
<td>26,378</td>
<td>13.33</td>
<td>100.00</td>
<td>1.52 (13.93)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Food Category</th>
<th>N</th>
<th>M (SD)</th>
<th>Sum</th>
<th>Min.</th>
<th>Max.</th>
<th>$M_{mcw}$ (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vegetables</td>
<td>400</td>
<td>77.57 (17.17)</td>
<td>27,995</td>
<td>11.00</td>
<td>100.00</td>
<td>1.16 (15.14)</td>
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<tr>
<td>Fruits</td>
<td>218</td>
<td>78.29 (16.13)</td>
<td>15,659</td>
<td>15.67</td>
<td>100.00</td>
<td>-0.65 (13.21)</td>
</tr>
<tr>
<td>Sweets</td>
<td>356</td>
<td>78.93 (15.27)</td>
<td>26,443</td>
<td>13.33</td>
<td>100.00</td>
<td>1.68 (13.74)</td>
</tr>
<tr>
<td>Salty extras</td>
<td>16</td>
<td>80.40 (10.35)</td>
<td>1,126</td>
<td>57.67</td>
<td>95.33</td>
<td>-0.07 (8.01)</td>
</tr>
<tr>
<td>Pastries</td>
<td>14</td>
<td>78.67 (19.25)</td>
<td>1,023</td>
<td>22.67</td>
<td>95.33</td>
<td>-2.39 (18.26)</td>
</tr>
<tr>
<td>Bread</td>
<td>284</td>
<td>75.52 (16.33)</td>
<td>19,407</td>
<td>19.33</td>
<td>100.00</td>
<td>-1.55 (13.46)</td>
</tr>
<tr>
<td>Pasta</td>
<td>226</td>
<td>77.89 (16.43)</td>
<td>16,123</td>
<td>22.33</td>
<td>100.00</td>
<td>0.39 (15.93)</td>
</tr>
<tr>
<td>Cereals</td>
<td>133</td>
<td>75.05 (16.63)</td>
<td>9,082</td>
<td>29.67</td>
<td>100.00</td>
<td>-3.01 (14.13)</td>
</tr>
<tr>
<td>Potatoes</td>
<td>61</td>
<td>80.47 (19.07)</td>
<td>4,426</td>
<td>7.00</td>
<td>100.00</td>
<td>1.91 (16.82)</td>
</tr>
<tr>
<td>Dairy products</td>
<td>366</td>
<td>75.46 (16.53)</td>
<td>25,127</td>
<td>22.33</td>
<td>100.00</td>
<td>-1.37 (14.49)</td>
</tr>
<tr>
<td>Meat</td>
<td>194</td>
<td>78.26 (16.01)</td>
<td>13,382</td>
<td>22.33</td>
<td>100.00</td>
<td>0.26 (14.19)</td>
</tr>
<tr>
<td>Eggs</td>
<td>38</td>
<td>79.22 (16.21)</td>
<td>2,852</td>
<td>36.00</td>
<td>100.00</td>
<td>0.95 (15.2)</td>
</tr>
<tr>
<td>Meat substitutes</td>
<td>23</td>
<td>83.62 (11.61)</td>
<td>1,672</td>
<td>59.67</td>
<td>100.00</td>
<td>5.39 (10.44)</td>
</tr>
<tr>
<td>Fish</td>
<td>26</td>
<td>71.82 (18.65)</td>
<td>1,580</td>
<td>34.33</td>
<td>98.67</td>
<td>-4.58 (16.84)</td>
</tr>
</tbody>
</table>

Note. Eating happiness ranged from 1 (low) to 100 (high). $M_{mcw}$ = person-mean centred average happiness score. Food categories are in accordance to the German Nutrient Database.
4.4.2 Food Categories and Experienced Eating Happiness

All eating episodes were categorised according to their food category based on the German Nutrient Database (German: Bundeslebensmittelschlüssel), which covers the average nutritional values of approximately 10,000 foods available on the German market and is a validated standard instrument for the assessment of nutritional surveys in Germany. As shown in Table 4.1, eating happiness differed significantly across all 14 food categories, \( F(13, 2131) = 1.78, p = .04 \). On average, experienced eating happiness varied from 71.82 (\( SD = 18.65 \)) for fish to 83.62 (\( SD = 11.61 \)) for meat substitutes. Post hoc analysis, however, did not yield significant differences in experienced eating happiness between food categories, \( p \geq .22 \). Hence, on average, “unhealthy” food choices such as sweets (\( M = 78.93, SD = 15.27 \)) did not differ in experienced happiness from “healthy” food choices such as fruits (\( M = 78.29, SD = 16.13 \)) or vegetables (\( M = 77.57, SD = 17.17 \)). In addition, an intraclass correlation (ICC) of \( \rho = .22 \) for happiness indicated that less than a quarter of the observed variation in experienced eating happiness was due to differences between food categories, while 78% of the variation was due to differences within food categories.

However, as Figure 4.1 (left side) depicts, consumption frequency differed greatly across food categories. Frequently consumed food categories encompassed vegetables which were consumed at 38% of all eating occasions (\( n = 400 \)), followed by dairy products with 35% (\( n = 366 \)), and sweets with 34% (\( n = 356 \)). Conversely, rarely consumed food categories included meat substitutes, which were consumed in 2.2% of all eating occasions (\( n = 23 \)), salty extras (1.5%, \( n = 16 \)), and pastries (1.3%, \( n = 14 \)).

4.4.3 Amount of Experienced Eating Happiness by Food Category

To account for the frequency of consumption, we calculated and scaled the absolute experienced eating happiness according to the total sum score. As shown in Figure 4.1 (right side), vegetables contributed the biggest share to the total happiness followed by sweets, dairy products, and bread. Clustering food categories shows that fruits and vegetables accounted for nearly one quarter of total eating happiness score and thus, contributed to a large part of eating related happiness. Grain products such as bread, pasta, and cereals, which are main sources of carbohydrates including starch and fibre, were the second main
source for eating happiness. However, “unhealthy” snacks including sweets, salty extras, and pastries represented the third biggest source of eating related happiness.

Figure 4.1. Left side: Average experienced eating happiness (colour intensity: darker colours indicate greater happiness) and consumption frequency (size of the cycle) for the 14 food categories. Right side: Absolute share of the 14 food categories in total experienced eating happiness.

4.4.4 Experienced Eating Happiness by Meal Type

To further elucidate the contribution of snacks to eating happiness, analysis on the meal type level was conducted. Experienced in-the-moment eating happiness significantly varied by meal type consumed, $F (4, 1039) = 11.75, p < .001$. Frequencies of meal type consumption ranged from snacks being the most frequently logged meal type ($n = 332$; see also Table 4.1) to afternoon tea being the least logged meal type ($n = 27$). Figure 4.2 illustrates the wide dispersion within as well as between different meal types. Afternoon tea ($M = 82.41, SD = 15.26$), dinner ($M = 81.47, SD = 14.73$), and snacks ($M = 79.45, SD = 14.94$) showed eating happiness values above the grand mean, whereas breakfast ($M = 74.28, SD = 16.35$) and lunch ($M = 73.09, SD = 18.99$) were below the eating happiness mean. Comparisons between meal types showed that eating happiness for snacks was
significantly higher than for lunch \( t(533) = -4.44, p = .001, d = -.38 \) and breakfast, \( t(567) = -3.78, p = .001, d = -.33 \). However, this was also true for dinner, which induced greater eating happiness than lunch \( t(446) = -5.48, p < .001, d = -.50 \) and breakfast, \( t(480) = -4.90, p < .001, d = -.46 \). Finally, eating happiness for afternoon tea was greater than for lunch \( t(228) = -2.83, p = .047, d = -.50 \). All other comparisons did not reach significance, \( t \leq 2.49, p \geq .093 \).

![Figure 4.2](image.png)

**Figure 4.2.** Experienced eating happiness per meal type. Small dots represent single eating events, big circles indicate average eating happiness, and the horizontal line indicates the grand mean. Boxes indicate the middle 50% (interquartile range) and median (darker/lighter shade). The whiskers above and below represent 1.5 of the interquartile range.

### 4.4.5 Control Analyses

In order to test for a potential confounding effect between experienced eating happiness, food categories, and meal type, additional control analyses within meal types were conducted. Comparing experienced eating happiness for dinner and lunch suggested that dinner did not trigger a happiness spill-over effect specific to vegetables since the foods consumed at dinner were generally associated with greater happiness than those consumed at other eating occasions (Appendix 4.1). Moreover, the relative frequency of vegetables
consumed at dinner (73%, \( n = 180 \) out of 245) and at lunch were comparable (69%, \( n = 140 \) out of 203), indicating that the observed happiness-vegetables link does not seem to be mainly a meal type confounding effect.

Since the present study focuses on “food effects” (Level 1) rather than “person effects” (Level 2), we analysed the data at the food item level. However, participants who were generally overall happier with their eating could have inflated the observed happiness scores for certain food categories. In order to account for person-level effects, happiness scores were person-mean centred and thereby adjusted for mean level differences in happiness. The person-mean centred happiness scores (\( M_{\text{cwc}} \)) represent the difference between the individual’s average happiness score (across all single in-the-moment happiness scores per food category) and the single happiness scores of the individual within the respective food category. The centred scores indicate whether the single in-the-moment happiness score was above (indicated by positive values) or below (indicated by negative values) the individual person-mean. As Table 4.1 depicts, the control analyses with centred values yielded highly similar results. Vegetables were again associated on average with more happiness than other food categories (although people might differ in their general eating happiness). An additional conducted ANOVA with person-centred happiness values as dependent variables and food categories as independent variables provided also a highly similar pattern of results. Replicating the previously reported analysis, eating happiness differed significantly across all 14 food categories, \( F(13, 2129) = 1.94, p = .023 \), and post hoc analysis did not yield significant differences in experienced eating happiness between food categories, \( p \geq .14 \). Moreover, fruits and vegetables were associated with high happiness values, and “unhealthy” food choices such as sweets did not differ in experienced happiness from “healthy” food choices such as fruits or vegetables. The only difference between the previous and control analysis was that vegetables (\( M_{\text{cwc}} = 1.16, SD = 15.14 \)) gained slightly in importance for eating-related happiness, whereas fruits (\( M_{\text{cwc}} = -0.65, SD = 13.21 \)), salty extras (\( M_{\text{cwc}} = -0.07, SD = 8.01 \)), and pastries (\( M_{\text{cwc}} = -2.39, SD = 18.26 \)) became slightly less important.
4.5 Discussion

This study is the first, to our knowledge, that investigated in-the-moment experienced eating happiness in real time and real life using EMA based self-report and imagery covering the complete diversity of food intake. The present results add to and extend previous findings by suggesting that fruit and vegetable consumption has immediate beneficial psychological effects. Overall, of 14 different main food categories, vegetables consumption contributed the largest share to eating happiness measured across eight days. Thus, in addition to the investment in future well-being indicated by previous research (Mujcic & Oswald, 2016), “healthy” food choices seem to be an investment in the in-the-moment well-being.

Importantly, although many cultures convey the belief that eating certain foods has a greater hedonic and mood boosting effect, the present results suggest that this might not reflect actual in-the-moment experiences accurately. Even though people often have a spontaneous “unhealthy = tasty” intuition (Raghunathan et al., 2006), thus indicating that a stronger happiness boosting effect of “unhealthy” food is to be expected, the induced eating happiness of sweets did not differ on average from “healthy” food choices such as fruits or vegetables. This was also true for other stereotypically “unhealthy” foods such as pastries and salty extras, which did not show the expected greater boosting effect on happiness. Moreover, analyses on the meal type level support this notion, since snacks, despite their overall positive effect, were not the most psychologically beneficial meal type, i.e., dinner had a comparable “happiness” signature to snacking. Taken together, “healthy choices” seem to be also “happy choices” and at least comparable to or even higher in their hedonic value as compared to stereotypical “unhealthy” food choices.

In general, eating happiness was high, which concurs with previous research from field studies with generally healthy participants. De Castro, Bellisle, and Dalix (2000) examined weekly food diaries from 54 French subjects and found that most of the meals were rated as appealing. Also, the observed differences in average eating happiness for the 14 different food categories, albeit statistically significant, were comparable small. One could argue that this simply indicates that participants avoided selecting bad food (De Castro et al., 2000). Alternatively, this might suggest that the type of food or food categories are less decisive for experienced eating happiness than often assumed. This relates to recent findings in the field of comfort and emotional eating. Many people believe that specific types of food have greater comforting value. Also in research, the foods eaten as response to negative
emotional strain, are typically characterised as being high-caloric because such foods are assumed to provide immediate psycho-physical benefits (Tomiyama et al., 2015). However, comparing different food types did not provide evidence for the notion that they differed in their provided comfort; rather, eating in general led to significant improvements in mood (Wagner et al., 2014). This is mirrored in the present findings. Comparing the eating happiness of “healthy” food choices such as fruits and vegetables to that of “unhealthy” food choices such as sweets shows remarkably similar patterns as, on average, they were associated with high eating happiness and their range of experiences ranged from very negative to very positive.

This raises the question of why the idea that we can eat indulgent food to compensate for life’s mishaps is so prevailing. In an innovative experimental study, Adriaanse, Prinsen, de Witt-Huberts, de Ridder, and Evers (2016) led participants believe that they overate. Those who characterised themselves as emotional eaters falsely attributed their over-consumption to negative emotions, demonstrating a “confabulation”-effect. This indicates that people might have restricted self-knowledge and that recalled eating episodes suffer from systematic recall biases (Robinson, 2014). Moreover, Boelsma, Brink, Stafleu, and Hendriks (2010) examined postprandial subjective wellness and objective parameters (e.g., ghrelin, insulin, glucose) after standardised breakfast intakes and did not find direct correlations. This suggests that the impact of different food categories on wellness might not be directly related to biological effects but rather due to conditioning as food is often paired with other positive experienced situations (e.g., social interactions) or to placebo effects (Tomiyama et al., 2015). Moreover, experimental and field studies indicate that not only negative, but also positive, emotions trigger eating (Boh et al., 2016; Sproesser et al., 2013). One may speculate that selective attention might contribute to the “myth” of comfort food (Wagner et al., 2014) in that people attend to the consumption effect of “comfort” food in negative situation but neglect the effect in positive ones.

The present data also show that eating behaviour in the real world is a complex behaviour with many different aspects. People make more than 200 food decisions a day (Wansink & Sobal, 2007) which poses a great challenge for the measurement of eating behaviour. Studies often assess specific food categories such as fruit and vegetable consumption using Food Frequency Questionnaires, which has clear advantages in terms of cost-effectiveness. However, focusing on selective aspects of eating and food choices might provide only a
selective part of the picture (De Castro et al., 2000; Sproesser et al., 2013; Taut et al., 2012). It is important to note that focusing solely on the “unhealthy” food choices such as sweets would have led to the conclusion that they have a high “indulgent” value. To be able to draw conclusions about which foods make people happy, the relation of different food categories needs to be considered. The more comprehensive view, considering the whole dietary behaviour across eating occasions, reveals that “healthy” food choices actually contributed the biggest share to the total experienced eating happiness. Thus, for a more comprehensive understanding of how eating behaviours are regulated, more complete and sensitive measures of the behaviour are necessary. Developments in mobile technologies hold great promise for feasible dietary assessment based on image-assisted methods (Boushey et al., 2017).

As fruits and vegetables evoked high in-the-moment happiness experiences, one could speculate that these cumulate and have spill-over effects on subsequent general well-being, including life satisfaction across time. Combing in-the-moment measures with longitudinal perspectives might be a promising avenue for future studies for understanding the pathways from eating certain food types to subjective well-being. In the literature different pathways are discussed, including physiological and biochemical aspects of specific food elements or nutrients (Rooney et al., 2013).

The present EMA based data also revealed that eating happiness varied greatly within the 14 food categories and meal types. As within food category variance represented more than two third of the total observed variance, happiness varied according to nutritional characteristics and meal type; however, a myriad of factors present in the natural environment can affect each and every meal. Thus, widening the “nourishment” perspective by including how much, when, where, how long, and with whom people eat might tell us more about experienced eating happiness. Again, mobile, in-the-moment assessment opens the possibility of assessing the behavioural signature of eating in real life. Moreover, individual factors such as eating motives, habitual eating styles, convenience, and social norms are likely to contribute to eating happiness variance (Renner et al., 2012; Stok et al., 2017).

A key strength of this study is that it was the first to examine experienced eating happiness in non-clinical participants using EMA technology and imagery to assess food intake. Despite this strength, there are some limitations to this study that affect the interpretation of the
results. In the present study, eating happiness was examined on a food based level. This neglects differences on the individual level and might be examined in future multilevel studies. Furthermore, as a main aim of this study was to assess real life eating behaviour, the “natural” observation level is the meal, the psychological/ecological unit of eating (Pliner & Rozin, 2000), rather than food categories or nutrients. Therefore, we cannot exclude that specific food categories may have had a comparably higher impact on the experienced happiness of the whole meal. Sample size and therefore Type I and Type II error rates are of concern. Although the total number of observations was higher than in previous studies (see for example, Boushey et al. 2017 for a review), the number of participants was small but comparable to previous studies in this field (Inauen et al., 2016; Schüz, Bower, et al., 2015; Stein & Corte, 2003; Zepeda & Deal, 2008). Small sample sizes can increase error rates because the number of persons is more decisive than the number of nested observations (Bolger, Stadler, & Laurenceau, 2012). Specially, nested data can seriously increase Type I error rates, which is rather unlikely to be the case in the present study. Concerning Type II error rates, Aarts, Verhage, Veenvliet, Dolan, and Van Der Sluis (2014) illustrated for lower ICCs that adding extra observations per participant also increases power, particularly in the lower observation range. Considering the ICC and the number of observations per participant, one could argue that the power in the present study is likely to be sufficient to render the observed null-differences meaningful. Finally, the predominately white and well-educated sample does limit the degree to which the results can be generalised to the wider community; these results warrant replication with a more representative sample.

Despite these limitations, we think that our study has implications for both theory and practice. The cumulative evidence of psychological benefits from healthy food choices might offer new perspectives for health promotion and public-policy programs (Mujcic & Oswald, 2016). Making people aware of the “healthy = happy” association supported by empirical evidence provides a distinct and novel perspective to the prevailing “unhealthy = tasty” folk intuition and could foster eating choices that increase both in-the-moment happiness and future well-being. Furthermore, the present research lends support to the advocated paradigm shift from “food as health” to “food as well-being” which entails a supporting and encouraging rather constraining and limiting view on eating behaviour.
4.6 Acknowledgments

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Author contributions statement

B.R. & H.S. developed the study concept. All authors participated in the generation of the study design. D.W., K.V., L.K. & K.Z. conducted the study, including participant recruitment and data collection, under the supervision of B.R. & H.S.; D.W. & K.V. conducted data analyses. D.W. & K.V. prepared the first manuscript draft, and B.R. & H.S. provided critical revisions. All authors approved the final version of the manuscript for submission.

Competing financial interests

The authors declare no competing financial interests.
4.7 Appendix

Appendix 4.1

Descriptive statistics for eating happiness for lunch and dinner by food category.

<table>
<thead>
<tr>
<th>Food Category</th>
<th>Lunch N</th>
<th>M (SD)</th>
<th>Sum</th>
<th>Dinner N</th>
<th>M (SD)</th>
<th>Sum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vegetables</td>
<td>140</td>
<td>73.88 (19.08)</td>
<td>10,343</td>
<td>180</td>
<td>81.49 (14.71)</td>
<td>14,669</td>
</tr>
<tr>
<td>Fruits</td>
<td>19</td>
<td>80.44 (14.56)</td>
<td>1,528</td>
<td>24</td>
<td>84.69 (16.03)</td>
<td>2,033</td>
</tr>
<tr>
<td>Sweets</td>
<td>19</td>
<td>75.72 (18.63)</td>
<td>1,439</td>
<td>9</td>
<td>81.11 (17.14)</td>
<td>730</td>
</tr>
<tr>
<td>Salty extras</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Pastries</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>1</td>
<td>22.67</td>
<td>23</td>
</tr>
<tr>
<td>Bread</td>
<td>49</td>
<td>73.28 (18.38)</td>
<td>3,591</td>
<td>78</td>
<td>80.77 (13.49)</td>
<td>6,300</td>
</tr>
<tr>
<td>Pasta</td>
<td>85</td>
<td>73.4 (18.51)</td>
<td>6,239</td>
<td>84</td>
<td>81.06 (14.32)</td>
<td>6,809</td>
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<td>Cereals</td>
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<td>1,754</td>
<td>19</td>
<td>82.88 (14.66)</td>
<td>1,575</td>
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<td>Potatoes</td>
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<td>75.66 (22.39)</td>
<td>2,421</td>
<td>23</td>
<td>87.17 (10.27)</td>
<td>2,005</td>
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<td>Dairy products</td>
<td>75</td>
<td>70.02 (18.96)</td>
<td>5,251</td>
<td>117</td>
<td>80.40 (14.09)</td>
<td>9,407</td>
</tr>
<tr>
<td>Meat</td>
<td>71</td>
<td>76.12 (17.11)</td>
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<td>70</td>
<td>80.82 (15.53)</td>
<td>5,657</td>
</tr>
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<td>Eggs</td>
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<td>14</td>
<td>82.24 (11.78)</td>
<td>1,151</td>
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<tr>
<td>Meat substitutes</td>
<td>7</td>
<td>86.09 (11.01)</td>
<td>603</td>
<td>13</td>
<td>82.28 (12.13)</td>
<td>1,070</td>
</tr>
<tr>
<td>Fish</td>
<td>14</td>
<td>68.98 (21.55)</td>
<td>966</td>
<td>7</td>
<td>76.48 (12.57)</td>
<td>535</td>
</tr>
<tr>
<td>Total</td>
<td>203</td>
<td>73.09 (18.99)</td>
<td>14,838</td>
<td>245</td>
<td>81.47 (14.73)</td>
<td>19,959</td>
</tr>
</tbody>
</table>

Note. Eating happiness ranged from 1 (low) to 100 (high). Within meal type, multiple selection of food categories was possible. NA = no data available.
5

General Discussion
5. General Discussion

The rising prevalence of NCDs challenges health psychology research to find effective intervention strategies to change individual health behaviors. In particular, changing eating behavior is one of the major issues in health promotion. The aim of the present dissertation was therefore to examine new opportunities for understanding and changing eating behavior by taking an in-the-moment approach. App-based mobile interventions were examined as innovative delivery modes for targeting eating behavior changes. Further, a comprehensive understanding of eating behavior, and its underlying psychological determinants was established as a prerequisite for changing it. To meet these objectives, three interim goals were pursued (for a summary see Table 5.1).

First, the potential of app-based mobile interventions for changing eating behavior was determined in a systematic review and meta-analysis which showed beneficial effects on nutrition behaviors and proved that app-based mobile interventions can support eating behavior changes such as increases in fruit and vegetable intake. Furthermore, the positive changes observed in nutrition-related health outcomes including obesity indices and clinical metabolic parameters suggest that app-based mobile interventions are a promising means of preventing NCDs.

Second, eating motives were comprehensively investigated as core determinants of daily eating behavior through both a dispositional and in-the-moment assessment approach. Comparing the two approaches revealed that although both assessments generally correspond, the majority of eating motives were overestimated when people indicated why they typically eat (dispositional assessment) compared to when asked in the moment of consumption (in-the-moment assessment). Moreover, a sophisticated analysis on the motive and person levels revealed considerable inter- and intra-individual differences, which highlight the importance of targeting person- and situation-specific triggers when aiming to change eating behavior.

Third, eating happiness was identified as an important psychological determinant for in-the-moment eating behavior. Since eating happiness for healthy food choices such as fruits and vegetables were at least comparable to or even higher in their hedonic value than stereotypically unhealthy food choices, it can be concluded that the consumption of fruits and vegetables has both long-term and immediate beneficial psychological effects. The
resulting ‘happy = healthy’ association further indicates that the promotion of eating happiness can trigger both happy and healthy food choices.

Bringing together these findings of an in-the-moment investigation of eating motives and eating happiness with the beneficial effects of app-based mobile interventions for eating behavior changes offers new opportunities for future health promotion. Using an app-based mobile intervention to promote eating happiness experienced in-the-moment as an important psychological determinant can pave the way towards a new understanding of changing eating behavior. Highlighting a more positive and wellbeing-centered approach to changing eating behavior shifts the focus from a ‘food-as-health’ perspective towards a ‘food-as-well-being’ perspective.

The results of the individual research questions are discussed in detail in the respective chapters (Chapters 2 – 4). The following section provides a general discussion of this research in addition to overall implications of the present findings.
Table 5.1

Aims, findings and implications of the present dissertation.

<table>
<thead>
<tr>
<th>Aims</th>
<th>Findings</th>
<th>Implications</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>1. App-Based Mobile Interventions</strong></td>
<td><strong>Aims</strong></td>
<td><strong>Findings</strong></td>
</tr>
<tr>
<td>Determine the effectiveness of app-based mobile interventions as an innovative delivery mode for changing eating behavior and its associated health outcomes in a systematic review and meta-analysis.</td>
<td>Data from 41 studies including 6,348 participants and 373 outcomes showed positive effects on nutrition behaviors ( g = 0.19 ) and nutrition-related health outcomes ( g = 0.23 ), including small-to-moderate effect sizes for obesity indices ( g = 0.30 ).</td>
<td>App-based mobile interventions have a promising potential for changing eating behavior and subsequent health outcomes across a broad spectrum of the population.</td>
</tr>
<tr>
<td>Identify building blocks of successful interventions by analyzing different intervention characteristics and Behavior Change Techniques (BCTs).</td>
<td>Interventions comprised four main BCTs: Goals and planning, feedback and monitoring, shaping knowledge, and social support. However, different intervention characteristics did not moderate the effects significantly ( p &gt; 0.05 ).</td>
<td>Additional research is needed to investigate which intervention components are effective in changing eating behavior as a prerequisite for changing subsequent health outcomes.</td>
</tr>
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</table>

| 2. In-the-Moment Eating Motives | Investigate the motives determining daily food choices using two methodological approaches: a dispositional vs. an in-the-moment assessment. | Although the correspondence of dispositional and in-the-moment eating motives was good \( ICC = 0.52 \), the majority of motives were overestimated in the dispositional assessment \( p < .001, d = 1.97 \). | Combining dispositional and in-the-moment assessments are important to target differences between why people think they eat and why they actually eat in-the-moment. |
| | Analyze differences both between and within individuals to target why people think they eat and why they actually eat in the moment of consumption. | On the person level, inter-individual differences in intra-individual motive profiles were revealed, showing that dispositional and in-the-moment eating motives differed in dependence of the person, the motive and the situation. | Including inter- and intra-individual differences allows interventions to be tailored to the person and situation for intervening in critical moments that determine daily eating behavior. |

| 3. In-the-Moment Eating Happiness | Examine eating happiness experienced in-the-moment to explore which food choices are associated with high eating happiness. | Across 1,044 eating episodes, the hedonic value of fruits and vegetables proved to be at least comparable to stereotypically unhealthy food choices such as sweets or pastries \( p > 0.05 \). | Healthy food choices seem to also be happy food choices, and the consumption of fruits and vegetables has both long-term and immediate beneficial psychological effects. |
| | Explore eating happiness in relation to different food categories and meal types to cover the whole diversity of food intake. | Out of 14 different main food categories, vegetable consumption contributed the largest proportion of total eating happiness. | This offers a starting point for changing eating behavior by highlighting a more positive and wellbeing-centered perspective on eating. |
5.1 The Relevance of App-Based Mobile Interventions for Health Promotion

The first aim of the present dissertation was to examine the potential of app-based mobile interventions as an innovative strategy for achieving changes in eating behavior across a large spectrum of the population. Chapter 2 used a systematic review and meta-analysis of data from 41 studies, comprising 6,348 participants from healthy and clinical samples and 373 investigated outcomes, to show that app-based mobile interventions are effective in changing nutrition behaviors and nutrition-related health outcomes.

Beneficial positive effects were demonstrated for changes in nutrition behaviors, including significant effects for increasing fruit and vegetable intake. These findings encourage the implementation of app-based mobile interventions to facilitate changes in eating behavior. These findings further lead to the assumption that app-based mobile interventions can be employed as a promising tool for changing health behaviors in primary prevention. Since they can address a large spectrum of the population in a cost-effective way (Marcolino et al., 2018; Whittaker et al., 2016), app-based mobile interventions hold great promise for improving public health. By enabling health behavior changes they can support both the treatment and prevention of diseases such as obesity and diabetes (Albrecht, 2016; Free et al., 2013; Martínez-Pérez, de la Torre-Díez, & López-Coronado, 2013).

Underpinning these findings, positive effects were also shown for nutrition-related health outcomes such as obesity indices, blood pressure, and blood lipids. For instance, the conducted meta-analyses showed that app-based mobile interventions could significantly reduce body weight and BMI with small-to-moderate effect sizes. These effects are line with prior research that has quantified the magnitude of the influence of app-based mobile interventions (Covolo et al., 2017; Liu et al., 2015; Lyzwinski, 2014; Mateo et al., 2015; Schippers et al., 2017; Teasdale et al., 2018). These promising findings can serve to encourage research, practice, and policy makers to consider app-based mobile interventions as a cost-effective and scalable way of combatting NCDs in the general population (see also Coughlin et al., 2015).

Furthermore, since technological developments are constantly growing, intervention effectiveness is expected to increase accordingly. More and more possibilities for assessing and changing health behaviors and health outcomes will arise, including for example automatic time and place trackers, the automated tracking of physical activity, advanced
possibilities to facilitate the recording of food intake (e.g. in form of barcode scans or the automated coding of food pictures), and a wide range of additional sensors to assess context variables (Boushey et al., 2017; Elliston & Ferguson, 2018; Maringer et al., 2018; Schembre, Liao, O’Connor, et al., 2018).

Nevertheless, besides determining whether app-based mobile interventions are effective or not for changing health behaviors and health related-outcomes, it is also important to specify the maintenance of these effects. Previous work demonstrated that weight loss attempts often evoke positive effects in the short-term, but lead to weight gain in the long-term (Mann et al., 2007). Moreover, systematic reviews and meta-analyses that investigated the effectiveness of both traditional and technology-based weight loss interventions have shown that the greatest weight losses occur during the first six months (Hutchesson et al., 2015; Wadden et al., 2014). Therefore, investigating the long-term effectiveness of app-based mobile interventions will be a major step in determining their overall impact.

Specifying the effects of app-based mobile interventions according to short-, medium-, and long-term follow-ups, the meta-analyses only showed positive effects for studies targeting intermediate follow-up intervals. Different factors may have caused the higher effectiveness for intermediate outcomes, such as a smaller number of included studies or biases in the conduction, analysis, and reporting of included primary research studies (for a detailed discussion, see Chapter 2). Much more seriously, however, there has been no evaluation of or evidence provided for long-term effects (see also Albrecht, 2013, 2016; Van Heerden et al., 2012). The reviewed studies have been limited to time spans ranging from 14 days (Rabbi et al., 2015) to 24 months (Godino et al., 2016; Svetkey et al., 2015) with an average duration of 24 weeks. However, to evaluate whether app-based mobile interventions can also achieve permanent and sustainable changes in eating behavior and outcomes, investigations of their effectiveness need to be extended to longer time periods.

Taken together, although open research questions remain, the findings from the present review and meta-analysis underscore the indicated potential of app-based mobile interventions as a useful means for health promotion and strongly suggest that patients, health professionals, guideline developers, and policy makers should be made fully aware of their relative merits for changing eating behavior and related health outcomes.
The question raised by the huge potential of app-based mobile interventions for health promotion is how to use and implement them in the most effective way to promote health behavior changes.

5.2 Implications for Future App-Based Mobile Interventions

To exploit the full potential of app-based mobile interventions and derive implications for future interventions, an important milestone of the present dissertation was to examine app features and intervention characteristics to identify the building blocks of successful intervention approaches. For this purpose, different intervention characteristics and BCTs were examined in detail as the active ingredients of interventions.

Identifying the characteristics of successful interventions has proven to be extremely difficult. As also noted in prior work (see e.g. Coughlin et al., 2015), a considerable heterogeneity was observed in the designs of the intervention studies reviewed which limits the possibility of drawing generalizable conclusions about the building blocks and characteristics of successful interventions. In addition to calling for a more standardized, systematic and rigorous investigation, including the conducting and transparent reporting of intervention effects (see also Afshin et al., 2016; Atkins & Michie; 2013; Mateo et al., 2015), the present meta-analysis also attempted to resolve the existing heterogeneity by moderator analyses. However, neither intervention characteristics such as duration and type of app (commercial vs. non-commercial) nor study designs (RCTs vs. non-RCTs) and targeted samples (clinical vs. healthy sample) moderated the effects significantly. This highlights the robustness of the results, but does not allow more specific conclusion about effective intervention components to be drawn.

In terms of BCTs, an average of four BCTs were implemented in the reviewed interventions to promote eating behavior changes. This finding is in line with former reviews on sedentary behavior (Dunn, Gainforth, and Robertson-Wilson, 2018), physical activity (Middelweerd et al., 2014), and physical activity plus diet (Direito et al., 2014). However, while prior studies indicated that additionally-implemented BCTs do enhance intervention effectiveness (Lara et al., 2014; Michie et al., 2009; Samdal et al., 2017; Webb et al., 2010), the number of implemented BCTs was not revealed as a significant moderator in the present meta-analyses and no ‘optimal number’ of implemented BCTs could thus be derived.
Considering the intervention content, the four BCTs included most frequently were goal setting and planning, giving feedback and monitoring one’s own behavior or behavioral outcomes, shaping knowledge by making information available, and providing social support. This is in line with prior research evaluating the implementation of BCTs for both mobile and non-mobile interventions. The effectiveness of these BCTs has been proven not just for eating behavior (Direito et al., 2014; Lara et al., 2014; Samdal et al., 2017; Schoeppe et al., 2016), but also for promoting different health behaviors such as physical activity and sedentary behavior (Direito et al., 2016; Dunn et al., 2018; Middelweerd et al., 2014), medication adherence (Morrissey, Corbett, Walsh, & Molloy, 2016), and weight loss (Lyzwinski, 2014; Schippers et al., 2017).

However, not all reviewed interventions that implemented these four core behavior change strategies showed a high effectiveness (for possible explanations, see Chapter 2). Although the present dissertation aimed to identify individual BCTs or clusters associated with effective interventions in order to develop future app-based mobile interventions and provide recommendations for research and practice, the available empirical evidence does not allow systematic key characteristics of successful models to be pinpointed accurately.

One possible explanation for this finding might be that although there have been strong calls in recent research and literature for BCTs to be used to facilitate behavior change, no guidelines have been provided to specify their concrete implementation. So far, it remains unclear which BCTs or combination of BCTs should be implemented to promote a specific target behavior or induce changes in specific target audiences. Moreover, the lack of a theoretical foundation of both BCTs and app-based mobile interventions remains an important issue (Prestwich et al., 2014; West et al., 2013). It is acknowledged that health behavior interventions are more effective if they are based in theory (Atkins & Michie, 2013; Coughlin et al., 2015; Dunn et al., 2018; Mummah, 2016; Webb et al., 2010; West et al., 2017; Zhao et al., 2016), which was already established by Lewin (1943), who stated that ‘there is nothing as practical as a good theory’ (see e.g. Mc Cain, 2015). Especially in psychological research, using a theory-based rather than a ‘just-try-it’ approach is of crucial importance to understanding, verifying, and replicating the underlying processes of behavior change. The need to create more theory-driven approaches for improving health behaviors and promote the translation of behavioral theory and evidence into practice has been already stressed (Mummah, 2016; West et al., 2017). Therefore, in order to determine the
mechanisms by which behavior changes can be facilitated most effectively, a practical and theoretical framework of behavior change interventions is needed. This framework should specify what behavior change interventions work ‘how well, for whom, in what setting, for what behaviors and why’ (see Michie et al., 2018, p. 221; Human Behavior Change Project, 2019).

However, even if such a framework is provided, the major point of critique, i.e. that neither the BCT taxonomy nor current models of health behavior change address the dynamic properties of mobile delivery modes, persists. Since app-based mobile interventions distinguish themselves by being interactive, adaptive, and time-sensitive (Riley et al., 2011), more dynamic concepts are needed that target the essential aspects of timing and dynamic interaction. This includes for instance the timing of feedback and reminders, or tailoring goals to individual progress and capacities as essential components for effective mobile interventions (König, 2018; Nahum-Shani et al., 2015; Riley et al., 2011).

On that count, the Fogg Behavior Model (FBM; Fogg, 2009b), which highlights the importance of in-the-moment motivations, abilities, and triggers for performing a behavior (see Chapter 1), has become especially helpful by providing a more dynamic and behavior-centered theoretical basis for the present findings. Integrating the present findings into the FBM (Fogg, 2009b) provides an important starting point for the development of future app-based mobile interventions for changing eating behavior.

5.3 A New Intervention Approach: Combining Motivation, Ability and Trigger

By examining in-the-moment eating behavior and its underlying psychological determinants, the findings of the present dissertation suggest a new intervention approach for changing eating behavior including important motivators with a promising ability factor and in-the-moment triggers. First, assessing in-the-moment eating motives identified core motivators for daily eating behavior. Second, investigating eating happiness experienced in-the-moment highlighted eating happiness as an important simplicity factor for facilitating eating behavior changes. Third, combining those two findings with the promising effects of app-based mobile interventions for changing eating behavior indicates the potential of implementing in-the-moment behavioral triggers.
5.3.1 In-the-Moment Eating Motives as Core Motivators for Eating Behavior

In order to investigate eating motives as core motivators for daily eating behavior, dispositional and in-the-moment assessed eating motives were investigated in Chapter 3. Comparing the two approaches showed that longitudinally assessed eating motives (in-the-moment approach) generally mirror eating motives assessed through the classical cross-sectional method (dispositional approach). An exception is provided by the mean levels. In dependence of the respective assessment method, mean levels for eating motives deviated markedly and the majority of eating motives were overestimated when people indicated why they typically eat what they eat as opposed to when asked in the eating situation.

Furthermore, the findings highlight the situational importance of motives such as visual appeal, liking, and pleasure. In contrast to motives that seem to be more important when individuals reflect generally on why they typically eat what they eat, including motives such as need and hunger, habit, price, sociability, and natural concern, the motives visual appeal, liking, and pleasure showed high in-the-moment manifestations. Therefore, these motives can be considered as core motivators for the eating situation. Hence, when aiming to implement in-the-moment interventions, as app-based mobile interventions aspire to do (Nahum-Shani et al., 2015; Nahum-Shani et al., 2014), motives such as visual appeal, liking, and pleasure should be addressed predominantly.

An additional analysis on the person and motive level, which was facilitated through the ‘Smart Profile Explorer’, acknowledges person- and situation-specific differences in eating motives. Targeting the inter-individual differences allows interventions to be tailored to the individual, e.g. in dependence of a person’s most prominent eating motives. Focusing on the intra-individual differences further allows interventions to be tailored to the situation and implemented when they are needed the most. Therefore, by knowing the dispositional and situational triggers, interventions for changing eating behavior can be adapted and tailored not only to the individual but also to the situation.

5.3.2 In-the-Moment Eating Happiness as an Ability Factor for Changing Eating Behavior

According to Fogg (2009b), building on existing strengths and capacities requires less resources, since the complexity and difficulty of the target behavior is reduced. Hence, the ability to perform a behavior is enhanced (Fogg, 2009b). Chapter 3 demonstrated that
visual appeal, liking, and pleasure are core in-the-moment eating motives, which is in line with the findings that feelings of positive emotions derived from eating are of great importance for daily food choices (L. G. Block et al., 2011; Pettigrew, 2016). It can therefore be concluded that eating happiness constitutes a highly familiar, often experienced, and quite intuitive behavior. Improving one’s eating happiness might consequently be a relatively ‘simple’ strategy for individuals to pursue.

The findings of Chapter 4 showed that eating happiness experienced in-the-moment is highly associated with healthy food choices such as fruits and vegetables. This finding indicates a ‘happy = healthy’ association. Making people aware of this ‘happy = healthy’ association can counteract the prevailing ‘unhealthy = tasty’ stereotype. Moreover, the finding that happy food choices can also be healthy food choices provides a promising starting point for future interventions. Fostering eating happiness experienced in-the-moment can be used as an innovative strategy for improving both healthy and happy eating behaviors.

5.3.3 Using App-Based Mobile Interventions to Implement In-the-Moment Triggers

The third constituting mechanism to promote behavior changes proclaimed in the FBM (Fogg, 2009b) are triggers. In particular, the timing of the trigger has been shown to be of crucial importance (Fogg, 2009b). In order to facilitate behavior changes, a trigger needs to prompt at an opportune moment, in which motivation and ability are high. Through their real-life and real-time approach, app-based mobile interventions have the possibility to not only investigate which eating situations are characterized by high motivation and ability, but also to use these moments for in-the-moment triggers. By combining the three principles of motivation, ability, and trigger, an innovative intervention strategy for changing eating behavior delivered via app-based mobile technologies can be derived. Using in-the-moment triggers to promote eating happiness could serve as an important motivator that drives human food choices and, simultaneously, as an important cue for healthy eating.

The app-based mobile intervention called ‘The Happy Eater’ (Renner et al., 2018) is a first attempt to investigate the idea of promoting eating happiness by a fully automated smartphone app. ‘The Happy Eater’ intervention synthesizes the advantages of new technological developments, together with eating motives and eating happiness, as a
comprehensive in-the-moment approach to changing eating behavior. ‘The Happy Eater’ app (Renner et al., 2018) aims to enhance eating happiness by providing individualized, real-time feedback about eating happiness experienced in-the-moment. For this purpose, a smartphone app was developed which allows the capture of not only eating behavior by a mobile Visual Food Record, but also the assessment of eating motives and eating happiness as experienced in-the-moment. Feasibility and acceptability of this innovative intervention strategy have been investigated in pilot trials and focus groups, and have yielded overall positive results (Allgaier, 2016). Intervention effects of the ‘Happy Eater’ app are being investigated in an eight-week, large-scale, randomized controlled trial, including 156 individuals from the general population. The evaluation of the effectiveness includes changes in eating happiness, food intake, and related psychological and physiological parameters. First evidence provides promising results in terms of increased eating happiness due to the intervention (Renner et al., 2018). Detailed results are expected to be published in 2019.

Positive results of further interventions, which applied innovative simplified triggers for changing eating behavior (König, 2018; König & Renner, 2018, 2019), provided additional indicators for the potentially fruitful impact of this approach. For instance, König and Renner (2018) outlined the strategy of promoting color variety as an intuitive cue for healthy food choices. They established a ‘colorful = healthy’ association in an observational EMA study. A subsequent intervention study (König & Renner, 2019), proved that triggering colorful meals in the moment of food choice was associated with a healthier diet in terms of increased vegetable consumption. In addition to these changes in eating behavior, participants evaluated this strategy as enjoyable and simple to perform. Therefore, implementing an in-the-moment trigger based on the ‘colorful = healthy’ association turned out to be an effective as well as positively evaluated approach for changing eating behavior.

Accordingly, promoting eating happiness in the moment of consumption based on the demonstrated ‘happy = healthy’ association by using a smartphone app might constitute a fun and simple but effective way of changing individual eating behavior. Moreover, establishing this positive, and intuitive intervention strategy might offer a new perspective for health promotion by shifting the focus from a ‘food-as-health’ towards a ‘food-as-well-being’ perspective.
5.4 Establishing a New Perspective: From ‘Food-As-Health’ to ‘Food-As-Well-Being’

5.4.1 A ‘Food-as-Health’ Perspective on Changing Eating Behavior

The perspective of ‘food-as-health’ is currently predominant in research, policy, and the media. A majority of eating-related intervention approaches pursue restrictive strategies with a focus on recommendations for energy intake and nutrient compositions, and the adherence to dietary guidelines (König, 2018; Mummah, 2016; Onvani, Haghighatdoost, Surkan, Larijani, & Azadbakht, 2017; Pettigrew, 2016). Therefore, in current intervention practice, individuals are confronted with recommendations about what and how much food should ideally be consumed. However, research shows that these self-regulatory strategies, which form the basis of diets and restrained eating, are not only associated with negative thoughts and feelings (Dodds & Chamberlain, 2017) but also counterproductive. They seldom lead to long-term weight-losses and enhance the risk of future weight gain (Mann et al., 2007; Van Strien et al., 2014).

Moreover, by taking a restrictive approach, eating behavior is often reduced to its nutrients (Sproesser, Klusmann, et al., 2018). Indeed, it is undisputable that certain foods contain important nutrients such as vitamins and fiber, which are associated with positive effects on health (Ames, Shigenaga, & Hagen, 1993; Patterson & Block, 1988). However, in this limited perspective, eating is reduced to a summation of micronutrients and a mere function of physiological health (L. G. Block et al., 2011). This neglects fundamental psychological aspects of eating behavior. Therefore, promoting eating happiness aims to shift the perspective of ‘food-as-nutrition’ or ‘food-as-health’ towards a ‘food-as-well-being’ perspective, introducing a more positive approach rather than restrictions and restraints (L. G. Block et al., 2011; Pettigrew, 2016).

5.4.2 A ‘Food-as-Well-Being’ Perspective on Changing Eating Behavior

Pursuing the strategy of promoting eating happiness (see Renner et al., 2018) widens the focus towards a more holistic perspective on changing eating behavior. Using the rising ‘food-as-well-being’ perspective as a promising starting point for interventions (König, 2018; Landry et al., 2018; Pettigrew, 2016) is also acknowledged in prior research. Woolley and Fishbach (2016) for example showed that a focus on eating pleasure as a means of
immediate hedonistic rewarding might lead to a higher consumption of low-calorie, low-energy-dense foods. Moreover, as Rozin (2005) speculates from his observations of French people, emphasizing the experience and momentary joy of eating is associated with a healthier lifestyle and better health. This is in line with recent evidence which shows that a positive relationship with eating is associated with decreased health risk factors (Sproesser, Klusmann, et al., 2018). Based on two different studies, the authors conclude that a positive view of one’s eating behavior might be a promising way to promote physical and psychological health (Sproesser, Klusmann, et al., 2018). Further research also argued for implementing eating pleasure as a promising strategy to promote healthy eating (Jallinoja, Pajari, & Absetz, 2010; Pettigrew, 2016; Vogel & Mol, 2014), and early evidence indicates positive effects on diet quality (Carbonneau et al., 2017).

The present dissertation adds important evidence to these findings. Based on this evidence, eating behavior can be changed by encouraging a ‘positive psychological, physical, emotional, and social relationship with food’ (see L. G. Block et al., 2011, p. 6). Replacing the ‘food-as-health’ with a ‘food-as-well-being’ perspective can establish a new psychological and wellbeing-centered focus on changing eating behavior. Promoting eating happiness experienced in-the-moment as an innovative strategy for changing eating behavior provides a promising new avenue for health promotion.

5.5 Outlook and Future Directions in Health Promotion

The findings of the present dissertation add important evidence to a growing body of literature and provide important insights for the implementation of app-based mobile interventions for changing health behaviors. Although the potential of app-based mobile interventions is not yet fully exploited, they are destined to become an important tool for large-scale public health promotion.

Furthermore, an in-the-moment assessment approach for eating motives and eating happiness in daily life enabled a deeper understanding of eating behavior and its underlying determinants. In addition, a new methodological approach was developed to analyze the resulting high-dimensional and complex in-the-moment data. Instead of using aggregated means, the ‘Smart Profile Explorer’ (see Chapter 3) takes both inter-individual differences and intra-individual variability into account. Moreover, since a transparent and open data sharing approach has evolved into a crucial endeavor for ensuring the quality of scientific
work, the methods developed represent a valuable alternative for sharing data and allowing an interactive exploration of the published data among other researchers.

Based on the findings resulting from this innovative assessment and analysis approach, an app-based mobile intervention strategy is suggested, which provides a more positive and wellbeing-centered perspective on changing eating behavior, shifting the focus from a ‘food-as-health’ towards a ‘food-as-well-being’ perspective.

Despite these promising results and achievements of the present dissertation, future research is needed to address two important milestones, which go beyond app-based mobile interventions, for further improving health behavior change interventions. First, app-based mobile interventions represent an individual-centered and very reflective tool to change health behaviors, since they require conscious, goal-directed effort (Marteau, Hollands, & Fletcher, 2012; Mummah, 2016). In the example of eating behavior, participants need to self-manage their own eating behavior by recording it in the app. However, eating is often not initiated by conscious deliberations but rather is based on habits or triggered automatically by the environment (Allan, Querstret, Banas, & de Bruin, 2017; Stok et al., 2017). Studies showed that environmental characteristics such as portion sizes highly influence food intake, often without conscious awareness (Ello-Martin, Ledikwe, & Rolls, 2005; Rozin, Kabnick, Pete, Fischler, & Shields, 2003; Wansink & Kim, 2005; Wansink, Painter, & North, 2005; Zlatevska, Dubelaar, & Holden, 2014). Research has therefore focused on possibilities for altering people’s food environments to induce behavior changes. For example, environmental strategies such as choice architecture interventions (see e.g. Thaler, Sunstein, and Balz, 2014) have tried to induce healthy food choices in restaurants and cafeterias, shops, or workplaces, with promising results (for a review see Bucher et al., 2016; Skov, Lourenco, Hansen, Mikkelsen, & Schofield, 2012). Future research should therefore also further investigate how these environmental behavior change strategies as a different and additional approach for changing health behaviors can improve health promotion.

Second, the present dissertation focusses on the example of eating behavior as an important determinant for health promotion. However, recent research showed that health behaviors often cluster within individuals (Poortinga, 2007), which indicates that a health behavior often co-occurs with other health behaviors (Fine, Philogene, Gramling, Coups, & Sinha, 2004; Pronk et al., 2004; Sallis, Prochaska, & Taylor, 2000). It was shown that
intervention effects can transfer from one health behavior to another. For instance, physical activity interventions can lead to changes in eating behavior although eating was not targeted in the intervention (Fleig, Lippke, Pomp, & Schwarzer, 2011). Presuming synergistic effects between different health behaviors (Fleig, Küper, Lippke, Schwarzer, & Wiedemann, 2015), recent evidence supports the potential of multiple behavior interventions (J. J. Prochaska, Spring, & Nigg, 2008). Due to these findings of cross-behavioral associations between different health behaviors, it is suggested that understanding and changing health behaviors need to be addressed from a multi-behavioral approach in order to use synergies for creating more effective interventions (Fleig et al., 2015; Fleig & Mata, 2018; Noar et al., 2008; J. J. Prochaska et al., 2008).

## 5.6 Concluding Remarks

In conclusion, the findings of the present dissertation highlight the importance of investigating a behavior comprehensively before aiming to change it. A real-life and real-time understanding of eating behavior and its underlying psychological determinants, facilitated by an in-the-moment assessment, allowed deriving an intervention strategy with a new perspective for health promotion. By using in-the-moment triggers, eating happiness can be promoted as an important motivator that drives human food choices and an important cue for healthy eating. This innovative intervention strategy has the potential of triggering both healthy and happy eating behaviors, and shifting the focus from a ‘food-as-health’ towards a ‘food-as-well-being’ perspective.

Furthermore, the findings of the present dissertation encourage research and practice to establish app-based mobile interventions as effective delivery modes for changing health behaviors. The evidence provided by this dissertation may hope to serve as a basis for investigating the effective implementation of app-based mobile interventions. It further encourages future studies to support the development of app-based mobile interventions from an early stage approach to a theory- and evidence-based intervention strategy with the aim of achieving maintaining health behavior changes in order to counteract the rising prevalence of NCDs.
5.7 List of Contributions

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In the following, contributions are detailed based on the criteria suggested by the International Committee of Medical Journal Editors (ICMJE; http://www.icmje.org/).

For Chapter 2, K.V., D.W., H.S., and B.R. designed the systematic review, K.V., D.W., and B.R. did the search, K.V. and D.W. did the screening, data extraction process, assessed data quality and analysed data with critical comments from B.R., H.S., and H.B.; K.V., D.W. and B.R. drafted the manuscript with input from H.S. and H.B.

For Chapter 3, B.R. and H.S. developed the study concept. All authors participated in the generation of the study design. D.W. conducted data analyses and M.B. developed and implemented the visualization tool for the data with input from D.W., K.V., and B.R. The manuscript draft was prepared by D.W. and B.R, and finalized with comments from H.S., K.V., L.K., K.Z., and G.S.

For Chapter 4, B.R. and H.S. developed the study concept. All authors participated in the generation of the study design. D.W., K.V., L.K. and K.Z. conducted the study, including participant recruitment and data collection, under the supervision of B.R. and H.S.; D.W. and K.V. conducted data analyses. D.W. and K.V. prepared the first manuscript draft, and B.R. and H.S. provided critical revisions.
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