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How Social Media Use Influences Health Behaviors – A Social-Cognitive Perspective

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Michael Kilb

Disputation:	11. August 2022
Dekan (Fakultät für Sozialwissenschaften):	Prof. Dr. Michael Diehl
Erstbetreuerin:	Prof. Dr. Jutta Mata
Zweitbetreuer:	Prof. Dr. Frank Kalter
Gutachterinnen:	Prof. Dr. Theda Radtke
	Prof. Dr. Sabine Sonnentag

For my family –

by kin and by heart.

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Contributions Based on This Dissertation

This dissertation is based on three manuscripts that have been published or are in preparation and immediately before the submission.

Manuscripts included in this dissertation

Manuscript 1

Kilb, M., & Mata, J. (2022). *How social media influences offline health behaviors: A behavioral science perspective* [Manuscript in preparation].

Manuscript 2

Kilb, M., Giese, H., & Mata, J. (2022). *How social media affects healthy eating in senders and receivers of eating-related online postings: Two field experiments with intensive longitudinal data* [Submitted for publication].

Manuscript 3

Kilb, M., Dickhäuser, O., & Mata, J. (2022). A theory-based video intervention to enhance communication and engagement in online health communities: Two experiments. *Health Psychology and Behavioral Medicine*, *10*(1), 199–228. https://doi.org/10.1080/21642850.2022.2032074

Summary

Social media represents an important and omnipresent social environment that impacts human health. However, little is known about when and how health-related social media use influences health behaviors. Based on three manuscripts, including a theoretical framework and four empirical studies, this dissertation comprehensively examined how specific types of health-related social media use might influence health behaviors, emphasizing effects on eating behavior. The research conducted in this dissertation is theoretically embedded in the reasoned action approach and self-determination theory.

In the first manuscript, I outlined a conceptual framework to better understand mechanisms of action underlying health-related social media effects. According to this framework, social media use can be characterized by four essential factors: (1) communication features used, (2) directionality of interaction, (3) communicated contents, and (4) engagement level. These factors are essential for identifying the active ingredients of health-related social media use and communication that might cause health behavior change (i.e., the behavior change techniques that might be contained or whose enactment might be triggered). Behavior change techniques are, in turn, assumed to cause health behavior change through changes in psychosocial determinants of health behaviors. I also pointed out that social media contributes to increased social influences on health behaviors due to its omnipresence and high accessibility. It might also intensify these influences due to the unique characteristics of the social media environment (e.g., omnipresence, curation algorithms, network homophily).

In the second manuscript, I experimentally examined the effects of posting about fruit and vegetable consumption on the intake of senders (posters) and receivers of these postings (Study 1, $N = 81$) and the senders' intake in the context of a behavior change goal (Study 2, $N = 128$). I explored the effects' underlying mechanisms of action (i.e., active behavior change techniques and their effect on psychosocial determinants of health behaviors) and the

temporal dynamics of effects using intensive longitudinal data. Results show that public intake-related social media postings lead to higher fruit and vegetable intake of senders and receivers (Study 1). It further supported eating behavior change goals but not more strongly than private self-monitoring of intake (Study 2), suggesting that self-monitoring might be the most active behavior change technique. The examined psychosocial determinants of eating behavior did not mediate potential effects on eating behavior change. There were positive dose-response relationships within-person on a daily level. On days on which senders used social media more than usual related to their postings, they reported higher fruit and vegetable intake, perceived social support, and goal commitment (but lower self-efficacy). Furthermore, on days on which they posted more intake-related postings than usual, they reported higher fruit and vegetable intake (only in Study 2), intentions, self-efficacy, goal commitment, and more favorable attitudes. The results suggest that eating-related social media effects might be more transient and in timely proximity to actual social media use and need more time to unfold. The effects are complex (especially regarding the effects on psychosocial determinants) and likely dependent on the intensity of social media use and the social responses in reaction to postings.

In the third manuscript, I investigated need-support provision in health-related social media communication as potential mechanisms of action for supporting health behavior change. I developed a short educational video about need-supportive communication strategies. The effects of watching the video on the use of these strategies in written responses to fictive social media postings were experimentally tested (Study 1, $N = 76$). I found that these strategies can be learned and applied in written communication immediately after watching the intervention video and one week later. The effects did not translate to a real-world setting, a forum-based health behavior intervention supported by an online support community (Study 2, $N = 537$). Participants who watched the intervention video did not show higher use of need-supportive communication strategies compared to participants who watched a control video. Due to this missing effect on strategy use, they did also not report higher perceived need-support, goal attainment (regarding fruit and vegetable intake and physical activity-related behavior change goals), and more favorable values in psychosocial determinants. There were positive effects on participant engagement (i.e., higher number of postings and subjective forum visit frequency in participants who watched the intervention video). Possible reasons for the missing effect on the use of the strategies might be the high goal attainment in both experimental groups, a misfit of the communication strategies and posting content, and low overall participant engagement. The solid theoretical foundation suggests the usefulness of need-supportive communication for supporting health behavior change. Thus, future research should identify populations that might benefit from the video intervention and increasing need-support (e.g., individuals with behavior change barriers) and foster the application of need-supportive communication strategies (e.g., through incentivizing role models or training of content moderators).

This dissertation emphasizes the relevance of social media in influencing health behaviors and supporting health behavior change, highlighting the positive role of social media. When and how social media influences health behaviors is dependent on the actual enactment of effective motivation and behavior change strategies. Future research should take the complexity of social media effects into account and examine both, within- and between-person effects, and the interactivity between senders and receivers of social media communication. Therefore, researchers should make greater use of experimental methods with high ecological validity, intensive longitudinal data with longer time periods, big data approaches and combining different data sources, and advanced analysis methods such as social network analysis. Social media environments need to be considered to better understand influence factors for health behaviors and for effective health promotion and prevention.

1. General Introduction

In the last decade, the distribution and use of social media have rapidly increased: Most people in Western countries such as the US or Germany use social media regularly in their daily life (e.g., Beisch & Schäfer, 2020; Pew Research Center, 2021). Even a large proportion of children use social media: For example, 60% of British children between the age of 8 and 11 years have at least one social media profile (Ofcom, 2022). Within social media, online communities can evolve, in which persons often but not necessarily share different characteristics such as interests in specific topics (e.g., physical activity or eating) and interact with each other. Health-related use of social media (e.g., posting or viewing alcohol- or eating-related content) is associated with risk and health behaviors (e.g., Curtis et al., 2018; Sina et al., 2022). Social media can also be utilized to intentionally support and deliver health behavior interventions (Petkovic et al., 2021). Many disciplines such as health psychology, media and communication studies, medicine, and medical informatics have started to research the impact of social media on health behaviors and their potential for improving health through delivering lifestyle-based interventions (e.g., Abbar et al., 2015; Chen & Wang, 2021; Lefebvre & Bornkessel, 2013; Moorhead et al., 2013). However, the broad reaching implications of social media's omnipresence and high rates of social media use are still relatively neglected in discussions and debates about factors influencing health behaviors and health (e.g., Granheim et al., 2022). As diverse as the different disciplines are, the diverse are the theoretical and methodological approaches to examine health-related social media effects. However, the different research areas share the following similarities: Most research to date is only cross-sectional or experimental but low in ecological validity (Curtis et al., 2018; Sina et al., 2022), and possible underlying psychosocial mechanisms rarely get tested (e.g., Hawks et al., 2020; Petkovic et al., 2021). Furthermore, social media use is rather broadly conceptualized, for example, as overall or active vs. passive social media use (cf.

Parry et al., 2022). These shortcomings of the existing literature raise important questions: Which specific activities in and types of social media use impact health behaviors, and what are the underlying mechanisms of action?. With this dissertation, I want to shed more light on *whether* and *when* health-related social media effects occur, and *how* they might work, to advance the research field and derive implications for health-promotion and prevention.

The first aim of the dissertation is to contribute to a better understanding of the specific social media activities and types of social media use that can support health behavior change. I address this aim by outlining a theoretical framework combining research in media and communication studies (Meier & Reinecke, 2021; Valkenburg et al., 2016), health psychology, and recent developments in behavior change science, specifically the experimental medicine approach to health behavior change (Hagger, Moyers, et al., 2020; Nielsen et al., 2018; Sheeran et al., 2017). The theoretical framework allows an interdisciplinary, extensive, and detailed perspective on social media use and potential pathways to health behavior change (Manuscript 1). It enables advanced future research on health-related social media effects. To further enhance the understanding of social influences in the digital era, I discuss similarities and differences between online and offline social influences.

The second and third aims of the dissertation are to shed more light on the causality and temporal dynamics of health-related social media effects. Most research is only cross-sectional, low in ecological validity, and does not examine temporal dynamics and within-person effects, with some recent exceptions (see, e.g., Parry et al., 2022; Sina et al., 2022; Strowger & Braitman, 2022 for reviews). Relatedly, the fourth aim of the dissertation is to examine the active behavior change techniques in social media use and changes of theoretically derived psychosocial determinants of health behaviors as underlying mechanisms of action behind these effects. In four empirical studies (Manuscripts 2 and 3), I take a social-cognitive perspective to explain health-related social media effects with extensively tested psychological theories. Therefore, I utilize an extended version of the reasoned action approach (Fishbein & Ajzen, 2011), self-determination theory (Deci & Ryan, 2000; Ryan & Deci, 2017), and a theoretical integration of both (Hagger & Chatzisarantis, 2009). In two field experiments with intensive longitudinal data (Manuscript 2), I examine the causal effects of healthy eating-related posting on the change in eating behavior and potentially mediating psychosocial determinants of health behaviors (perceived social support, perceived social norms, attitudes, self-efficacy, and goal commitment). I also examine the daily associations of *intra*individual variations in eating-related social media activities with the respective psychosocial determinants and eating behavior. In two experimental studies (Manuscript 3), I also examine how the increase of need-support provision through written social media postings in a peer-based online support community affects goal attainment of eating and physical activity behavior change goals. I examine perceived need-support, autonomous motivation, perceived social support, perceived social norms, attitudes, and self-efficacy as important psychosocial determinants that might mediate the effects of need-support provision on goal attainment.

The fifth aim of the dissertation is to test how social media can be used and optimized for health behavior change interventions. In the second manuscript (Study 2), I test whether eating-related social media posting can serve as a more effective form of the behavior change technique self-monitoring of behavior (due to the publicness of monitoring and social feedback; Harkin et al., 2016; Simeon et al., 2020) to support individuals with eating behavior change goals (C.-F. Chung et al., 2017). Furthermore, I focus on improving one of the core features of health behavior interventions using social media, namely the social interaction and communication of social media users via postings. Although it is one of the main active ingredients of interventions, *how* people communicate with each other is usually neglected in research. I look at interpersonal communication within health-related online support communities through the lens of self-determination theory (Deci & Ryan, 2000; Ntoumanis et al., 2017). I developed and tested a short video intervention to improve need-supportive social media communication in a health behavior change intervention based on online support communities (Manuscript 3, Study 1 and 2).

To sum up, I aim to (1) outline an integrative conceptual framework to provide a better understanding of health-related social media effects, examine the (2) causality and (3) temporal dynamics of health-related social media effects, and (4) psychosocial determinants of health behaviors that might explain effects on health behaviors. Finally, I aim to (5) examine how social media could be used and optimized as an intervention tool to support health behavior change. In the following sections, I will discuss the theoretical foundation and evidence for health-related social media effects, emphasizing eating-related social media use and eating behavior change.

1.1. Health-Related Social Media Effects

Social media are internet-based channels that allow users to self-present and interact with other users in real-time and asynchronously (C. T. Carr & Hayes, 2015). The value derived from using social media typically stems from user-generated content and the perception of interaction with others (C. T. Carr & Hayes, 2015), which is distinct from mass media use (e.g., newspaper or radio), where users consume the content of one specific source without significant further interaction (Valkenburg et al., 2016). Different types of platforms can be subsumed under the umbrella term social media (C. T. Carr & Hayes, 2015), for example, professional network sites (e.g., LinkedIn), chat boards and discussion forums (e.g., Reddit), online dating platforms (e.g., Tinder), or online social networking sites (e.g., YouTube, Facebook, Twitter, or Instagram). Most social media platforms contain four essential elements: (1) individualized profiles, (2) a network element, (3) a content stream, and (4) a messaging element (Bayer et al., 2020). Online *social networking sites* are a very popular sub-form of social media that share three distinct characteristics (Ellison & Boyd, 2013). First, users have an individual and unique profile containing self- and other-provided information and system-level data (Ellison & Boyd, 2013). Second, users can publicly display connections with other users on the platform (Ellison & Boyd, 2013). Third and most importantly, users can create content and consume and interact with user-generated content typically provided through their connections (Ellison & Boyd, 2013). Within social media and social networking sites, *online communities* can evolve in which different users share common interests (e.g., specific music genres, healthy eating, or physical activity) and interact with each other. These communities can form differently but predominantly through joining topic-centered forums (e.g., Pappa et al., 2017) or groups on social networking sites (e.g., Bender et al., 2011), the creation of friendship networks (e.g., Aral & Nicolaides, 2017), or the mutual communication via specific hashtags (e.g., #vegan on Instagram; Pilař et al., 2021).

Health-related social media effects describe changes in individual-level health-related behaviors or cognitions that result from social media use (cf. Bayer et al., 2020). Health behaviors represent behaviors that contribute to the maintenance, repair, or improvement of health; typical examples that are very important regarding chronic non-communicable diseases such as cancers are physical activity and a balanced diet high in fruits and vegetables (cf. GBD 2019 Risk Factors Collaborators, 2020). Social media use is a high-level construct that can and should be further distinguished in more specific and nuanced activities within the social media environment for a better understanding of (health-related) social media effects (Bayer et al., 2020; Parry et al., 2022). One common differentiation is between active vs. passive social media use (e.g., Valkenburg et al., 2021). Active social media use typically refers to engaging in active communication and social exchange in the form of one-to-one (e.g., private messages) or one-to-many (e.g., posting public status updates). Passive social media use, on the contrary, typically refers to the mere exposure to and monitoring of social media communication (e.g., postings or messages). However, the results of a recent systematic review show that many different operationalizations exist and that some activities are not clearly differentiated. For example, liking and commenting have been operationalized as both active and passive use (Valkenburg et al., 2021). Although some researchers take a more nuanced perspective on social media use, for example, by focusing on one specific activity such as social media postings and their respective content (e.g., Cavallo, Tate, et al., 2014; Pappa et al., 2017), to the best of my knowledge no classification system for different types of health-related social media use exists so far. To address this gap in the literature, I outline an integrative conceptual framework for understanding health-related social media effects with a more detailed perspective on social media use, including different communication features and the directionality of interaction in collaboration with my colleague (see Manuscript 1, section 2). One important characteristic that is very relevant to social media effects is the *interactivity* in social media: Both senders and receivers of messages typically interact with each other (Valkenburg, 2017; Valkenburg et al., 2016). Therefore, self- or sender effects and reception- or receiver effects can be differentiated (comparable to the distinction between active and passive social media use). However, both are closely intertwined and may depend on each other (Valkenburg, 2017). For example, one person might post about their eating behavior on social media, which may influence their eating behavior both via self-persuasion and received social feedback in the form of comments and likes from receivers of these postings (Valkenburg, 2017). The postings may further have spill-over effects on receivers of the postings and influence their eating behavior, for example, through normative processes (Higgs & Thomas, 2016).

Two research areas can be broadly distinguished. First, there is research on health-related social media effects of naturally occurring health-related social media use, which can take place in both individualized content streams as found in social networking sites and topic-centered online health communities. Second, there is research on health-related social media effects in targeted health behavior interventions using social media. In research on naturally occurring health-related social media effects the focus lies on the effect of health-related social media use on health outcomes or behaviors such as eating behavior (e.g., Pappa et al., 2017; Qutteina et al., 2022). An essential difference to targeted health behavior interventions is that social media users do *not* necessarily intend to change their health behavior, for example, when exposed to eating-related postings by chance or when they post eating-related content for mere entertainment purposes. In contrast, health behavior intervention research increasingly focuses on utilizing social media for delivering and supporting targeted health behavior interventions (Petkovic et al., 2021). In this line of research, people who participate in the interventions typically intend to change their behavior to some level. Before I review the current literature on eating-related social media effects and essential research gaps (see section 1.2.), I will briefly outline how health-related social media use might influence health behaviors and health behavior change. The assumed pathways are also discussed in more detail in Manuscript 1 (section 2).

1.1.1. Mechanisms of Action Underlying Health-Related Social Media Effects

As mentioned, health-related social media effects describe changes in health-related cognitions and behaviors of individuals in response to social media use (Bayer et al., 2020). Underlying mechanisms of action are not fully understood yet, but health psychology and behavioral sciences can help to provide a better understanding of these effects.

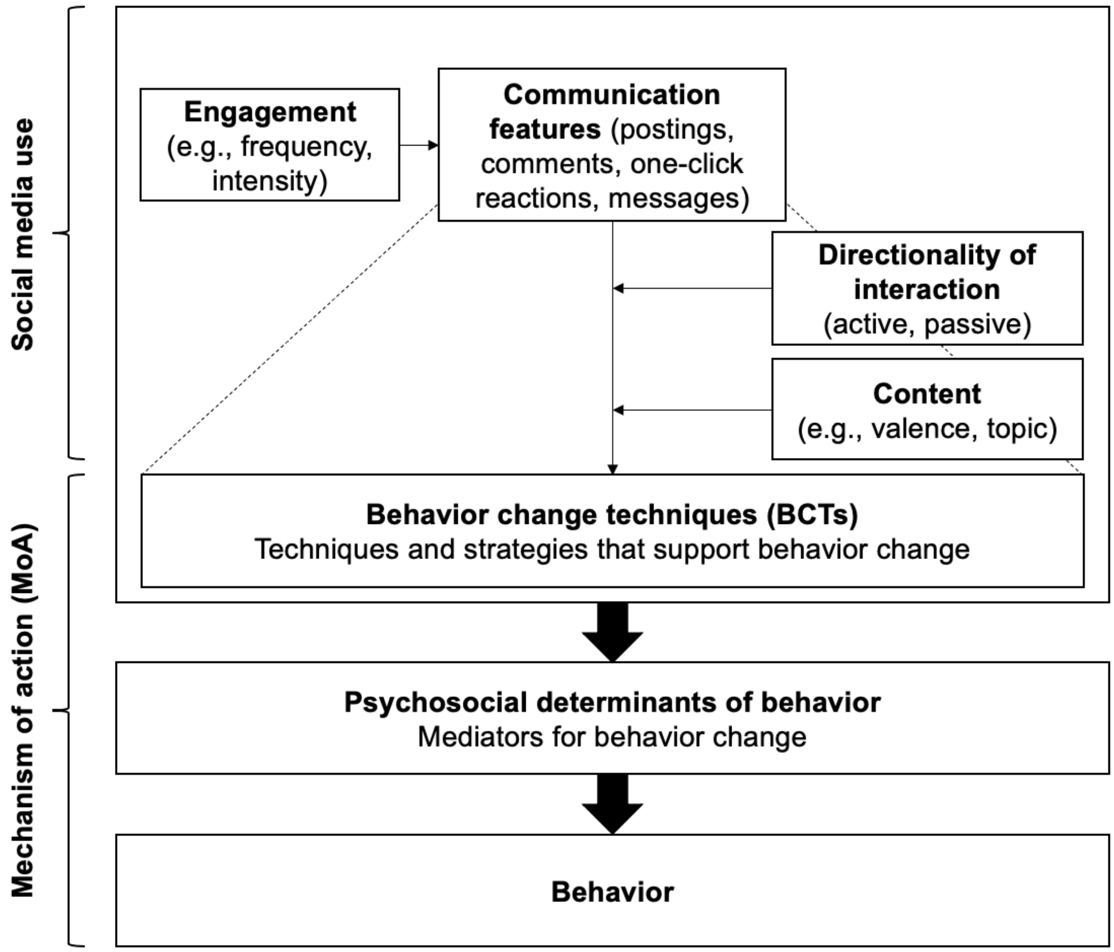
1.1.1.1 Psychosocial Determinants of Health Behaviors. Many different behavioral theories and models exist in health psychology and behavioral sciences that aim to predict health behaviors and explain health behavior change (Davis et al., 2015). Social-cognition models represent the most dominant group of theories within this literature (Conner & Norman, 2015). In social-cognitive theories, cognitive factors (e.g., attitudes or intentions) are assumed to be proximal determinants of health behaviors that influence the execution of health behaviors (Conner & Norman, 2015). A prominent example of social-cognition models is the theory of planned behavior (Ajzen, 1991), which includes attitudes, subjective norms, perceived behavioral control, and behavioral intentions as key determinants of behavior. Health behavior change is assumed to work through changes in these *psychosocial determinants of health behaviors* (Hagger, Moyers, et al., 2020; Nielsen et al., 2018; Sheeran et al., 2017). Across the different theories, determinants of behavior (change) at the theory level can be subsumed under higher-level categories; for example, the determinant “attitude” from the theory of planned behavior represents one form of “beliefs about consequences” (Cane et al., 2012; Carey et al., 2019). Comparably, changes in health behaviors in response to health-related social media use (both within interventions and naturally occurring social media communication) can be expected to be mediated by changes in psychosocial determinants of health behaviors (Myneni et al., 2016; Petkovic et al., 2021). However, how do health-related social media use and communication influence psychosocial determinants of health behaviors?

1.1.1.2. Behavior Change Techniques in Social Media Use. Health-related social media use and social media-based interventions can contain or trigger the initiation and execution of different behavior change techniques (Myneni et al., 2016; Simeon et al., 2020). A *behavior change technique* represents “an observable, replicable, and irreducible component of an intervention designed to alter or redirect causal processes that regulate behavior; that is, a technique is proposed to be an “active ingredient” (e.g., feedback, self-monitoring, and reinforcement)” (Michie et al., 2013, p. 82). These techniques have been formally categorized and labeled in behavior change technique taxonomies to systematize existing knowledge and improve research on health behavior change (e.g., Michie et al., 2013; Teixeira et al., 2020). If not stated otherwise, all mentioned techniques in this dissertation are coded with the Behavior Change Techniques Taxonomy version 1 (Michie et al., 2013). Behavior change techniques are assumed to induce changes in psychosocial determinants of health behaviors derived from health behavior theories and thus be responsible for successful health behavior change (Hagger, Moyers, et al., 2020; Sheeran et al., 2017). Many behavior change techniques are self-enactable; that is, techniques can be and are sometimes required to be initiated and executed by the individual itself (Knittle et al., 2020). For example, the technique "self-monitoring of behavior" requires the active monitoring of the own behavior (Knittle et al., 2020; Michie et al., 2013). Some social media features can themselves represent a behavior change technique, for example, the provision of one-click reactions such as likes that express overt endorsement of other social media users and their contents represent a form of social support (Simeon et al., 2020). Which specific behavior change techniques might be at work also depends on the respective content of social media communication. For example, social media postings could suggest goal setting or self-monitoring as helpful strategies for healthy eating, communicate instructions on how to perform a behavior, or model the successful behavior execution via cooking healthy recipes (cf. Michie et al., 2013; Simeon et al., 2020). Regularly posting about the engagement in health behaviors such as a healthy diet on social media (C.-F. Chung et al., 2017), for example, via pictures of consumed foods, can also represent a form of public self-monitoring of the behavior (cf. Michie et al., 2013). In the second manuscript (section 3), I examine the effects of this specific type of social media use (and the respective behavior change techniques) on eating behavior change and potentially affected psychosocial determinants. Additionally, *how* people communicate with each other on social media might influence motivation and behavior change (Ntoumanis et al., 2017; Teixeira et al., 2020). I address this topic in the third manuscript (section 4).

1.1.1.3. How Do Different Types of Social Media Use Influence Health Behaviors? In a nutshell, mechanisms of action underlying health behavior change in response to health-related social media use can be characterized by the behavior change techniques at work (Myneni et al., 2016; Simeon et al., 2020) and the psychosocial determinants of health behaviors (Myneni et al., 2016; Petkovic et al., 2021) that change in response to the enactment of these techniques (Hagger, Moyers, et al., 2020). However, a detailed look at health-related social media use is necessary to understand which behavior change techniques are at work. Because of the shortcomings in the social media literature, particularly the poor operationalization and differentiation of social media use (Parry et al., 2022; Valkenburg et al., 2021) and a missing framework for understanding health behavior-related social media effects, I outline an integrated conceptual framework to simultaneously address these two research gaps together with my colleague (Manuscript 1, section 2). Briefly, four different factors for describing social media use can be differentiated: (1) the specific social media *communication features* (e.g., postings, messages, likes, and comments) used in social media, (2) the *contents* which are communicated through the different features (e.g., pictures of food, empowering texts), as well as (3) the *directionality of interaction* (active vs. passive use of these features) and (4) the person's level of *engagement* (e.g., frequency or intensity of use). The combination of these four factors, in turn, is assumed to determine which behavior change techniques are ultimately at work or triggered when using social media and thus determine when and through which mechanisms of action health-related social media use influences health behaviors and health behavior change (see Figure 1). In the next section, I will discuss the evidence base of health-related social media effects in the eating behavior domain and identify critical research gaps.

Figure 1

Theoretical Framework for Health-Related Social Media Effects



Note. The higher the engagement of a person, the more the person is interacting with different social media features (e.g., postings or comments). The resulting social media activities can be either active (e.g., providing comments) or passive (e.g., receiving comments) depending on the directionality of interaction. The combination of the specific communication features, the directionality of interaction (e.g., active vs. passive use), and the content of the activities (e.g., what topic is depicted in the postings) triggers different behavior change techniques (e.g., increasing “1.9 Commitment” and receiving “6.3 Information about others’ approval” in the form of likes). The enactment of the specific behavior change techniques influences psychosocial determinants of behavior, which in turn affect human behavior (mechanism of action).

1.2. Eating-Related Social Media Use and (Healthy) Eating Behavior

Food and eating are prevalent topics in social media (Abbar et al., 2015; Hu et al., 2014; Mejova et al., 2015; Pilař et al., 2021). For example, food represents one of the eight main photo categories on Instagram (Hu et al., 2014). There is a vast amount of eating-related content on Instagram, especially food pictures: For example, more than 480 million postings are tagged with the hashtag #food and more than 283 million with #foodporn (as of April 8, 2022). Posting about food is especially prevalent in adolescents and young adults (Holmberg et al., 2016) and they are often exposed to predominantly unhealthy food pictures by peers and (influencer) marketing (Cassidy et al., 2021; Coates et al., 2019a; Qutteina et al., 2019).

An unhealthy diet, characterized by high intakes of processed foods, sugar-sweetened beverages, added salt and sugar, and trans and saturated fat intake (de Ridder et al., 2017), represents a major risk factor for premature death and chronic diseases such as cancers or cardiovascular diseases (GBD 2017 Diet Collaborators, 2019; GBD 2019 Risk Factors Collaborators, 2020). On the contrary, a healthy diet is associated with reduced premature mortality and a reduced risk for chronic diseases (de Ridder et al., 2017; Schulze et al., 2018). No clear definition of a healthy diet exists, but most dietary guidelines recommend a varied and balanced diet that is high in fruits and vegetables, polyunsaturated fatty acids, whole grains and fiber, low-fat dairy, fish, legumes, and nuts, and on the contrary low in fat, sugar, salt, processed foods, and saturated fatty acids (de Ridder et al., 2017).

Adolescents and young adults frequently do not meet healthy dietary recommendations, such as the recommended intake of five portions of fruits and vegetables, a core component of a healthy diet (e.g., Mensink et al., 2013). Simultaneously, these age groups are heavy users of social media (Pew Research Center, 2021) and are frequently exposed to food cues and eating-related social media content (e.g., Qutteina et al., 2019). Therefore, it is essential to understand the impact of eating-related social media use on eating behavior, underlying mechanisms, and possibilities and opportunities of using social media to support healthy eating, especially among adolescents and young adults. We addressed these research questions in Manuscripts 2 and 3. In the following, I will provide a short overview of the research area and important research gaps which I focused on in this dissertation.

1.2.1. Effects of Naturally Occurring Eating-Related Social Media Use

Most research in the eating behavior domain has looked at the effects of social media use on body image and disordered eating (e.g., B. R. Kim & Mackert, 2022; Rounsefell et al., 2020). Regarding social media effects on food choice and the amount of consumed foods, research outside an intervention context is relatively scarce, especially for healthy food intake (see A. Chung et al., 2021; Hawks et al., 2020; Sina et al., 2022 for reviews). Thus, existing research disproportionately focused on maladaptive eating styles or adverse psychological outcomes, and neglected effects on eating behavior and a potentially *positive* role of social media until recently.

Existing studies on the effect of social media use on food choice and intake primarily focus on passive social media use and provide evidence for receiver effects (i.e., the exposure to eating-related social media content influences eating behavior and cognitions). Eating-related social media content, particularly food pictures or videos, can activate reward-related brain areas and increase appetite and thus food intake; this especially holds for pictures and videos of unhealthy foods (Boswell & Kober, 2016; Sina et al., 2022; Spence et al., 2016). Above and beyond these primarily physiological mechanisms, social-cognitive processes can play a significant additional role (e.g., Hawkins et al., 2021; Sina et al., 2022). Watching food brand videos on YouTube has been associated with unhealthy food and beverage consumption in children and adolescents (Baldwin et al., 2018). Qualitative and quantitative research further suggests that social media could promote unhealthy and healthy food choices (Hawkins et al., 2020; Qutteina et al., 2022; Vaterlaus et al., 2015). For example, the exposure to unhealthy foods on social media is indirectly associated with higher consumption of unhealthy foods via perceived descriptive norms (Qutteina et al., 2022). On the contrary, the exposure to healthy foods on social media is indirectly associated with higher consumption of healthy foods via higher food literacy (Qutteina et al., 2022). Experimental laboratory studies show mixed results: Some studies show a positive effect of viewing videos and pictures of (other social media users with) healthy foods on healthy food choices or the intention to eat healthy snacks, partially via normative mechanisms (Hawkins et al., 2021; Ngqangashe & Backer, 2021), whereas others do not find effects (Coates et al., 2019b; Folkvord & de Bruijne, 2020). Similarly, some studies find comparable effects on unhealthy food intake and choice (Coates et al., 2019b; Ngqangashe & Backer, 2021), whereas others do not (Folkvord & de Bruijne, 2020; Hawkins et al., 2021). Differences between studies might be explained by different experimental manipulations and measures, preventing meta-analytical analyses (Sina et al., 2022).

Regarding sender effects (i.e., the influence of actively contributing to eating-related social media communication on eating behavior and cognitions in persons without specific eating goals), little to no empirical research exists (Sina et al., 2022), and many studies focus on more distal outcomes such as weight loss (Hawks et al., 2020). Therefore, I focus more broadly on studies (some of which are also conducted in an intervention context) analyzing sender effects with data from individuals who aim to change their weight and thus necessarily their eating behavior. In one online weight loss community, the combined number of postings and comments made by community members was positively associated with their weight loss (Pappa et al., 2017). Furthermore, the engagement in discussions that might provide social support was also associated with weight loss (Pappa et al., 2017). In a small-scale social media-based weight loss intervention, the combined number of posts, comments, and reactions *contributed by participants themselves* predicted their weight loss (Xu & Cavallo, 2021). There was also a statistically non-significant tendency for a positive association with increased self-efficacy (Xu & Cavallo, 2021). One qualitative study suggests that young women use social media to support their own and others' healthy eating goals by posting about their eating behavior (C.-F. Chung et al., 2017). Experimental and interventional studies with people who aim to change their eating behavior support this practice by showing that self-monitoring of the own eating behavior is more effective in groups (compared to alone) for supporting eating behavior change (Meng et al., 2017) and that small-sized smartphone-based social support groups support healthy eating goals (Inauen et al., 2017). Furthermore, research in other health behavior domains, such as sun-safety behavior (Nabi et al., 2019), hygiene behavior (S. C. Kim & Hawkins, 2020), physical activity behavior (Y. Liu & Kashian, 2021), smoking (Yoo et al., 2016), or alcohol consumption (Geusens et al., 2020), suggests that sender effects might also exist in the eating behavior domain. However, again, most of the latter research is only cross-sectional.

To sum up, the existing research suggests that eating-related social media effects (particularly receiver effects) exist. However, the literature has several shortcomings. First, research on sender effects is generally lacking. Second, most research consists of cross-sectional or short-term experimental studies conducted in an artificial laboratory setting with low ecological validity (cf. Sina et al., 2022). This limits the generalizability of the results to daily eating behavior and conclusions regarding the causality of real-world eating-related receiver (and sender) effects and underlying psychosocial mechanisms. Third, although there has recently been a call for a stronger focus on the temporal dynamics of effects and a within-person perspective in both health psychology (Dunton et al., 2021) and communication and media studies (Thomas et al., 2021), only a few studies have yet examined within-person effects of social media use on health behaviors (see, e.g., Hendriks et al., 2021 for a recent exception). This hinders the examination of temporal dynamics in eating-related social media effects. My colleagues and I addressed these research gaps in two field experiments with intensive longitudinal data (Manuscript 2, section 3). In one of these studies (Study 2), we also tested whether eating-related postings on social media could support individual eating-behavior goals.

1.2.2. Social Media-Based Interventions Targeting Eating Behavior Change

In social media-based eating behavior interventions, participating individuals typically have the goal of changing their eating behavior. In these interventions, social media is often used to deliver the intervention material (e.g., Jane et al., 2017) or as one of several intervention components to provide a supportive environment for behavior change (e.g., Godino et al., 2016). The interventions are typically conducted in groups together with other intervention participants. In contrast, little research has focused on the potential of utilizing social media for *individuals*, for example, by receiving social support from their own personal social media network, although people naturally engage in activities such as posting about healthy eating to support their eating behavior change (C.-F. Chung et al., 2017; Simunaniemi et al., 2011). In a recent systematic review and meta-analysis by the Cochrane Collaboration, the authors concluded that social media-based interventions effectively change health behaviors, especially physical activity (Petkovic et al., 2021). However, few interventions address eating behavior, and the existing studies show substantial heterogeneity in their methodology and results (Petkovic et al., 2021). The systematic review identified only eight studies on diet quality, three studies on calorie intake, and one study on calcium intake, parent modeling of healthy eating, and breastfeeding. In most of the sub-meta-analyses (for the disaggregated outcomes), the overall effects were statistically non-significant (Petkovic et al., 2021). Nevertheless, for more distal outcomes (weight loss and BMI reduction) of interventions typically targeting both eating and physical activity combined, the interventions had small beneficial overall effects (Petkovic et al., 2021). Importantly, meta-analytically testing the *unique* effects of social media components within interventions is not possible because the interventions usually consist of several components combined; therefore, it has been demanded that future research should identify the active ingredients of multicomponent interventions and the unique role of social media (Petkovic et al., 2021).

In a nutshell, there are several shortcomings in the literature on social media-based interventions. First, most studies allow no conclusions regarding which component (e.g., social media group, face-to-face meetings, or the use of information websites) might be the active ingredient in multicomponent interventions and whether it might be the social media component. Together with my co-authors, I address this research gap by examining specific aspects of interactive social media. First, I examine the unique effects of social media postings in supporting eating behavior change goals (Study 2, Manuscript 2; see section 3). Second, I explore the role of need-support provision in both eating- and physical activity-related social media communication (written postings) in a forum-based peer-support intervention with additional goal-setting (Study 2, Manuscript 3; see section 4). Second, interventions typically have been conducted in group settings. We, therefore, tested the potential of using social media as an intervention tool for *individuals* without any other intervention participants but only by relying on their personal social media networks (Study 2, Manuscript 2; see section 3). In the third manuscript, additionally to examining the effects of a social media-based intervention (now in a group setting) on eating behavior change, we also examined the effects on physical activity. Interventions targeting physical activity are particularly promising (Petkovic et al., 2021). Furthermore, physical inactivity is a significant risk factor for premature death and disabilities due to chronic diseases (GBD 2019 Risk Factors Collaborators, 2020; I.-M. Lee et al., 2012), similar to unhealthy eating (GBD 2017 Diet Collaborators, 2019; GBD 2019 Risk Factors Collaborators, 2020) and similar underlying mechanisms of action (i.e., active behavior change techniques and responsible psychosocial determinants) can be expected in eating- and physical activity-related social media effects (cf. Petkovic et al., 2021).

1.3. Using Health Behavior Theories to Examine Psychosocial Mechanisms of Action

Health behavior theories can be used to identify potential mechanisms of action (Hagger, Moyers, et al., 2020) underlying health-related social media effects (i.e., the psychosocial determinants that cause health behavior change, and the behavior change techniques that cause changes in these determinants). To empirically examine the role of theoretically-derived psychosocial determinants of health behaviors, the research conducted in this dissertation is guided by the reasoned action approach (Fishbein & Ajzen, 2011) and the self-determination theory (Deci & Ryan, 2000; Ryan & Deci, 2017).

1.3.1. The Reasoned Action Approach

The reasoned action approach (Fishbein & Ajzen, 2011) constitutes a theoretical refinement and extension of the theory of planned behavior (Ajzen, 1991), which includes additional theory-overarching behavioral determinants such as self-efficacy from social-cognitive theory (Bandura, 1997, 1998). Within the reasoned action approach, attitudes can be sub-divided (Fishbein & Ajzen, 2011) into *instrumental* attitudes (the cognitive aspect of attitudes, e.g., seeing a behavior as useful) and *experiential* attitudes (the affective aspect of attitudes, e.g., seeing a behavior as enjoyable). Furthermore, subjective norms can be differentiated into the perceived behavior (perceived *descriptive* norms) of a specific referent group and the perceived social approval of a behavior (perceived *injunctive* norms) in a specific referent group (cf. Cialdini et al., 1991). Perceived behavioral control is also sub-divided into perceived autonomy and perceived capacity. Perceived *autonomy* refers to perceived control over the behavior, which is similar to perceived behavioral control from the theory of planned behavior (Fishbein & Ajzen, 2011). Perceived *capacity* refers to the perceived capability to perform a behavior if intended, similar to self-efficacy (Fishbein & Ajzen, 2011). The psychosocial determinants are assumed to indirectly influence health behaviors via behavioral intentions, except for perceived autonomy and capacity, which are assumed to have an additional direct effect on health behaviors (Fishbein & Ajzen, 2011;

McEachan et al., 2016). However, the results of a meta-analysis show that only perceived capacity or self-efficacy (and not perceived autonomy) consistently predicts health behaviors and intentions (McEachan et al., 2016). Experiential attitudes and perceived descriptive norms may further have an additional direct effect on health behaviors (McEachan et al., 2016). More generally, the theory of planned behavior and the reasoned action approach have been successfully applied to predict health behaviors (McEachan et al., 2011, 2016) and change health behaviors (Sheeran et al., 2016; Steinmetz et al., 2016).

The discussed literature on eating-related social media effects (section 1.2.) and the reasoned action approach (section 1.3) suggests that determinants from the reasoned action approach, extended by some additional determinants, might help explain eating-related social media effects. More specifically, changes in (perceived) social norms, attitudes, self-efficacy, and perceived social support might mediate effects on eating behavior. In the following, I discuss how social media use could influence these psychosocial determinants. As this dissertation emphasizes eating-related social media effects, I focus on eating-related social media use.

1.3.1.1. Social Media Use and Psychosocial Determinants From the Reasoned Action Approach. Perceived descriptive and injunctive social norms (Cialdini et al., 1991) of receivers might change in response to eating-related social media use, for example, viewing healthy food pictures or likes regarding these postings: It provides important information regarding the actual behavior of social media users and the social approval regarding the behavior (Hawkins et al., 2021; Higgs & Thomas, 2016; Rimal & Lapinski, 2015). The reactions of the social network (e.g., likes or comments containing discussions about consumed foods or recipes) might also change the perceived social norms of senders via comparable processes (Higgs & Thomas, 2016). Research from other health behavior domains further supports a mediating role of changes in perceived social norms for health behavior change in response to health-related social media use (Geusens et al., 2020; Rui & Liu, 2021; Yoo et al., 2016).

Self-efficacy (Bandura, 1997) may also change in response to social media use. Posting about consumed healthy foods could increase self-efficacy through the mere self-monitoring of personal successes (Bandura, 1997; Prestwich et al., 2014). Furthermore, social feedback in the form of supportive and encouraging comments or likes could intensify mastery experiences and provide verbal persuasion about capabilities, thereby enhancing self-efficacy (Bandura, 1997; de la Peña & Quintanilla, 2015; Prestwich et al., 2014). Social media postings could also increase the self-efficacy of receivers via the provision of tips, successfully modeling the enactment or change of health behaviors, or empathetic words of empowerment (Bandura, 1997; de la Peña & Quintanilla, 2015; Prestwich et al., 2014). Research from other health behavior domains (H.-M. Kim, 2022; S. C. Kim & Hawkins, 2020) and computer-mediated support groups (Yang, 2020) further suggests that self-efficacy might play a not negligible role.

Attitudes could also change in response to social media use. First, publicly posting about the enactment of health behaviors could change attitudes via self-persuasion and self-concept changes (Aronson, 1999; Valkenburg, 2017). Furthermore, as social media use can inform about normative accepted behaviors by peers and other social media users (Higgs & Thomas, 2016; Simeon et al., 2020), this could also change the attitudes of receivers exposed to eating-related social media communication when participants identify with senders (e.g., Stok, Verkooijen, et al., 2014; Terry et al., 2000). Additionally, the mere repeated exposure to eating-related content could also increase the positive attitudes of both senders and receivers (Mata et al., 2018). Research from other health behavior domains also suggests that sender effects might work through changes in attitudes (Geusens et al., 2020; Geusens & Beullens, 2019).

1.3.1.2. Social Media Use, Perceived Social Support and Goal Commitment. Perceived social support might further increase in response to social media use. Social support is also associated with healthy eating (e.g., Shaikh et al., 2008) and eating behavior change (e.g., Scholz et al., 2013). It could be especially relevant for people with behavior change intentions (cf. Fitzsimons & Finkel, 2010), as typically found in social media-based health behavior interventions. Social support can be easily provided through one-click reactions such as likes or supportive comments in response to postings (de la Peña & Quintanilla, 2015; Simeon et al., 2020). Furthermore, posting helpful tips or healthy recipes and empowering texts to the social network may also increase their perceived social support (de la Peña & Quintanilla, 2015; Simeon et al., 2020). Relatedly, the participation in computer-mediated support groups, where users are typically both senders and receivers, has been shown to increase social support (Yang, 2020).

Goal commitment, which reflects the dedication to and responsibility for a specific target (Klein et al., 2012), might also be an important determinant of eating behavior change for senders who post about current health behavior goals. Goal commitment could increase because of the publicness of goals (Klein et al., 1999, 2020) and the anticipated and received feedback from the social media network (Klein et al., 1999; Valkenburg, 2017). Higher goal commitment relates to higher goal attainment (Klein et al., 1999), and publicly set behavior change goals are more effective than privately set goals (Epton et al., 2017).

The included studies in a recent Cochrane review on social media-based health behavior interventions suggest that an increase in intentions, self-efficacy, social support, and more favorable attitudes and subjective norms could be important determinants (Petkovic et al., 2021). However, there were non-significant overall effects of social media-based interventions on these determinants due to a low study number and substantial heterogeneity in study designs and effect sizes (Petkovic et al., 2021). Nevertheless, it is important to note that the review supports the relevance of perceived social support and the psychosocial determinants from the reasoned action approach (Fishbein & Ajzen, 2011) for understanding health-related social media effects. In a nutshell, changes in perceived social norms, perceived social support, attitudes, and self-efficacy might underly sender and receiver effects, at least to some extent. Furthermore, goal commitment might be relevant for senders who post about eating behavior change goals. We experimentally examine the effect of health-related social media use on these determinants in Manuscripts 2 and 3, as experimental and intensive longitudinal research on effects on psychosocial determinants is still lacking.

1.3.2. Self-Determination Theory

Additionally to changes in determinants from the reasoned action approach, changes in determinants from self-determination theory (Deci & Ryan, 2000; Ryan & Deci, 2017) could underly health-related social media effects. Self-determination theory is a macro–theory of human motivation consisting of six sub-theories (Deci & Ryan, 2000; Ryan & Deci, 2017). According to self-determination theory, motivation can be differentiated into different forms: amotivation, intrinsic motivation, and extrinsic motivation (Deci & Ryan, 2000; Ryan & Deci, 2017). In the case of amotivation, the person has no intention to perform a specific behavior. In contrast, in the case of intrinsic motivation, a behavior is performed out of pure interest and joy and without any external rewards (Deci & Ryan, 2000; Ryan & Deci, 2017). Most behaviors are at least to some point extrinsically motivated, and extrinsic motivation can be sub-divided into four different styles of behavioral regulation, which fall along a continuum of controlled and autonomous regulation (Deci & Ryan, 2000; Ryan & Deci, 2017). Behaviors based on autonomous motivation are assumed to be more strongly internalized and integrated into the person's identity and important personal values. Behaviors based on controlled motivation are assumed to be less internalized and more externally regulated, for example, because of expected rewards or social pressure (Deci & Ryan, 2000). Autonomous motivation is crucial for the long-term regulation of protective health behaviors such as eating (Teixeira et al., 2011) and physical activity (Teixeira et al., 2012). Importantly, empirical research supports the continuum structure of self-determined motivation (Howard et al., 2017), and the theory has been successfully applied to predict and change health behaviors (Ng et al., 2012; Ntoumanis et al., 2021). According to self-determination theory, there are three basic psychological needs that are essential for the internalization of the behavioral regulation and the formation of autonomous motivation: the needs for autonomy, competence, and relatedness (Deci & Ryan, 2000; Ng et al., 2012; Ryan et al., 2008). When people feel ownership and self-endorsement in performing a behavior, when they feel effective in performing a behavior, and when they feel connected to and unconditionally supported by others in the process of behavioral regulation, it is more likely that the behavior gets internalized and integrated into their personal values and identity (Deci & Ryan, 2000; Ryan et al., 2008; Ryan & Deci, 2017). Thereby, the fulfillment of the three needs is indirectly associated with health outcomes via higher autonomous motivation and self-regulation (Ng et al., 2012). Importantly, the fulfillment or thwarting of the three needs is strongly influenced by the (social) environment and social agents (Ryan et al., 2008; Ryan & Deci, 2017; Teixeira et al., 2020).

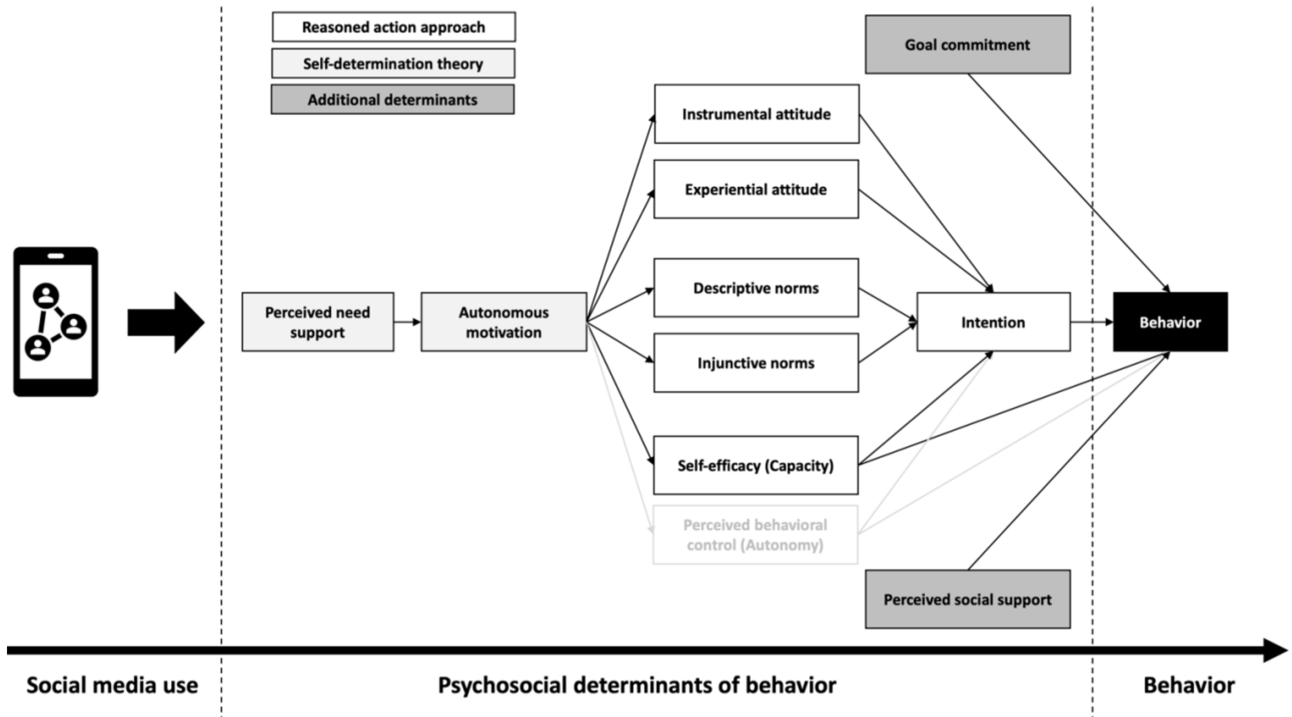
1.3.2.1. Social Media Use and Perceived Need-Support. People's communication style can be more or less *need-supporting* or -thwarting and thereby drive or undermine the formation of autonomous motivation (Ntoumanis et al., 2017). As interpersonal communication is the key activity and ingredient of social media use (both in naturally occurring social media interactions and within social media-based interventions), self-determination theory can provide a useful theoretical framework to understand favorable conditions for positive health-related social media effects and improve social media-based interventions. Although not yet examined with regard to the core feature of social media-based interventions, interpersonal communication, interventions based on self-determination theory have been shown to be effective in increasing perceived need-support, autonomous motivation, and, ultimately, health behavior change (Ntoumanis et al., 2021). Changes in perceived need-support and autonomous motivation are further associated with health behavior change (Ntoumanis et al., 2021) and increases in perceived need-support predict health behavior change indirectly via increases in autonomous motivation (e.g., Silva et al., 2011). Therefore, *how* participants communicate with each other in social media-based interventions can influence behavior change. More specifically, the provision of need-support via social media communication could increase perceived need-support and, ultimately health behavior change (Martela et al., 2021; Ntoumanis et al., 2017). I address this topic together with my colleagues in two studies by developing and testing an educational video intervention about need-supportive communication strategies that aim to improve the provision of need-support in social media communication (Manuscript 3; see section 4).

1.3.3. Theoretical Integration of Self-Determination Theory and the Reasoned Action Approach

Self-determination theory and the reasoned action approach have been integrated in past research, as they complement each other (Hagger & Chatzisarantis, 2009, 2012). The integrated model, also known as the trans-contextual model in education research, suggests that autonomous motivation indirectly influences behavior via attitudes, subjective norms, perceived behavioral control, and intentions, at least partially (Hagger & Chatzisarantis, 2009). Comparable to self-determination theory, autonomy support from key social agents is assumed to foster autonomous motivation (Deci & Ryan, 2000; Hagger & Chatzisarantis, 2012; Ryan et al., 2008). Longitudinal data and cross-lagged analyses support the assumed causal pathways from autonomous motivation to the determinants of the theory of planned behavior, the assumed indirect effects on behavior, and the relevance of perceived autonomy support (e.g., Chan et al., 2020; Kalajas-Tilga et al., 2022). Therefore, I used the integrated model to examine mechanisms of action of health-related social media communication for supporting health behavior change in a forum-based health behavior intervention (Manuscript 3). Figure 2 shows an overview of the underlying theoretical model of this dissertation.

Figure 2

Integrated Theoretical Model of the Dissertation



Note. Social media use is assumed to cause changes in psychosocial determinants of behavior that lead to behavior change. Psychosocial determinants of behaviors are derived from the reasoned action approach (Fishbein & Ajzen, 2011), self-determination theory (Ryan & Deci, 2017), and their theoretical integration (Hagger & Chatzisarantis, 2009), extended by additional determinants (perceived social support and goal commitment). Determinants from self-determination theory are only examined in Manuscript 3; goal commitment is only examined in Manuscript 2. Perceived behavioral control is part of the reasoned action approach but was not examined in this dissertation.

1.4. Research Aims and Contributions

The research aims of this dissertation are fivefold. As already mentioned, to the best of my knowledge, no classification system for social media use and no overarching framework for understanding health-related social media effects exist. The first aim of this dissertation thus is the development of a conceptual framework addressing both research gaps simultaneously (Manuscript 1; see section 2). This framework aims to depict different factors that can describe social media use, including different social media communication features and the communicated contents. My co-author and I combine this more differentiated approach to social media use with recent developments in the health behavior change literature. Thereby, we contribute to a better understanding of health-related social media effects from a theoretical point of view and bridge the media and communication studies and health psychology literature. Besides this theoretical contribution, I aim to provide several empirical contributions to the literature. More specifically, I focus on one specific social media feature and activity, namely social media postings, and on the specific content of social media postings in both persons with and without behavior change goals (Manuscript 2 and 3).

This dissertation's second and third aim lies in examining the (1) causality and (2) temporal dynamics in eating-related social media effects on the real-world eating behavior of both senders and receivers. As outlined earlier, research on eating-related social media effects is characterized by several shortcomings (cf. Sina et al., 2022). First, the potentially *positive* role of social media for healthy eating behavior change is often neglected. Second, most research consists of cross-sectional or short-term experimental studies with low ecological validity conducted in an artificial laboratory setting. Third, research on sender effects is generally lacking. Fourth, no research focused on the temporal dynamics and within-person effects in eating-related social media effects. Together with my colleagues, I provide several significant contributions to the literature by addressing these research gaps with two field experiments combined with intensive longitudinal data through repeated measurements of subjective daily experiences and coded objective social media data (Manuscript 2; see section 3). We examined the effects of mere posting on both senders' and receivers' healthy eating behavior in a dyadic design (Study 1) and on senders' healthy eating behavior in the context of a behavior change goal (Study 2). Thereby, the results of the two experiments provide the first *causal* evidence on potentially health-promoting effects in senders (and receivers), emphasizing a potentially positive role of social media in improving real-world eating behavior. Furthermore, we examine dose-response relations of intraindividual variations in eating-related social media activities with daily eating behavior. The conducted analyses contribute to a better understanding of the causality and the temporal dynamics in healthy eating-related social media effects.

The fourth research aim of this dissertation lies in the examination of psychosocial, social-cognitive mechanisms underlying health behavior-related social media effects, with a particular focus on eating behavior. Together with my colleagues, I address this aim in Manuscript 2 by examining effects on both eating behavior and social-cognitive determinants of eating behavior derived from the reasoned action approach (Fishbein & Ajzen, 2011) and the literature on eating-related social media effects. More specifically, we explore the potential role of changes in attitudes, perceived social norms, self-efficacy, and perceived social support for explaining eating-related social media effects. Additionally, we examine goal commitment as a further determinant in Study 2. As potential mechanisms of action usually do not get examined experimentally in the social media literature, our two studies provide important empirical contributions to the literature by rigorously testing potential mechanisms with experimental methods (cf. Sheeran et al., 2017). Furthermore, together with my colleagues, I focus on the core component of social media use, interpersonal communication, and examine need-support provision within this communication (Ntoumanis et al., 2017). Thereby, we provide the first two studies examining need-support provision in social media communication and increases in perceived need-support as potential mechanisms of action for supporting health behavior change (Manuscript 3; see section 4). Based on the integration of self-determination theory and the reasoned action approach (Hagger & Chatzisarantis, 2009), we also examine the effect of increasing the use of need-supportive communication strategies in social media communication on autonomous motivation, perceived social support, perceived social norms, self-efficacy, and attitudes.

The fifth and last aim of this dissertation is to examine how social media could be used and optimized for supporting health behavior change. My colleagues and I make important contributions to the literature by experimentally isolating the unique effects of specific types of social media use (social media postings containing food pictures in Manuscript 2, Study 2; use of need-supportive communication strategies in written postings in Manuscript 3) through using strong control groups. We further contribute to the literature by examining how social media could be used as an intervention tool for individuals instead of being used in group-based interventions, as typically done (Manuscript 2, Study 2; see section 3). Additionally, we also examine whether the improvement of communication quality (through increased provision of need-support) could increase goal attainment and engagement of intervention participants in group-based interventions with individuals sharing the same behavior change goals (Manuscript 3; see section 4). Thereby, we contribute – to the best of my knowledge – the first application of self-determination theory to social media-based health behavior interventions directly targeting participating individuals to improve their mutual social interaction and support.

Thus, in a nutshell, I aim to advance the field of health-related social media effects with this dissertation and to shed light on *whether*, *when*, and *how* social media use can influence health behaviors and support health behavior change (with a particular focus on eating behavior change). I address this overarching aim by taking a comprehensive approach with theoretical and empirical work. Throughout the dissertation, I take a psychological, social-cognitive perspective on health-related social media effects and integrate research from different research areas.

1.5. Dissertation Outline

The present dissertation consists of five sections. In the first section, I already provided an overview of the current literature on health-related social media effects with a particular emphasis on eating behavior, important research gaps in the literature, and the aims of the current dissertation. The second, third, and fourth sections present a total of three manuscripts that resulted as part of this dissertation. The three manuscripts can be read independently and present both a theoretical perspective on health-related social media effects and results from four empirical studies. In the following paragraphs, I briefly outline the three manuscripts' content, research questions, and hypotheses.

In section 2 (Manuscript 1), my colleague and I propose a conceptual framework for understanding health-related social media effects. We combine a more nuanced look at social media use with recent developments in the behavior change literature. We argue that four factors can be differentiated in social media use, which should be simultaneously considered to understand health behavior-related social media use and potentially effects on health behaviors: (1) different social media *communication features*, (2) communication *content*, a person's (3) *directionality of interaction* and (4) *engagement*. The combination of these four factors is assumed to determine which behavior change techniques might be at work in affecting psychosocial determinants of health behaviors that, ultimately, cause health behavior change. As the social media environment is still relatively neglected in discussions and debates about influences on health behaviors (e.g., Granheim et al., 2022), we also discuss why social media likely increases the total amount of social influences on health behaviors due to the unique characteristics of the social media environment.

In section 3 (Manuscript 2), I examine the causality and temporal dynamics of eating-related sender- and receiver-effects on eating behavior and underlying mechanisms of action. Furthermore, I examine the potential of eating-related food postings for supporting eating behavior change in individuals. Together with my colleagues, I conducted two field experiments combined with intensive longitudinal data (multiple repeated measurements of eating-related social media use, eating behavior, and psychosocial determinants) and coded behavioral social media data for seven consecutive days. In both studies, we experimentally manipulated whether senders posted *publicly* about their fruit and vegetable intake via social media. In Study 1 (n = 41 dyads, N = 81 participants), we examine the effects of mere posting about fruit and vegetable consumption on the intake, perceived social support, and perceived social norms of dyads (both senders and network members). In Study 2 (N = 128), we examine the effect of posting about fruit and vegetable intake in the context of a behavior change goal (33% increase of baseline intake) on senders' intake and several mechanisms of action (i.e., perceived social support, perceived social norms, intentions, attitudes, self-efficacy, and goal commitment). Furthermore, we analyze dose-response associations of *intra*individual variations in the daily number of study-related postings regarding intake (coded behavioral social media data) and subjective social media usage related to the study, respectively intake (subjective diary data), with daily fruit and vegetable intake and the psychosocial determinants mentioned above. It was hypothesized that public posting about fruit and vegetable intake on social media would cause stronger increases in intake and psychosocial determinants from baseline to follow-up compared to public posting about a control topic and simultaneous private-self-monitoring of intake (Study 1) and to private posting about intake respectively self-monitoring of intake in a private chat (Study 2). Furthermore, increases in psychosocial determinants were hypothesized to at least partially mediate effects on intake. It was also expected that daily *intra*individual variations in study-related social media activities (number of social media postings and subjective social media usage) regarding intake would be positively associated with daily intake and the psychosocial determinants.

In section 4 (Manuscript 3), I examine one key ingredient in social media-based health behavior interventions, interpersonal communication through written social media postings. I specifically look at communication *quality* from the lens of self-determination theory (operationalized as need-supportive communication). I test whether need-support could be increased through a short theory-based intervention video and thereby boost the effectiveness of social media as an intervention tool to support health behavior change and increase the engagement of participants. In Study 1 ($N = 76$), my co-authors and I develop a video intervention educating about need-supportive communication strategies in social media communication. my colleagues and I further validate the video by experimentally testing whether the theory-based video (compared to a control video about general netiquette rules) can increase need-supportive communication strategy use in written responses to fictive social media postings. In Study 2 ($N = 537$), we experimentally test whether participants watching the theory-based video intervention (compared to participants watching the control video) show higher use of need-supportive communication strategies in real social media postings in a 2-week health behavior change intervention with a forum-based online support community. It was expected that this higher strategy use would result in higher perceived need-support from the other forum members, higher goal attainment (regarding health behavior change), and higher participant engagement in participants viewing the intervention video (compared to the control video). Drawing on the integrated model of the self-determination theory and the reasoned action approach, we additionally expected higher autonomous motivation, self-efficacy and perceived social support, and more positive attitudes and perceived social norms.

In the fifth and final section of this dissertation, I summarize and integrate the implications of the theoretical manuscript, and the results and implications of the four conducted empirical studies. I further discuss the strengths and limitations of this dissertation, outline implications for future research and practice, and draw a general conclusion.

2. Manuscript 1: How Social Media Influences Offline Health Behaviors: A Behavioral Science Perspective

This manuscript is in preparation:

Kilb, M., & Mata, J. (2022). *How social media influences offline health behaviors: A behavioral science perspective* [Manuscript in preparation].

Abstract

Social media is an essential part of people's social environment, especially in the health domain. Yet, how online social media environments differ from offline social environments and, specifically, how health-related social media use affects offline health behaviors are not well understood. Taking into account contemporary developments in behavioral sciences, we outline a theoretical framework for health-related social media effects. Social media use can be characterized by four essential factors: the specific social media *communication features* used, the *directionality of interaction*, the *content* of social media communication, and a person's *engagement*. Depending on the specific combination of these four factors, social media use contains or triggers different behavior change techniques. The enactment of these behavior change techniques leads to changes in important—often psychosocial—determinants of health behaviors and eventually causes health behavior change. We argue that health-related social media use intensifies social influences on health behaviors because of social media's unique characteristics, namely, high accessibility and omnipresence, fast adaptability, and social identification processes. This review highlights the importance and potential of social media for health behavior change and health. It gives a conceptual overview on how and when social media use influences health behaviors, providing an important basis for future research.

Health Behaviors Are Social

Chronic diseases such as cardiovascular diseases, chronic respiratory conditions, and different cancer types are major threats to human health (Murray et al., 2020). Importantly, human health can be substantially influenced by behavior: Unbalanced eating, smoking, alcohol or drug use, and physical inactivity are main risk factors for chronic diseases and premature death (Murray et al., 2020). Humans evolved as a social species, embedded in social networks that influence health via a range of social processes such as normative influence and social support (Berkman et al., 2000; J. Zhang & Centola, 2019). One important pathway by which social networks affect health is through health behaviors (Berkman et al., 2000; J. Zhang & Centola, 2019).

Many theories such as the transactive goal dynamics theory (Fitzsimons et al., 2015), reasoned action approach (Fishbein & Ajzen, 2011), social-cognitive theory (Bandura, 1998), and self-determination theory (Deci & Ryan, 2000) suggest that health behaviors are influenced by interpersonal factors such as social support, social comparison, or social norms (Davis et al., 2015; Hagger, Cameron, et al., 2020; Michie et al., 2014). Empirical research supports these theoretical assumptions. For example, health traits (e.g., overweight) and health behaviors are correlated within families or groups of friends (e.g., Cornelius et al., 2016; Knobl et al., 2022). Also, communicating and changing health-related social norms lead to changes in health intentions and behavior (Robinson, Thomas, et al., 2014; Sheeran et al., 2016); health-related social support is related to health behaviors (Kent de Grey et al., 2018; Olander et al., 2013); and targeting dyads instead of individuals with health behavior interventions leads to enhanced behavior change (R. M. Carr et al., 2019).

How (Social) Health Behavior Change Works: Mechanisms of Action and Behavior Change Techniques

Although meta-analyses have shown the importance of social factors for health behavior change, the processes and mechanisms underlying health behavior change are barely understood. Huge efforts have been undertaken in the last decade to systematize existing knowledge and create taxonomies for a better understanding of how human behavior change works (Carey et al., 2019; Johnston et al., 2021; Michie et al., 2013, 2017; Sheeran et al., 2017). Health behavior change is assumed to work through changes in important determinants of health behaviors, for example, psychological constructs such as beliefs about consequences (e.g., outcome expectancies) or beliefs about capabilities (e.g., self-efficacy), that are caused by the enactment of various behavior change techniques (Carey et al., 2019; Hagger, Moyers, et al., 2020; Sheeran et al., 2017), such as receiving information about health consequences or feedback on outcomes of behavior (Michie et al., 2013), that actively contribute to behavior change. Most of these techniques are assumed to be "self-enactable"—that is, people can apply them by themselves to support behavior change (Knittle et al., 2020). Different taxonomies exist but one common cross-behavior taxonomy in the health context is the Behavior Change Technique Taxonomy, version 1 (BCTTv1; Michie et al., 2013; all behavior change techniques mentioned in this review refer to the BCTTv1). The most recent and comprehensive integration of multiple different taxonomies includes a total of 123 motivation and behavior change techniques (Knittle et al., 2020).

Interpersonal processes affect health behaviors through different mechanisms of action (i.e., different behavior change techniques and psychosocial determinants of health behaviors). Specific to the social nature of human interaction are behavior change techniques such as "3.1 Social support (unspecified)" and "6.3 Information about others' approval," and psychosocial determinants in the social influences domain (e.g., perceived social support and perceived social norms). Some recent work has focused specifically on identifying "social" behavior change techniques and mechanism of action, for example, in dyadic (Scholz et al., 2020) or group-based (Borek et al., 2019) health behavior interventions. This interesting field is still in its infancy but is rapidly and continuously developing. Which behavior change techniques and mechanisms of action are at work ultimately depends on the specific situation.

For example, in a social interaction situation, peers could influence others by supporting them in setting goals, by providing emotional support, or by modeling the target behavior, which are all behavior change techniques (Michie et al., 2013). Because of this complexity and to improve clarity, we use the term *social influence* throughout the rest of the manuscript for all interpersonal processes that might trigger the enactment of behavior change techniques.

Social Influences in the Digital Era: Social Media Use and Health Behaviors

Humans are heavily connected in online social networks via the internet, especially social media. In 2019, 51% of the world population used the internet and many Western countries in North America and Europe have uptake rates as high as 70%–80% of their population (International Telecommunication Union, 2020; Roser et al., 2015). Most internet users also use social media such as Facebook or Instagram, especially in the age range of 18–29 years (Pew Research Center, 2021). Despite the wide distribution and use of social media, the social media environment and its influence on human behavior is underresearched in many areas of psychology, especially in the health behavior domain (e.g., Hawks et al., 2020). Social media is broadly defined as “internet-based, disentrained, and persistent channels of masspersonal communication facilitating perceptions of interactions among users, deriving value primarily from user-generated content” (C. T. Carr & Hayes, 2015, p. 49). Most social media applications share four common features: individual profiles, streams, networks, and messaging functions (Bayer et al., 2020). Social networking sites and social media in general allow users to build large online social networks through which (health-related) information can spread (Cinelli, Quattrociocchi, et al., 2020; Lerman & Ghosh, 2010; Wang et al., 2019). Social media can be seen as a frequently changing part of humans’ daily (health) information and choice architecture (Granheim et al., 2022; Kozyreva et al., 2020), which is increasingly used by the public to actively seek and share health-related information and social support through online communities (Chen & Wang, 2021). It is also used by institutions to disseminate health information (Chen & Wang, 2021), and companies use social media to encourage health-promoting or health-damaging behaviors (e.g., consuming fast food) via paid advertisements and (influencer) marketing. For example, an analysis of 15 randomly selected Instagram accounts from all accounts of a well-known fast food chain operating in 101 countries showed that more than 10 million people followed these 15 accounts and they generated around 3.9 million likes, 165,00 comments, and 38.2 million video views (Cassidy et al., 2021). Children and young adults are also often exposed to food cues by peers and food marketing by social media influencers (Coates et al., 2019a; Qutteina et al., 2019). This readily available content and the social cues (i.e., likes and comments) can influence both health and risk behaviors. For example, eating- and alcohol-related social media use has been shown to be associated with eating and drinking behavior (e.g., Curtis et al., 2018; Sina et al., 2022). Social media is also increasingly used to deliver health behavior interventions (Petkovic et al., 2021). In sum, most social media users are intentionally or unintentionally exposed to health-related social media communication, and some of them are also actively contributing to this communication.

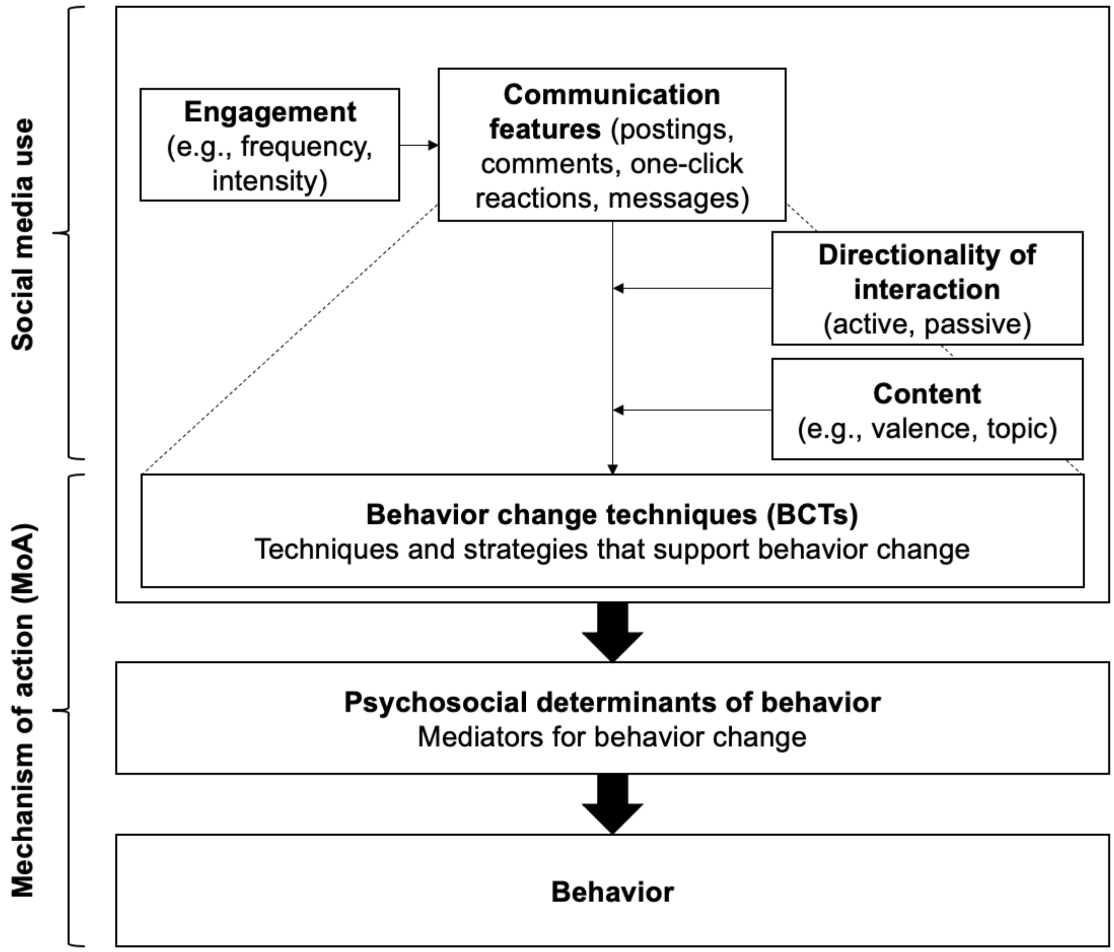
Several reviews, meta-analyses, and commentaries have noted the opportunities of social media to influence health behaviors and health promotion (e.g., Johansson et al., 2021; Lefebvre & Bornkessel, 2013; Maher et al., 2016; Moorhead et al., 2013; Petkovic et al., 2021). However, two essential questions remain unanswered: (1) Through what features and mechanisms of action can health-related social media use influence health behaviors? (2) How do online and offline social influences differ in their effect on offline health behaviors? We first outline a conceptual framework for examining social media effects on health behaviors and then describe the differential effects of online social media environments versus offline social environments on health behaviors. We eventually argue that social media environments intensify social influences on health through their unique features.

How Social Media Affects Health Behaviors: A Conceptual Behavioral Science Framework

The mechanisms of action underlying the effects of social media use on health behaviors have not been researched so far. We suggest, and others have suggested that social media influences health behaviors through changes in—often psychosocial—determinants of behavior (mediators), which change following the enactment of specific behavior change techniques (Myneni et al., 2016; Petkovic et al., 2021; Sheeran et al., 2017; Simeon et al., 2020). In the following section, we outline a theoretical framework for understanding health-related social media effects by integrating these assumptions with research on computer-mediated communication (see Figure 1). In this framework, we combine elements of channel- and communication-centered approaches to computer-mediated communication (Meier & Reinecke, 2021) that are essential for interpersonal social media communication. These are integrated with the experimental medicine approach to health behavior change (Hagger, Moyers, et al., 2020; Sheeran et al., 2017). We suggest that the strength of social media effects on health behaviors and their underlying mechanisms of action (i.e., involved behavior change techniques and psychosocial determinants) depend on four essential factors: (1) the types of interactive social media communication features, (2) the directionality of interaction with these features, (3) the specific content delivered through these features, and (4) a person's engagement.

Figure 1

Theoretical Framework for Health-Related Social Media Effects



Note. The higher the engagement of a person, the more the person is interacting with different social media features (e.g., postings or comments). The resulting social media activities can be either active (e.g., providing comments) or passive (e.g., receiving comments) depending on the directionality of interaction. The combination of the specific communication features, the directionality of interaction (e.g., active vs. passive use), and the content of the activities (e.g., what topic is depicted in the postings) triggers different behavior change techniques (e.g., increasing “1.9 Commitment” and receiving “6.3 Information about others’ approval” in the form of likes). The enactment of the specific behavior change techniques influences psychosocial determinants of behavior, which in turn affect human behavior (mechanism of action).

Interactive Communication Features in the Social Media Environment

Communication features are comparable to the lowest level of hierarchy ("features") in the channel-centered approach (Meier & Reinecke, 2021) and are core elements of social media across different platforms that allow interpersonal communication (Bayer et al., 2020). These features can be conceptualized as communication tools (e.g., Smock et al., 2011) and represent the building blocks of social media environments that allow interpersonal communication among users and thus direct how users approach and use social media (Bayer et al., 2020). The communication features can be broadly categorized into (a) postings in a personal, topic-based, or group-based feed, (b) one-click reactions (e.g., likes), (c) comments, and (d) private messages, which are directed to either individuals (one-to-one) or groups of individuals (one-to-many/many-to-many). Communication features are an essential element of the framework because they can themselves represent behavior change techniques (Simeon et al., 2020) and are thus included as the highest hierarchical level.

Directionality of Interaction With Communication Features

The directionality of interaction is central to the communication-centered approach (Meier & Reinecke, 2021). At the highest level, directionality of interaction describes active versus passive use (Trifiro & Gerson, 2019, see Parry et al., 2022, and Verduyn et al., 2017, for the same distinction in social media use and well-being; and Short et al., 2018, in digital health behavior interventions). For example, one-way noninteractive sending (e.g., posting only) and two-way interactive communication (e.g., continuous message exchange) represent forms of active use, whereas one-way noninteractive receiving (e.g., only viewing postings) represents a form of passive use (Meier & Reinecke, 2021). This distinction is somewhat similar to the differentiation between sender and receiver effects (Valkenburg, 2017; Valkenburg et al., 2016). Detailed analyses of social media communication data support the benefits of differentiating between active and passive use for predicting health outcomes (Pappa et al., 2017; Xu & Cavallo, 2021). Active and passive use are often not clearly separated from each other in current research (Valkenburg et al., 2021). All communication features can, however, be used in either an active or a passive way: Active social media use includes the posting of texts, pictures, and videos, the provision of likes and comments, the sharing of others' content, and writing private messages. In contrast, passive social media use includes the exposure to social media postings, receiving likes and comments, and receiving private messages. Nevertheless, it is important to note that social media users often simultaneously use social media both actively and passively (e.g., by actively creating postings in social media and passively viewing social network responses to these postings, such as likes and comments). This interactivity likely reinforces and strengthens social media effects (Valkenburg, 2017; Valkenburg et al., 2016). For example, the potential effects of posting about one's health behaviors via social media on one's own health behavior change might strengthen with the number of received positive social responses via likes and comments.

Content Delivered Through Interactive Communication Features

Content communicated via communication features refers to an important factor on the message level in the communication-centered approach (Meier & Reinecke, 2021). The content of social media communication (especially postings, comments, and messages) varies considerably in valence, topic, and multiple other characteristics (Meier & Reinecke, 2021). The effect of using different communication features on health behavior always depends on the actual content. For example, a person with overweight could be exposed to both pro-weight-loss postings and body-positivity postings promoting size acceptance, which likely impact weight-regulating behaviors such as eating and physical activity differently. Furthermore, a person might post about health-promoting behaviors (e.g., healthy eating) or harmful behaviors (e.g., fast food consumption).

Engagement With Social Media

Engagement refers to the quantitative aspects of social media use (i.e., the frequency, duration, or intensity of use), particularly the active or passive use of the different communication features (cf. Short et al., 2018). For example, one person might post five times a day to their social media network whereas another might post only twice a week. Engagement is an important factor in digital health behavior interventions because it contributes to intervention success through exposure to intervention content (i.e., higher engagement leads to higher exposure; Short et al., 2018). This also applies to health-related social media use: Higher use of the different communication features potentially leads to a higher number and higher dose of activated behavior change techniques (Mata & Baumann, 2017) and, in turn, a higher probability of strong effects on psychosocial determinants and health behaviors. In measures of social media use, engagement is often conflated with the other factors and assessed as part of a rather broad conceptualization of social media use (cf. Parry et al., 2022; Valkenburg et al., 2021). However, engagement can be assessed more specifically according to the types of communication features used and the directionality of interaction. For example, the number of postings made and the number of reactions received can predict weight loss success and eating behavior in social-media-based interventions (Kilb et al., 2022; Pagoto et al., 2018; Xu & Cavallo, 2021).

The resulting framework provides an interdisciplinary perspective on how health-related social media effects might work. It bridges research on computer-mediated communication and health behavior change in a parsimonious framework. Additional factors on different levels of analysis (e.g., the interaction and message level) could play a moderating role regarding the occurrence and strength of health-related social media effects (e.g., if a posting is permanently or temporarily shared). Therefore, other factors can be examined as additional moderators within this framework (cf. Meier & Reinecke, 2021). Importantly, we included the—in our view—most essential factors that determine what behavior change techniques might be at work and influencing the strength of effects, namely, the interactive social media communication features used, the directionality of interaction, the specific content of communications, and a person's engagement.

Behavior Change Techniques in Social Media

What specific active ingredients of health behavior change (Michie et al., 2013) does health-related social media contain or trigger? This depends on the combination of content, directionality of use, and the specific communication features. For example, a person who is regularly posting about their fruit and vegetable intake is engaging in a form of public self-monitoring ("2.3 Self-monitoring of behaviour"). The silent observation of these postings through their social media network involves external monitoring ("2.1 Monitoring of behaviour by others without feedback") as an additional behavior change technique for posters. Furthermore, receiving positive comments in response to postings about behavior change struggles can contain many different behavior change techniques, such as "1.2 Problem solving," "3.1 Social support (unspecified)," "15.1 Verbal persuasion about capability," and many others. However, there are also types of social media activities that can be seen as behavior change techniques themselves, for example, receiving and providing likes in response to postings, which can be seen as a form of social support or reward ("3.1 Social support (unspecified)," "10.4 Social reward"), and social approval of the depicted content ("6.3 Information about others' approval"). A recent review about behavior change techniques in interactive social-media-based interventions showed that interventions contained 26 of the 93 behavior change techniques from the BCTTv1. The five techniques "3.1 Social support (unspecified)," "4.1 Instruction on how to perform the behavior," "9.1 Credible source," "6.2 Social comparison," and "5.1 Information about health consequences" are the most common in interactive social media components (Simeon et al., 2020). Notably, "3.1 Social support (unspecified)" was the most frequent behavior change technique (present in 72% of the interventions) and was coded when interventions contained some form of virtual rewards that expressed overt endorsement of other participants (e.g., via comments, likes, and resharing of content).

Until now, only a few studies have empirically examined explicit links between different types of health-related social media use and potential mechanisms of action for health behavior change (i.e., the behavior change techniques and psychosocial determinants of health behavior at work). Many studies examining health-related social media effects (a) did not test effects on psychosocial determinants of health behaviors in naturally occurring social media use and interventions (see e.g., Hawks et al., 2020; Petkovic et al., 2021) and (b) used rather broad measures of social media use instead of looking at the specific combination of utilized social media communication features, types of communicated content, and directionality of interaction. For example, researchers often solely test the overall effect of social-media-based interventions (Petkovic et al., 2021) and merely distinguish between active and passive social media use or examine only the influence of the duration or frequency of social media use (Parry et al., 2022). Measures are further often conflated both between and within the different factors and analysis level (see Meier & Reinecke, 2021; Valkenburg et al., 2021). Recently, the first studies testing effects on psychosocial determinants of health behaviors such as attitudes, perceived norms, perceived behavioral control, self-efficacy, and perceived social support (e.g., Cavallo et al., 2014; Geusens et al., 2020; Geusens & Beullens, 2019; Kilb et al., 2022; Kim & Hawkins, 2020; Peng et al., 2019) have been published. For example, sharing alcohol references on social media has been positively associated with attitudes toward binge drinking and perceived descriptive norms, and negatively associated with perceived behavioral control, whereas the passive exposure to alcohol references has been positively associated only with perceived descriptive and injunctive norms (Geusens et al., 2020). Some studies have also begun to use text mining, an even more finely grained approach, to examine different social media activities and content (Y. Liu & Yin, 2020; Pappa et al., 2017) or compare specific active and passive social media activities (Mi et al., 2022; Pagoto et al., 2018; Pappa et al., 2017; Xu & Cavallo, 2021). For example, active activities (i.e., postings, comments, and reactions to other postings) in a group-based weight loss intervention using social media predicted weight loss, whereas a passive measure (comments received) predicted changes in self-efficacy and indirectly predicted weight loss via self-efficacy changes (Xu & Cavallo, 2021). Furthermore, different topics (e.g., motivation or health goals) in postings and comments independently predicted weight loss in a large online weight loss community above and beyond the number of active and passive online activities such as the number of publicly documented weigh-ins (Pappa et al., 2017).

Overall, the results of the aforementioned studies suggest that health-related social media effects are complex, similar to offline social influences (cf. Borek et al., 2019). Importantly, given the research available to date, there is little reason to expect differences in active behavior change techniques or underlying mechanisms of action. Health-related social media effects are assumed to work through comparable mechanisms of action, that is, the enactment of different behavior change techniques and changes in psychosocial determinants of health behaviors (Myneni et al., 2016; Petkovic et al., 2021; Simeon et al., 2020). The underlying mechanisms of action likely depend on the engagement of the person, the type of social media communication feature used, the directionality of interaction, and the specific content in social media communication. Social media components in behavioral interventions contain comparable techniques to offline group-based health behavior interventions, for example, providing social feedback and social support, social comparison, or self-monitoring (Borek et al., 2019; Kilb et al., 2022; Simeon et al., 2020). One exception are virtual rewards, which are unique to social media (Simeon et al., 2020). Virtual rewards can be differentiated between overt endorsement from other participants, social and non-social virtual rewards by design; however, these three facets can be categorized in existing taxonomies (Simeon et al., 2020). Comparable psychosocial determinants on the individual level such as changes in attitudes, self-efficacy, normative beliefs, or social identity have been discussed as mechanisms of action in social media-based and offline group-based interventions (Borek et al., 2019; Geusens & Beullens, 2021; Petkovic et al., 2021). Influences of social media use on health behaviors have also been examined with existing health behavior theories (e.g., Geusens et al., 2020; Kim & Hawkins, 2020). Although not many social-media-specific behavior change techniques and mechanisms of action have been identified in theory or research so far, online social media likely amplifies the effects of the social environment on health behaviors. How online social environments (i.e., social media) affect health behaviors differently from offline social environments is discussed next.

Social Media Increases Social Influences on Health Behaviors

Online and offline social environments differ in several characteristics including network structure and content (Kozyreva et al., 2020; Marsh & Rajaram, 2019; McFarland & Ployhart, 2015). These include (a) higher accessibility to information, (b) larger amount of information, (c) rapid change and adaptivity of information and environments, (d) larger networks and higher visibility of weak or indirect ties, (e) higher permanence of content, (f) higher asynchronicity of social interactions, (g) different degrees of anonymity (depending on platforms and user preference), (h) higher personalization (e.g., through curation algorithms), and (i) higher visibility of social cues. It has been suggested that these differences influence the way people share, access, and process information (e.g., Marsh & Rajaram, 2019) and the meaning of constructs and processes (McFarland & Ployhart, 2015). There is little to no research on how social influences on health behaviors online and offline might differ in their underlying processes and mechanisms of action. As discussed above, there is little reason to expect differences in active behavior change techniques or underlying mechanisms of action. Instead, qualitative differences between online and offline environments, such as higher personalization and rapid adaptivity, and resulting phenomena such as echo chambers and homophily can intensify online (compared to offline) social influences. Furthermore, online social media environments likely differ in quantitative aspects. Unique characteristics of the social media environment—such as higher accessibility and immediacy of feedback from one's network—increase the total number of social influences on behavior. In the following, we describe how online social media increases the number of social influences on health behaviors—and intensifies that influence—via omnipresence, rapid changes in social environments, echo chambers, and network homophily.

Social Influence via Social Media Is Omnipresent

Many people, especially young adults and adolescents, regularly use social media (Pew Research Center, 2021). For example, 70% and 71% of U.S. adults between 18 and 29 years old use Facebook and Instagram, respectively, and 70% and 59% of those use it daily (Pew Research Center, 2021). Social media contributes to information diversity (Bakshy et al., 2015) and to shaping people's cognitions and behaviors, through both strong and weak ties (Bakshy et al., 2012; Marsh & Rajaram, 2019). In contrast to offline contexts, social cues, which represent active behavior change techniques (Simeon et al., 2020), are permanently and readily available on a large scale and at low cost—including from strong and weak ties as well as geographically close and distant ties (Marsh & Rajaram, 2019; McFarland & Ployhart, 2015). It has been shown that digital social cues, that is, the liking of content by a friend, increase the liking of and clicking on social media advertisements (Bakshy et al., 2012). Additionally, social cues on social media influenced real-world voting behavior in a large-scale social media experiment with 61 million Facebook users (Bond et al., 2012). Social media also provides the opportunity for social influences even when no person is present offline. In sum, the omnipresence of social media increases the total number of social influences and active ingredients for health behavior change (Mata & Baumann, 2017). It could represent both a compensatory and an additional social environment in situations without offline social influences.

Social Media Environments Rapidly Change Through User Behavior and Curation Algorithms

Individuals' engagement with social media (e.g., posting new content and interacting with the community about this content, following new accounts) rapidly changes their own social media environment and thus the content to which they are daily exposed (Berman & Katona, 2020; Kozyreva et al., 2020). Content algorithms have fast adaptability, and users influence the content of their individual feeds with every use of the social media application (Bakshy et al., 2015; Berman & Katona, 2020; Brugnoli et al., 2019). Many algorithms include the similarity of postings to earlier content the user interacted with, the recency of postings, or the relationship with other posters as important determinants of what content to display in the personal feed (e.g., TechCrunch, 2018). Thus, in the case of intended health behavior change or an initial interest in a specific health behavior, users can engineer their personal social media environment to support health behavior change. After a certain use time, users may create reinforcing echo chambers (Brugnoli et al., 2019), which can be supportive regarding their personal goals. In contrast, a person's offline social environment is generally more constant. It is defined by a comparatively smaller number of intimate friend and family relationships, and relationships in workplaces and organizations (e.g., Sallis et al., 2006, for an ecological model of health behaviors).

Social Media Creates Echo Chambers, Strengthening Specific Beliefs and Behaviors

Social media contributes to the evolvement of filter bubbles or echo chambers, in which like-minded individuals cluster in online social networks (Brugnoli et al., 2019; Cinelli et al., 2021; Del Vicario et al., 2016). Echo chambers contribute to biased spreading of information. This effect is more pronounced in social media channels in which users cannot actively tweak their personal feed themselves, for example, Twitter, Facebook, or Instagram (Cinelli et al., 2021). The clustering within online social networks and echo chambers can also reinforce already existing beliefs (Brugnoli et al., 2019) and lead to selective exposure, which fuels the false consensus effect, that is, overestimation of the prevalence of those attitudes and behaviors of others that are consistent with one's own attitudes and behaviors (Bunker & Varnum, 2021; E. Lee et al., 2019; Lerman et al., 2016). The majority illusion is not a completely new phenomenon and can also be found in offline social networks. However, because of the unrestricted availability of online social networks and fast adaptability of curation algorithms, the influence is omnipresent and fast-paced. Importantly, higher social media use is associated with weaker selective exposure (Cinelli, Brugnoli, et al., 2020), and whether echo chambers evolve depends on both platform algorithms and user preferences (Bakshy et al., 2015; Berman & Katona, 2020; Brugnoli et al., 2019). Thus, the phenomenon of echo chambers could be used to receive goal-consistent information and support intended health behavior change.

Homophily and Social Identification Increases Social Influence and Persuasion

Some characteristics of the social media environment and online social networks can further strengthen social influence and persuasion. Research has shown that people form online social networks and friendships depending on shared demographics and interests (e.g., Centola & van de Rijt, 2015; Lewis et al., 2012). This phenomenon, called "choice homophily," is well known and was first described in offline social networks (McPherson et al., 2001). Clearly, the characteristics of social media environments can accelerate these processes (e.g., via curation algorithms and friendship suggestions) and thus contribute to the fast evolvement of homophilous online social networks, which have been shown to strengthen online social influence (Aral & Nicolaides, 2017; Centola, 2011). For example, the social influence on running behavior in a large online social network was stronger for same-sex pairs compared to mixed pairs (Aral & Nicolaides, 2017). Especially young adults also connect with social media influencers with large numbers of followers with whom they identify more strongly (i.e., perceived similarity) compared to traditional celebrities and find them more credible information sources (Croes & Bartels, 2021; Djafarova & Rushworth, 2017; Jin et al., 2019; Schouten et al., 2020). Stronger identification with a norm-referent group has also been shown to increase social influence (Croes & Bartels, 2021; Stok et al., 2016). Thus, factors that are known to increase the effectiveness of social influence are likely enhanced in social media environments.

Conclusions

Taken together, initial research suggests that health-related social media use and communication influence health behaviors in active and passive users, and this might also apply to people without behavior change intentions. The effects are likely conditional on the factors described in our framework: user engagement and directionality of interaction, use of communication features, and communicated content. We argue that online social media environments amplify the importance of social influences on health behaviors compared to offline social networks because of their rapidly changing content and their network structure, faster and more prevalent development of echo chambers, and social network homophily. Furthermore, social media increases the total number of social influences on health behaviors because of the quantity of social cues and the omnipresence of social media in day-to-day life.

Importantly, the mechanisms of action underlying the effects of social media use on health behaviors are not yet understood. One reason might be that they are more dynamic and complex and thus need elaborate research designs, particularly factorial designs to test the effects of specific social media features, (real-world) experiments to examine causality in social media effects, or intensive longitudinal studies to disentangle between- and within-person effects. Furthermore, new analysis methods are needed, for example, text mining to make sense of the content of social media communication, or social network analysis of online social network data to disentangle social influence from choice homophily or to account for the interactivity in social media effects.

The behavioral science framework proposed here describes four factors that can help systematize assessments in future social media studies on health behaviors, suggests why social influences on health behaviors and health in general are amplified through social media, and points to important gaps in the literature, namely, the currently missing research on underlying mechanisms. Mechanisms of action (including involved behavior change techniques and psychosocial determinants) are central to the design of effective interventions that make good use of social media to promote health behaviors.

3. Manuscript 2: How Social Media Affects Healthy Eating in Senders and Receivers of Eating-Related Online Postings: Two Field Experiments With Intensive Longitudinal Data

This manuscript is in preparation:

Kilb, M., Giese, H., & Mata, J. (2022). *How social media affects healthy eating in senders and receivers of eating-related online postings: Two field experiments with intensive longitudinal data* [Manuscript submitted for publication].

Abstract

Young adults are frequently confronted with eating-related social media content. How such exposure influences eating in those who post and their network members is largely unknown. We conducted two intensive longitudinal field experiments combining self-reports with social media data. The posting behavior of young adults was manipulated. We examined how postings about fruit and vegetables affected intake in senders and their network members (Study 1, $N = 81$) and in senders with a specific eating behavior change goal (Study 2, $N = 128$). Potential psychosocial mechanisms of action were explored. Posting led to a higher intake of senders and network members, and to higher perceived social support and injunctive norms of senders (Study 1). Posting supported eating behavior change; the effect size was comparable to mere picture-based self-monitoring of intake (Study 2). Intraindividual variations in senders' daily eating-related social media activities were associated with their daily eating behavior and perceived social support (both studies), daily self-efficacy, experiential and instrumental attitudes, and goal commitment (Study 2). The current studies underline that social media environments should be considered in research and interventions targeting eating behavior of young adults.

Introduction

Social media is very popular, especially among adolescents and young adults (Pew Research Center, 2021). One topic of particular interest is communication about food (e.g., Hu et al., 2014). Given that adolescents and young adults also frequently do not meet dietary recommendations, such as eating five portions of fruit and vegetables per day (e.g., Mensink et al., 2013), social media are ideal platforms for promoting and supporting healthy eating among this age group.

Social media is typically used to deliver interventions or as an add-on in multicomponent interventions (cf. Petkovic et al., 2021). Thus, the potential of social media itself may still be underused for health promotion: Social media interventions could have supportive spillover effects (Valkenburg, 2017). For example, intervention effects may scale when a social media poster ("sender") influences which postings other individuals ("network members") view or respond to. How social media uniquely affects senders and network members has been rarely researched, especially in the context of eating behaviors (see, e.g., Hawks et al., 2020; Petkovic et al., 2021, for reviews), and potential underlying mechanisms have been largely ignored. To date, most of the research is cross-sectional or laboratory and, thus, does not allow conclusions about causality or lacks external validity (Sina et al., 2022).

Aims of the Current Experimental Studies

The goals of the current experimental studies were to examine the effects of healthy eating-related postings on eating behavior in senders and network members, and to identify potential underlying psychosocial mechanisms. The two studies extend existing research in several ways: First, they measure the unique effects of social media postings on eating behavior. Second, their experimental design allowed examining causal effects of social media on eating. Third, they explicitly tested theoretically derived mechanisms potentially underlying the relation between eating-related social media postings and eating behavior. Fourth, the studies are the first to provide insights into the temporal relations and dose-response relationships of intraindividual day-to-day variations in eating-related social media use and eating behavior.

Study 1: Effects of Posting About Fruit and Vegetables on Intake

Theoretical background: Social Media Use, Perceived Social Support, and Social Norms

Social media use may increase *social support* (Simeon et al., 2020), an interindividual resource assisting successful goal-striving (Fitzsimons & Finkel, 2010), and thereby facilitate healthy eating (e.g., Scholz et al., 2013). It can be provided through affirmative social responses to postings (e.g., likes, supportive comments) or directly addressing network members' instrumental and emotional needs, for example by providing healthy recipes or empathetic texts (de la Peña & Quintanilla, 2015; Simeon et al., 2020). Research also shows that participation in computer-mediated support groups, where active and passive activities are closely intertwined, increases social support (Yang, 2020).

Others' healthy and unhealthy eating styles may also change social norms and motivate people to adjust their eating accordingly (e.g., Giese et al., 2015). In social media, food postings and related discussions may update perceived descriptive eating norms of both senders and network members by displaying the actual eating behavior in the group (Higgs & Thomas, 2016). In addition, receiving likes and affirming comments further convey social approval of the depicted eating behavior (de la Peña & Quintanilla, 2015; Hawkins et al., 2021), and thus influence perceived injunctive eating norms (Higgs & Thomas, 2016) and the social image of healthy and unhealthy foods (e.g., König et al., 2017).

Hypotheses

We expected (H1) that posting about one's fruit and vegetable intake (FVI) on social media would lead to a stronger increase in senders' FVI compared to posting about a control topic; (H2) that network members whose study partner ("sender") post about FVI would show a stronger increase of FVI compared to network members whose study partner post about a control topic; (H3) stronger increases of the following psychosocial outcomes for senders who post about FVI (compared to about the control topic) and their network members: (a) perceived FVI-related social support, (b) perceived injunctive, and (c) descriptive FVI norms; (H4) that the effects in H1 and H2 would be at least partially mediated via increased (a) perceived FVI-related social support, (b) perceived injunctive FVI norms, and (c) descriptive FVI norms; and (H5) positive dose–response relationships between daily FVI-related social media activities and (a) daily FVI and (b) daily FVI-related social support in senders and network members.

Method

Design and Procedure

We conducted a field experiment with baseline and follow-up assessment, ecological momentary assessment (EMA; Shiffman et al., 2008) over 7 days, and coding of public online postings. Young adults (18-29 years) participated as dyads with one sender (i.e., the person that would receive an intervention) and one network member (i.e., a Facebook friend of their choice). Senders were randomized into one of two posting conditions: online posting about their FVI (intervention condition) or online posting about their favorite books and movies/ series (B&M; control condition). Postings in both conditions had to be made on Facebook. The resulting design is a 2 (posting: online posting about FVI vs. B&M) × 2 (time: baseline vs. follow-up) mixed design with additional daily experience sampling data (Figure 1). Participants received money or a combination of money and course credit as compensation, dependent on the number of daily social media postings and completed questionnaires: All senders were incentivized to post status updates consistent with their experimental condition (FVI vs. B&M) on their personal Facebook wall, and all network members were incentivized to react and comment on these postings (see Appendix A). To rule out that the effect of posting could be merely explained by differences in self-monitoring of FVI, we asked senders in the B&M condition to track at least one fruit and vegetable serving per day by uploading photos and short notes via the movisensXS app. An overview of all suggested behavior change techniques (BCTTv1; Michie et al., 2013) in the different experimental condition is provided in Appendix B.

The study was approved by the Institutional Review Board of the University of Mannheim and preregistered via the Open Science Framework (https://osf.io/5h2vu/). Importantly, a second between-subject manipulation was not reliably delivered due to technical difficulties. Therefore, we could not follow the preregistration protocol and had to exclude participants receiving the defective manipulation. The conducted analyses are matched to the preregistered analyses of Study 2, and the results should thus be considered exploratory.

At baseline, participants self-selected their role within the dyad (sender or network member) and provided informed consent. Senders were then randomized to their experimental posting condition and completed the questionnaires. During the intervention period (7 days), participants were invited to up to 8 daily surveys. Data were collected with Unipark (Questback GmbH, Cologne, Germany) and movisensXS, version 1.3 (movisens GmbH, Karlsruhe, Germany), which was used to trigger and administer the daily surveys.

Participants

Of the 96 initial participants (48 dyads), 41 senders and 40 network members provided sufficient data for analysis (Appendix C for participant flow chart). The final sample did not differ from the initial sample, except that excluded senders reported lower FVI at baseline, $t(33.37) = 4.82$, $p < .001$, $d = 1.21$, and excluded network members reported higher autonomous motivation for eating fruit and vegetables, $t(10.06) = -2.84$, $p = .017$, $d = -1.05$ (Appendix D for baseline characteristics).

Materials

Facebook Data. Every Facebook posting of senders during the intervention week was saved and coded by one rater regarding the day and content of postings (posting about B&M: yes/no; posting about FVI: yes/no). About half of the postings (46%) were coded by two independent raters. Intercoder agreement was high (Krippendorff's α: .815 for B&M; .821 for FVI content).

Baseline and Follow-Up Assessment. *FVI* in the last week was measured using four items adapted from the German Health Examination Survey's food frequency questionnaire (Haftenberger et al., 2010), for example: "How often did you eat fruit (e.g., apple, banana, or canned fruit)?", and "When you eat fruit, how much do you usually eat?". Average daily number of portions was calculated according to the adapted scoring scheme (Haftenberger et al., 2010). *Perceived FVI-related social support* from the study partner (network member) and the sender's Facebook network was measured with the Frequency subscale of the Child and Adolescent Social Support Scale for Healthy Behaviors (CASSS-HB; Menon & Demaray, 2013), adapted to eating fruit and vegetables (Cronbach's α study partner: .92; Facebook network: .89). The two scores were averaged to one overall perceived FVI-related social support score. *Perceived norms regarding the FVI* of the study partner and the Facebook network (perceived descriptive FVI norms) were measured with 12 items for each reference group (see Cullen et al., 2001). The items were adapted to the study partner and Facebook network (e.g., "most of my friends on Facebook eat vegetables at lunch"; Cronbach's α study partner: .85; Facebook network: .87). Perceived injunctive FVI norms were measured with six existing items (Di Noia & Cullen, 2015) adapted to the study partner and Facebook network (e.g., "My social network on Facebook thinks that eating vegetables at lunch is a good thing to do") and four additional self-generated items to also capture FVI more generally (Cronbach's α study partner: .89, Facebook network: .92). The scale means for the study partner and the network were averaged into one measure each for perceived descriptive norms and perceived injunctive norms.

Control variables were measured at baseline. *Education level* was assessed by asking about highest educational degree completed and coding according to the International Standard Classification of Education (ISCED) into the categories low (ISCED 0–2), medium

(ISCED 3–4), and high (ISCED 5–8). *Age*, *weight*, and *height* were assessed with open-ended questions. *General Facebook usage frequency* was measured asking how often participants used Facebook (participants chose the unit that best fit their usage pattern, i.e., how many times a week, day, or hour they used Facebook).

Daily Measures. *Daily study-related Facebook usage* was measured with two items for active and passive usage intensity (adapted from Verduyn et al., 2015), for example "How often/intensely did you actively use Facebook since the last survey for content relating to posts you made as part of the study?" with detailed descriptions of active and passive use. The two items were averaged. *Daily FVI was assessed with two items,* e.g., "How many portions of fruit did you eat since the last survey?". There was a strong correlation, $r = .70$, $t(38) = 6.11$, $p < .001$, between reported FVI in the intervention week assessed via follow-up questionnaire and the average of daily assessments. *Daily perceived FVI-related social support* was measured with four adapted items from the baseline questionnaire. Participants rated statements such as "Since the last survey, my study partner/my social network on Facebook… encouraged me to eat more fruit and vegetables." The ratings for study partner and Facebook network were averaged into one score.

Statistical Analysis

All analyses were performed separately for senders and network members using R version 4.1.2. For the dose–response analyses, all participants who provided follow-up data and a minimum of 2 days with at least 50% of possible surveys answered (i.e., four surveys) were included in the analyses. The same participants were included in the group/between-level analyses. Internal consistencies for daily measures were calculated using nested alpha (Nezlek, 2017). The sample size of the different posting conditions was as intended (20 participants per condition); however, the participant loss also led to a loss of statistical power (post-hoc power calculations indicate a power of 0.88 for detecting medium and 0.56 for detecting small to medium interaction effects, respectively). Because of the lower statistical power, we also report findings with p values < .100 in Study 1 as relevant to future studies.

Analyses of Intervention Effectiveness. We fitted mixed 2 (posting: about FVI vs. about B&M) × 2 (time: baseline vs. follow-up) ANOVAs on FVI, perceived FVI-related social support, and perceived descriptive and injunctive FVI norms with the R package afex. Follow-up tests were conducted with t-tests and Holm p-value adjustment.

The R package lavaan version 0.6-3 was used to analyze mediation effects for senders and network members on the group level (i.e., the expected indirect effects). We fitted three path models with the posting condition as independent variable (dummy coded), the standardized change in FVI from baseline to follow-up, and the standardized change values of each mediator variable from baseline to follow-up. Parameters, standard errors, and confidence intervals for total and indirect effects of posting condition on FVI were estimated using bootstrapping (percentile method) with 10,000 iterations.

Analyses of Dose–Response Relationships. To test for dose-response relationships for FVI and perceived social support of both senders and network members on a daily level, data were aggregated by calculating the daily means and the total portions of fruits and vegetables per day. In four multilevel models, we predicted for senders and network members separately, a) the daily FVI of senders and network members in zero-inflated negative-binomial multilevel models (Gelman & Hill, 2006) with the R packages glmmADMB and lmerTest, and b) perceived social support in multilevel regression models. The predictors "daily number of senders' FVI-related postings" and "senders' study-related Facebook usage" were centered around the person mean, continuous control variables at the person level (BMI, age, general Facebook usage frequency) were grand mean centered (Enders & Tofighi, 2007). Categorical control variables (sex, education level) were effect coded. In addition, we controlled for assessment day and random person-level intercepts. We standardized the regression coefficients of continuous variables in the dose–response analyses with the R package parameters.

Results

Manipulation Check for the Posting Manipulation

Senders in the FVI condition (M = 10.25, SD = 4.19) posted more postings about FVI than those in the B&M condition (M = 0.67, SD = 2.46), t(30.38) = –8.88, p < .001, d = –2.79, 95% CI [–3.63, –1.90] and vice versa (B&M condition B&M postings: M = 12.86, SD = 8.78; FVI condition: M = 0.00, SD = 0.00; t(20) = 6.71, p < .001, d = 2.07, 95% CI 1.18, 2.94]). Importantly, senders in the B&M condition (M = 11.86, SD = 6.56) tracked a similar number of total FVI pictures during the intervention week (via Facebook postings and the movisensXS app) as senders in the FVI condition (M = 10.25, SD = 4.19), t(34.21) = 0.94, p = .354.

Group-Level Effects of Posting

Effects of Posting on Senders' FVI and Psychosocial Outcomes. Posting about one's FVI on social media did not increase FVI more strongly than posting about B&M (see Table 1 and Figure 2; not confirming H1). However, the trajectories of FVI over time were different between the conditions: Follow-up tests showed a decreasing trend of FVI in senders who posted about B&M (p_{adj} = .090) but not in those who posted about FVI (see Table 1 and Figure 2), indicating that there could be systematic differences in a higher-powered sample.

In contrast, perceived FVI-related social support increased over time, and this increase differed between the two experimental conditions (i.e., significant Posting × Time effect; Table 1 and Figure 2). In line with H3a, follow-up tests showed that only participants posting about FVI reported an increase in perceived FVI-related social support (p_{adj} = .052), but participants posting about B&M reported a decrease (p_{adj} = .099). The same interaction and time trends were found for perceived injunctive norms (H3b) but not for perceived descriptive norms (H3c): Only participants posting about FVI reported an increase in perceived injunctive FVI norms (p_{adj} = .027; Table 1).

In the mediation analyses, posting about FVI (compared to posting about B&M) did not indirectly predict the change of senders' FVI via increases in FVI-related social support, perceived injunctive or descriptive FVI norms (see Appendix E). Thus, we did not find support for the expected mediation effects (H4a-c) in senders.

Effects of Posting on Network Members' FVI and Psychosocial Outcomes. Network members whose study partner ("sender") posted about FVI showed no stronger FVI increase compared to network members whose study partner posted about B&M (Posting × Time; Table 1 and Figure 1; H2). However, post-hoc tests revealed an increase of FVI in network members whose study partner posted about FVI (p_{adj} = .087) but not in those whose study partner posted about B&M (see Table 1 and Figure 2), again indicating that H2 effects may not have been statistically significant due to a lack of power.

In addition, we did not find the expected stronger increase of perceived social support and norm perceptions in network members whose study partner posted about FVI and thus no evidence for H3a-c (see Table 1 and Figure 2). Yet, network members of study partners who posted about FVI generally reported higher perceived higher social support and more FVI-friendly injunctive norms independent of questionnaire timing (effect of Posting; Table 1).

The mediation analyses showed that posting about FVI (compared to B&M) did not indirectly predict the change of network members' FVI via increases in FVI-related social support, perceived injunctive, or descriptive FVI norms (Appendix E). Thus, the hypothesized mediation effects (H4a-c) in network members could not be confirmed.

Dose-Response Relationships between Daily FVI-Related Social Media Activities and Daily FVI and FVI-Related Social Support

We included 127 days of 20 senders and 122 days of 19 network members from the FVI posting conditions to examine dose–response relationships (Tables F1 and F2). As expected, we found positive dose-response relationships between senders' daily study-related Facebook usage and daily FVI ($\beta = 0.16$, $p = .059$) and perceived FVI-related social support ($\beta = 0.17$, $p = .002$). That is, on days where senders used Facebook more than usual (compared to their personal mean), they reported higher FVI and perceived FVI-related social support. We did not find such relationships for the number of senders' daily FVI-related postings (see Table E1 and Figure 3). Thus, H5a and H5b were partially supported for senders.

We found positive dose-response relationships between network members' study-related Facebook usage and daily perceived FVI-related social support ($\beta = 0.08$, $p = .007$) but not daily FVI ($\beta = 0.04$, $p = .449$). That is, on days on which network members used Facebook more than usual, they reported higher perceived FVI-related social support. On days with more FVI-related postings by senders, network members did not report higher FVI or FVI-related social support (Table E2; Figure 3). Thus, H5a was not supported, H5b partially for network members.

Discussion

While Study 1 indicated that posting about FVI could positively affect FVI, perceived social support, and injunctive norms, particularly in senders of the postings, the sizes of these effects may be a bit smaller than expected and therefore could not be reliably evoked with the given sample size. The smaller impact of FVI postings could also be explained by the absence of a concrete behavior change goal set (e.g., Inauen et al., 2017). Moreover, the results illustrate that more experiments are warranted to improve our understanding of how FVI postings relate to FVI-related psychosocial factors. We addressed these issues in Study 2 by increasing the sample size, adding a goal-setting intervention, and examining additional psychosocial mechanisms that may mediate a posting-FVI relationship. We also simplified the recruitment and only included senders of postings.

Study 2: How Public Self-Monitoring via Social Media Affects FVI Change

Theoretical Background: Social Media Use and Related Psychosocial Mechanisms

Important psychosocial mechanisms for behavior change that have not been researched in Study 1 or other previous studies on eating behavior change in social media include: self-efficacy, attitudes, and goal commitment. We define these constructs and explain their importance for the current research in the following: *Self-efficacy* is the belief about one's capability to perform a specific behavior even when facing barriers and obstacles (Bandura, 1997). Dietary self-efficacy can be increased by self-monitoring personal nutrition successes via social media postings (Prestwich et al., 2014) or receiving positive reinforcement through likes and comments (Bandura, 1997; de la Peña & Quintanilla, 2015; Prestwich et al., 2014; Yang, 2020). Likewise, postings about FVI may affect senders' perception of favorability of FVI, that is, their *attitudes*, via self-persuasion and self-concept changes (Valkenburg, 2017). Even the mere exposure to food (pictures) via postings could influence attitudes (Mata et al., 2018). Increases in self-efficacy and favorableness of attitudes evoke health behavior change (Sheeran et al., 2016). Finally, postings could also increase *FVI-related goal commitment*. Goal commitment has been defined as the "volitional psychological bond reflecting dedication to, and responsibility for […]" a behavior (Klein & Cooper, 2012, p. 67). Senders' commitment regarding their FVI goals could increase through heightened publicness of goals, received or anticipated social feedback, and external monitoring (Klein et al., 1999; Valkenburg, 2017), eventually leading to higher goal attainment (Klein et al., 1999).

Hypotheses

We expected (H1) that public posting about one's FVI on social media would be more effective in increasing senders' (a) FVI and (b) FVI intentions compared to private "posting" of FVI (private picture-based self-monitoring of FVI); (H2) stronger increases of the following psychosocial outcomes for senders who publicly (compared to privately) post about

FVI: (a) perceived FVI-related social support, (b) perceived descriptive and (c) injunctive FVI norms, (d) FVI-related self-efficacy, (e) experiential and (f) instrumental FVI attitudes, and (g) goal commitment; (H3) that the effects in H1a and H1b would be at least partially mediated via the psychosocial outcomes (a) to (g) described in H2; (H4) there would be positive dose–response relationships between daily FVI-related social media activities and (H4.1a) daily FVI, (H4.1b) FVI intentions, and (H4.2) the psychosocial outcomes (a) to (g) described in H2.

Method

Design and Procedure

As in Study 1, we conducted a field experiment with baseline and follow-up assessment, EMA, and coding and analysis of public social media postings (both conditions) and private FVI-related postings (only private posting condition). Participants (senders) were randomized to one of two experimental posting conditions: (1) posting about their FVI publicly on their Instagram feed or (2) "posting" about their FVI privately in a WhatsApp chat with our study account (i.e., uploading FVI photos without any feedback). This resulted in a 2 (posting: public vs. private) × 2 (time: baseline vs. follow-up) mixed design with additional daily diary data (Figure 1). Thus, again, both groups tracked their FVI (BCTTv1: "2.3 Self-monitoring of behaviour"). Participants in the public posting condition additionally received responses (e.g., likes and comments) from their Instagram network (see Appendix B for all BCTTv1s). The study was approved by the Institutional Review Board of the University of Mannheim and preregistered via the Open Science Framework (https://osf.io/r7b9k/). Participants could choose between course credits or lottery tickets (for three 100€ online shopping vouchers) as compensation. The compensation was dependent on the number of daily FVI-related picture postings and completed questionnaires (see Appendix A).

At baseline, participants received an individualized goal to increase their daily FVI by 33% (BCTTv1: "1.1 Goal setting (behaviour)") for the upcoming week (e.g., participants who reported eating three portions of fruit and vegetables daily were asked to eat four in the upcoming week). Participants were then randomized to their experimental posting condition. During the intervention week, participants received a daily invitation (at 8.30 p.m.) to a survey that assessed daily social media use, FVI, and psychosocial constructs. After the intervention week, participants answered the follow-up questionnaire.

Participants

Of the 204 initial participants, 146 (71.57%) provided follow-up data, and 128 (62.75%) with $N = 368$ daily surveys fulfilled inclusion criteria (Appendix C for participant flow chart). Participants in the final sample were $M = 22.74$ years old ($SD = 4.66$), the majority was female (89.06%) and had a medium education level (74.22%). There were few baseline differences between participants in the initial versus final sample: Participants in the final sample had fewer Instagram followers ($M = 272.59$, $SD = 239.13$ vs. $M = 425.03$, $SD = 483.22$), $t(95.61) = 2.55$, $p = .012$, $d = 0.44$, and a higher overall number of FVI-related postings (public + private postings combined; $M = 15.95$, $SD = 7.27$ vs. $M = 9.43$, $= 7.44$), $t(64.01) = –4.86$, $p < .001$, $d = –0.90$. There were no baseline differences between the two experimental conditions except that participants in the public condition reported higher daily Instagram use compared to participants in the private condition ($M = 71.92$ min, $SD = 48.48$ vs. $M = 52.36$ min, $SD = 37.65$; $t(121.77) = –2.56$, $p = .012$, $d = –0.45$, see Appendix G for details).

Materials

Instagram Data. Participants' postings in both posting conditions during the intervention week were saved and coded daily. The coded content was similar to Study 1 and included day and whether a posting was about FVI or not. 12% of Instagram postings

(142/1,224) and 12% of WhatsApp postings (171/1,412) were coded by two raters. Intercoder agreement was high (Krippendorff's α = .883 for content on WhatsApp, .868 on Instagram).

Baseline and Follow-Up Measures. If necessary, all measures described here were adapted to the fruit and vegetable context. *FVI* in the last week was measured by asking how many servings of fruit [vegetables] participants typically ate per day in the last 7 days (Chapman et al., 2009). *FVI intentions* were measured with three items (Chapman et al., 2009; e.g., "I intend to eat fruit and vegetables several times a day"; Cronbach's α = .81). *Perceived FVI-related social support* from the Instagram community was measured with nine items from the Frequency subscale of the CASSS-HB adapted to a Likert agreement scale (e.g., "In general, I have the impression that my Instagram community encourages me to eat more fruit and vegetables"; Cronbach's α = .83). *Perceived descriptive and injunctive FVI norms* were assessed with four items each, adapted from FVI norm measures (Cullen et al., 2001; Di Noia & Cullen, 2015), and following measurement guidelines (Fishbein & Ajzen, 2011). For example, "In general, …I have the impression that most members of my Instagram community eat fruit and vegetables several times a day" and "…I have the impression that most members of my Instagram community approve of me eating fruit and vegetables several times a day" (Cronbach's α = .73 and .88). *Instrumental and experiential FVI attitudes* regarding eating fruit and vegetables several times per day were assessed with nine semantic differential scales (Conner et al., 2011). For example, "I find eating fruit and vegetables several times a day" … "useless–useful" or "unpleasant–pleasant." (Cronbach's α = .80 and .82). *FVI-related self-efficacy* for eating fruit and vegetables was assessed with seven items (e.g., "I am confident that I can eat healthy foods, such as fruit/vegetables, when there is junk food in my house") from the National Cancer Institute's Food Attitudes and Behaviors Survey (Erinosho et al., 2015; Cronbach's α = .78 at baseline). *Goal commitment* regarding the goal of increasing one's own FVI was assessed with five items at follow-up (Klein et al., 2001), for example "I am strongly committed to pursuing this goal" (Cronbach's α = .81). Control variables were measured only at baseline. They were equal to those in Study 1, except for general Facebook usage frequency, for which we instead assessed the *average daily duration of general Instagram usage (in minutes)* by asking how often participants used Instagram (daily vs. weekly) and for how many minutes (either per day or per week, depending on their first answer).

Daily Measures. The daily questionnaires assessed daily FVI and FVI intentions, daily (FVI)-goal-related Instagram (public condition) or WhatsApp usage (private condition), and daily perceptions of the psychosocial constructs from the baseline and follow-up questionnaire. The items were adapted to capture daily experiences (e.g., “Today, I had the impression that my Instagram community encourages me to eat more fruit and vegetables”; see Appendix H). *Daily (FVI)-goal-related Instagram usage intensity* was assessed with “How much (how often and for how long) did you use Instagram today to communicate about your nutrition goal?” after reading a detailed description of different types of use (Verduyn et al., 2015).

Statistical Analyses

All analyses were conducted as they were in Study 1, again using R version 4.1.2. Inclusion criteria were the same as in Study 1. We applied the same preregistered criteria for the group- and day-level analyses to match samples. In the dose–response analyses, FVI was not aggregated as in Study 1 because FVI was already assessed on the daily level. We fitted a linear mixed model because FVI was measured in 0.25 increments and normally distributed. We calculated a required sample size of $N = 126$ to detect medium-sized differences between both posting conditions at follow-up using GPower 3.1 (α-level = .05; statistical power = .80).

Results & Discussion

Manipulation Check for the Posting Manipulation

Participants in the public condition posted significantly more FVI-related Instagram postings ($M_{\text{public}} = 14.56$, $SD = 6.76$) than participants in the private posting condition

($M_{private}$ = 0.14, SD = 0.69), $t(66.53) = –17.23$, $p < .001$; $d = –2.93$. Importantly, participants in both conditions published a similar overall number of FVI-postings, irrespective of posting condition (M_{public} = 14.80, SD = 6.81 vs. $M_{private}$ = 17.23, SD = 7.61), $t(122.36) = 1.89$, $p = .061$, $d = 0.34$.

Group-Level Effects of Posting

Effects of Posting on Senders' FVI and Psychosocial Outcomes. Senders who posted publicly compared to senders who posted privately about FVI did not show the expected stronger increase in FVI (Table 2; Figure 2). Thus, H1a was not supported. There was a main effect of time, indicating a significant increase of FVI from baseline to follow-up across both posting conditions (Table 2). The same pattern of effects was found for FVI intentions (Table 2). Importantly, a statistically significant increase in FVI intentions was specific to the public FVI posting condition ($p_{adj} < .020$) and, in line with H1b, the interaction with time was marginally significant.

Psychosocial mechanisms were not more positively affected by publicly posting about FVI (H2a–g; see Table 2). There was an interaction effect for perceived descriptive FVI norms, but the pattern was opposite of our expectation, with a trend for decreased descriptive norm perception in the public posting condition (Table 2). Furthermore, instrumental FVI attitude declined from baseline to follow-up in both groups (Table 2). Finally, participants in the public posting condition generally reported higher FVI-related self-efficacy than participants in the private posting condition (effect of Posting; Table 2).

The mediation analyses showed that the hypothesized psychosocial mediators (see Appendix I) did not explain the potential relations between posting about FVI and change of FVI or FVI intentions from baseline to follow-up. Thus H3a-g were not supported.

Dose–Response Relationships between Daily Social Media Activities with Daily Eating and Psychosocial Mechanisms

We included 368 valid days of 66 participants in the public posting condition to examine dose–response relationships (see Appendix J and Figure 3 for statistical details). We found positive dose-response relationships between the daily number of public FVI postings with daily FVI ($\beta = 0.17$, $p < .001$) and FVI intentions ($\beta = 0.15$, $p < .001$): On days on which senders posted more FVI postings than usual, they reported higher FVI and FVI intentions. Senders also reported higher FVI ($\beta = 0.08$, $p = .006$) but not higher FVI intentions ($\beta = 0.04$, $p = .215$) on days on which they used Instagram more than usual. Thus, H4.1a was entirely and H4.1b partially supported.

We found positive dose-response relationships between the number of daily FVI postings and daily FVI-related self-efficacy ($\beta = 0.10$, $p = .015$), instrumental FVI attitudes ($\beta = 0.10$, $p = .003$), experiential FVI attitudes ($\beta = 0.08$, $p = .031$), and goal commitment ($\beta = 0.22$, $p < .001$). There were no relationships between the number of daily FVI postings and perceived FVI-related social support as well as descriptive and injunctive FVI norms. There were also positive relationships between the daily FVI-related Instagram usage and FVI-related social support ($\beta = 0.09$, $p = .004$), replicating the findings in Study 1. Further, daily FVI-related Instagram usage was positively related to goal commitment ($\beta = 0.09$, $p = .022$) and negatively with self-efficacy ($\beta = –0.08$, $p = .030$; see Figure 3). In sum, H4.2g on goal commitment was fully supported; the hypotheses regarding perceived social support (H4.2a), self-efficacy (H4.2d), experiential attitudes (H4.2e), and instrumental attitudes (H4.2f) were partially supported. H4.2b and H4.2c on descriptive and injunctive norms were not supported.

General discussion

These are the first studies to experimentally test the effect of eating-related social media activities on real-world eating behavior. Further, they also examined theoretically derived candidates for mechanisms of action. In two field experiments with additional intensive longitudinal and behavioral social media data, we found that eating-related postings on social media can lead to higher fruit and vegetable intake of senders and network members (Study 1). Posting supported senders in reaching eating behavior change goals (Study 2); this effect was comparable to mere picture-based self-monitoring. Yet, we found initial evidence that public posting might increase healthy eating *intentions* more than self-monitoring. On days on which senders used social media more than usual (Studies 1 and 2) and made more eating-related postings (Study 2), they also reported healthier eating. These findings extend previous cross-sectional and laboratory studies and provide first evidence for causal effects of eating-related social media postings on eating behavior. Interestingly, we also found dose-response relationships between daily eating-related social media use and eating behavior.

Study 1 further illustrated that FVI postings increased perceived FVI-related social support in senders and receivers of the postings, and perceived injunctive FVI norms of senders. While the experimental manipulations successfully evoked FVI social media postings in both studies, the effects on changes in FVI and other FVI-related psychosocial constructs were smaller than expected. One possible reason for these weaker effects is that one week of active social media posting might be too short for substantial changes; often, sustained health behavior changes takes several weeks or months (Kwasnicka et al., 2016). The effects of social media activities on psychosocial predictors and behavior itself might be transient and in temporal proximity to social media use. This is underlined by the positive dose-response relationships between daily FVI-related social media activities and attitudes, self-efficacy, goal commitment, social support, intentions, and FVI. As a result, FVI postings and related social media use may increase FVI and related cognitions on a given day; the overall effects may only accumulate slowly over time (see Scholz, 2019 for a discussion about the importance of theorizing temporal matters in health behavior change). Therefore, future research needs to consider between- and within-person effects when examining social media and health behavior change (see Dunton et al., 2021 for a related discussion on health behavior change in general), ideally over longer time intervals.

Surprisingly, we found little evidence for the role of psychosocial mechanisms of action underlying social media effects. Mechanisms of action may work in a more complex way and depend on the amount and content of social media postings and network responses on a daily level (Kilb & Mata, 2022). For example, within a weight-loss trial, the number of received comments in the social media group predicted self-efficacy change, whereas the connectedness of interaction partners predicted social support change (Xu & Cavallo, 2021).

Strengths and Limitations

Our studies have several strengths. First, they combine experimental manipulation of real-world social media behavior with daily diary and objective social media data. This provides a better understanding of between- and within-person effects of social media use on eating behavior. It also allows to draw conclusions about the causality of potential effects. Second, we looked at sender *and* network member effects, thus capturing social media platforms' social interactivity. Third, we focused on one specific type of social media activity, eating-related social media postings. Last, we tested theoretically derived mechanisms of action to explain how eating-related social media use affects offline eating.

The findings need to be interpreted considering the following limitations: In Study 1, some of the findings did not reach statistical significance due to the small sample size. We addressed this shortcoming in Study 2. We expected medium to strong effects of eating-related social media posting. However, given that our studies isolated the *additional* effect of social media postings from other effective behavior change techniques such as goal-setting (Study 2) and self-monitoring (Studies 1 and 2), it is maybe not surprising that earlier studies combining a larger variety of behavior change techniques in the intervention arm (e.g., Inauen et al., 2017) found stronger effects than we did. Furthermore, participants in Study 2 were a relatively homogeneous, predominantly female sample that reported healthy eating behavior already at baseline. This limits the generalizability of the results to more diverse populations, for example, people with less healthy eating habits. These potential ceiling effects in healthy eating may also explain why we did not find differences between public and private self-monitoring. Finally, our studies did not involve control groups without self-monitoring, which limits the conclusions regarding the effects of social media posting compared to no intervention in senders. However, this is also a strength, as we tried to isolate the effects of eating-related social media posting from self-monitoring of eating behavior.

Conclusions

Combining experimental manipulations of eating-related social media posting, daily diary data, and objective social media data in two independent studies, we found initial evidence that eating-related social media use can influence the eating behavior of senders and network members. The mechanisms of action underlying these effects remain mostly unclear, the most promising candidate being perceived eating-related social support. Our results suggest that the effects of social media on behavior and mechanisms are transient and depend on the social media activities (e.g., viewing, posting, or liking eating-related content), content of postings (e.g., personal successes, barriers), and reactions of the social network (e.g., supportive, socially approving). Future studies should use experimental designs with longer intervention periods, and researchers need to examine both, between- and within-person effects. Our experiments show that social media should be considered when researching the eating behavior of young adults.

Table 1

Mean Changes from Baseline to Follow-Up of Outcomes for the B&M and FVI Posting Conditions in Both Senders and Network Members (Study 1)

Outcome variable	Baseline – follow-up (Δ) *M* (*SE*)		Posting × Time interaction effect			Posting main effect			Time main effect		
	B&M	FVI	F	p	η_p^2	F	p	η_p^2	F	p	η_p^2
Senders	$n = 21$	$n = 20$									
FVI	–1.27 (0.60) †	–0.29 (0.74)	1.07	.307	.03	1.47	.233	.04	2.74	.106	.07
Perceived FVI-related social support	–3.30 (1.91) †	4.59 (1.90) †	8.56	.006*	.18	0.18	.675	.01	0.23	.637	.01
Descriptive FVI norms	0.01 (0.06)	0.19 (0.10)	2.31	.136	.06	0.75	.391	.02	2.73	.106	.07
Injunctive FVI norms	0.14 (0.13)	0.61 (0.22)*	3.40	.073†	.08	6.07	.018*	.14	8.76	.005*	.18
Network members	$n = 20$	$n = 20$									
FVI	–0.34 (0.72)	1.00 (0.46) †	2.44	.126	.06	0.19	.663	.01	0.59	.447	.02
Perceived FVI-related social support	–2.52 (1.80)	1.44 (1.89)	2.29	.138	.06	4.42	.042*	.10	0.17	.681	.00
Descriptive FVI norms	0.07 (0.08)	0.04 (0.05)	0.12	.731	.00	1.46	.234	.04	1.27	.267	.03
Injunctive FVI norms	0.21 (0.22)	–0.03 (0.14)	0.87	.356	.02	3.15	.084†	.08	0.47	.498	.01

Note. F, p, and η^2_p are derived from repeated measures analyses of variance. The significance level of the change scores shows the p-value from holm-corrected follow-up paired sample t-tests. B&M = books and movies. FVI = Fruit and vegetable intake. † $p < .100$. * $p < .050$.

Table 2

Mean Changes from Baseline to Follow-Up in Outcome Variables for the Private and Public Posting Conditions (Study 2)

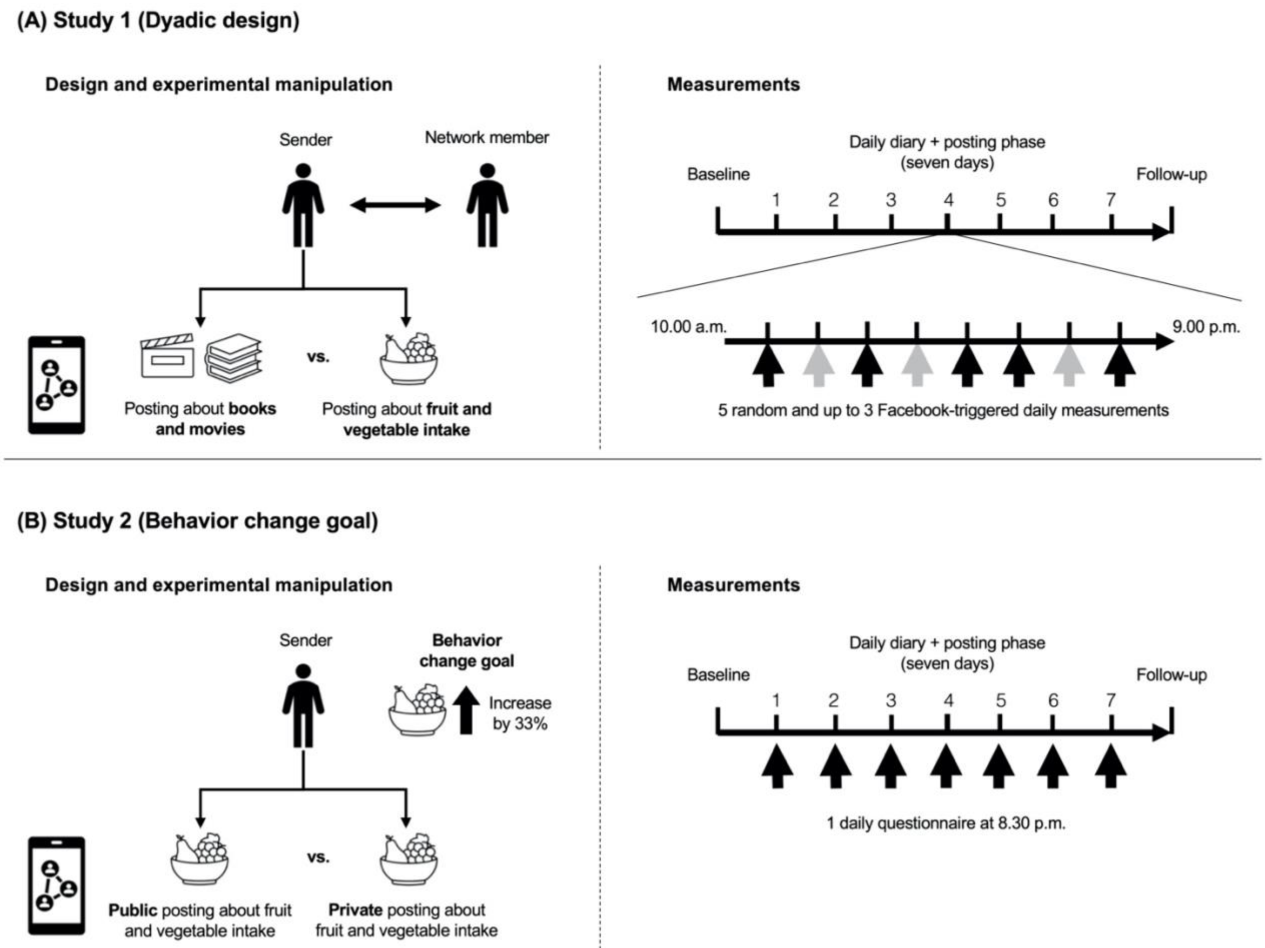
Outcome variable	Baseline – follow-up (Δ) *M* (*SE*)		Posting × Time interaction effect			Posting main effect			Time main effect		
	Private (n = 62)	Public (n = 66)	F	p	η_p^2	F	p	η_p^2	F	p	η_p^2
FVI	1.50 (0.46)*	1.51 (0.35)*	0.00	.984	.00	0.91	.341	.01	28.03	< .001*	.18
FVI intentions	0.04 (0.10)	0.30 (0.11)*	3.11	.080	.02	0.34	.561	.00	5.12	.025*	.04
Perceived FVI-related social support	1.29 (1.08)	0.23 (0.79)	0.65	.423	.01	0.26	.613	.00	1.32	.253	.01
Descriptive FVI norms	0.19 (0.12)	−0.14 (0.10)	4.40	.038*	.03	0.39	.534	.00	0.10	.754	.00
Injunctive FVI norms	0.04 (0.16)	0.09 (0.11)	0.06	.805	.00	0.89	.347	.01	0.52	.474	.00
Experiential FVI attitude	0.09 (0.09)	−0.01 (0.09)	0.62	.433	.00	0.45	.505	.00	0.45	.505	.00
Instrumental FVI attitude	−0.17 (0.06)*	−0.21 (0.09)*	0.13	.720	.00	0.39	.535	.00	11.18	.001*	.08
FVI-related self-efficacy	−0.04 (0.09)	−0.04 (0.07)	0.00	.955	.00	3.96	.049*	.03	0.50	.479	.00
Goal commitment	NA[a]	NA[a]	NA[a]	NA[a]	NA[a]	0.07	.794	.00	NA[a]	NA[a]	NA[a]

Note. F, p, and η^2_p are derived from repeated measures analyses of variance. The significance level of the change scores shows the p-value from holm-corrected follow-up paired sample t-tests. FVI = Fruit and vegetable intake. NA = Not applicable. * p < .050.

[a]Not applicable because goal commitment was only measured once at follow-up.

Figure 1

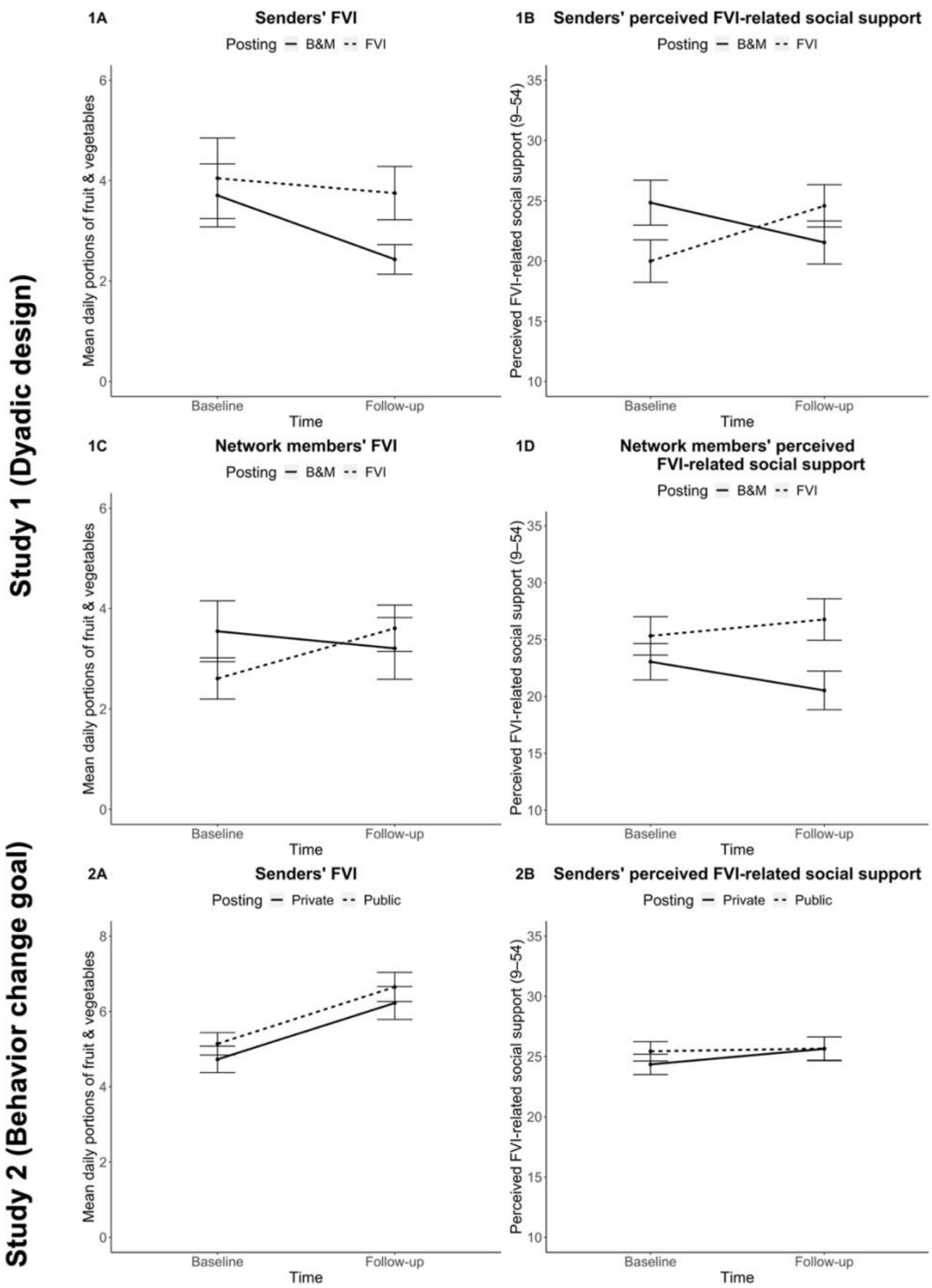
Study Designs of Study 1 and 2



Note. (A) In Study 1, participants were recruited as dyads, which comprised one sender (i.e., the person that received an intervention and posted) and one Facebook network member of their choice. Senders' online posting on Facebook was experimentally manipulated. Five daily surveys were randomly triggered (in 90-min time windows between 10:00 a.m. and 9:00 p.m.). Up to three additional surveys were triggered by participants' Facebook use (after using Facebook, participants were invited to a survey). After a survey was triggered, the Facebook trigger was inactivated for 2 hours to avoid triggering multiple surveys within a short time frame. (B) In Study 2, only senders were recruited and received a goal to increase their fruit and vegetable intake. Their online posting mode was experimentally manipulated (public posting on Instagram vs. private posting in WhatsApp chat). Senders answered one questionnaire per day.

Figure 2

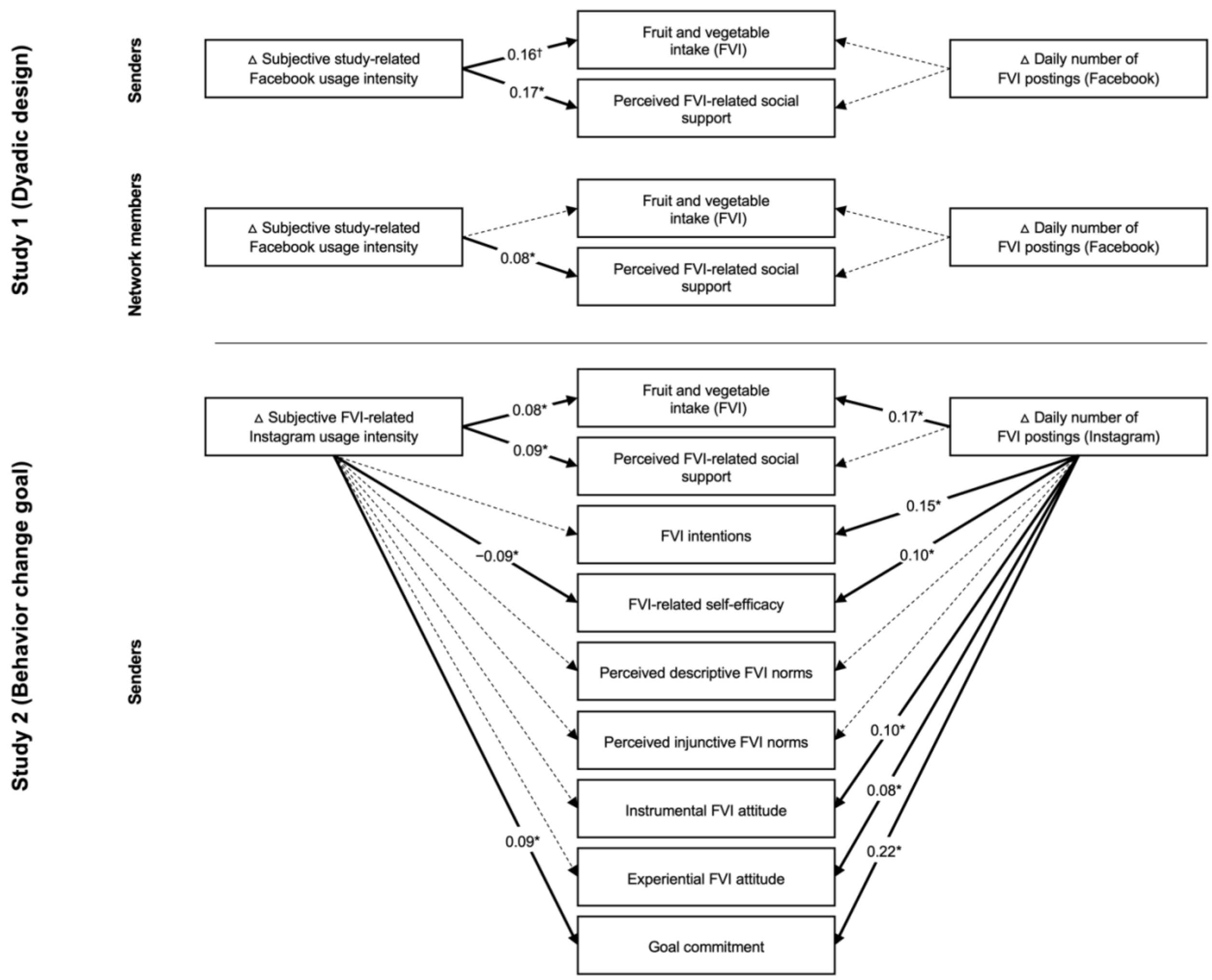
Group-Level Effects of Posting About Fruit and Vegetable Intake (FVI) on FVI and Perceived FVI-Related Social Support of Senders (Studies 1 and 2) and Network Members (Study 1)



Note. Study 1 had a dyadic design (sender + Facebook network member) without an additional behavior change goal for senders. In Study 2, senders participated alone but received a behavior change goal. Error bars represent the standard error of the means. Values in parentheses on the *y* axis show theoretical scale minima and maxima. FVI = fruit and vegetable intake.

Figure 3

Within-Person Effects of Fruit and Vegetable Intake (FVI)-Related Social Media Activities on FVI and Psychosocial Outcomes in Senders (Studies 1 and 2) and Network Members (Study 1)



Note. † $p < .100$, * $p < .050$. FVI = fruit and vegetable intake. Coefficients represent standardized estimates from multilevel models. Non-significant estimates are not shown for improved clarity. Study 1 had a dyadic design (sender + Facebook network member) without an additional behavior change goal for senders. In Study 2, senders participated alone but received a behavior change goal. In both studies, the effects on the different outcomes were estimated in separate models with the subsets of senders posting publicly about FVI on social media (and paired network members). Models were controlled for body mass index, age, education level, sex, amount of general daily Facebook (Study 1) or Instagram (Study 2) use, time since baseline (in days), and the number of daily surveys (only Study 1).

Data Availability Statement

The data that support the findings of this study are openly available in the Open Science Framework at https://osf.io/e5qbs/.

Declaration of Interests

We have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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CRediT Author Statement

Michael Kilb: Conceptualization, Methodology, Investigation, Formal analysis, Visualization, Data curation, Project administration, Writing - Original draft preparation, Reviewing, and Editing. **Helge Giese:** Conceptualization, Methodology, Validation, Resources, Writing - Reviewing and Editing. **Jutta Mata:** Conceptualization, Methodology, Resources, Funding acquisition, Project administration, Writing – Reviewing and Editing, Supervision.

Appendix A: Detailed Participant Reimbursement and Incentivization Scheme for Studies 1 and 2

Study 1

Overview of Overall Reimbursement

Participants received up to 57€ in exchange for participation. Students of the University of Mannheim and the University of Konstanz could choose to receive a mix of money and course credit instead (up to 29€ + 5.00 credits). Participants received 8€ (or 1.00 credit) for the baseline assessment, 6€ (or 0.75 credits) for the follow-up assessment, and up to 28€ (or 14€ + 3.25 credits) for the 56 daily surveys, dependent on their participation rate. More specifically, they received 0.25€ (or 0.05 credits) for every daily survey and a bonus of 8€ (+ 0.5 credits) or 14€ (+ 0.5 credits) if they responded to 70% or 85% of the daily questionnaires. Senders further received up to 15€ for the daily postings and network members received up to 11€ for the daily reactions to senders' postings (see below for details). Study credits were rounded to the next possible step (i.e., next 0.25 step).

Posting (Senders) and Reaction (Network Members) Incentivization

Senders received 1.25€ for the first posting of the day and less for every subsequent posting (i.e., 0.75€ for the second posting, 0.50€ for the third posting and 0.10€ for the fourth and every subsequent posting) up to a maximal amount of 15€. Network members received up to 0.80€ per reaction to senders' postings (0.40€ each for a like or comment on a posting) up to a maximal amount of 11€.

Study 2

Overview of Overall Reimbursement

Participants received up to 21 lottery tickets to win one of three 100€ online shopping vouchers in exchange for participation. Students of the University of Mannheim and the University of Konstanz could choose to receive course credit instead (up to 3.25 credits). All participants received three lottery tickets (or 0.5 credits) for the baseline assessment and three lottery tickets (or 0.5 credits) for the follow-up assessment. They also received up to 6.5 lottery tickets for the seven daily surveys (0.5 tickets for each survey + a bonus of three tickets if they responded to 100% of the daily surveys). Alternatively, they received up to 1.25 credits (~0.08 credits for each survey + 0.5 credits if they responded to 100% of the daily surveys). Finally, they received up to 8.75 lottery tickets (or 1.25 credits) for the daily FVI picture documentation (via WhatsApp private chat *or* Instagram posting). Lottery tickets and credits were rounded to the next possible step (i.e., integers for lottery tickets; next possible 0.25 step for study credits).

Posting Incentivization

Participants who actively documented their FVI with postings (via private WhatsApp chat *or* public Instagram postings, dependent on experimental condition) received 0.5 lottery tickets (or ~0.08 course credits) for the first two documentations of the day and 0.25 lottery tickets (or ~0.04 credits) for the third and fourth documentation up to a maximal amount of 8.75 lottery tickets (or 1.25 credits). For all further documentations, they did not receive additional lottery tickets or study credits.

Appendix B: Coded Intervention Content in Both Studies

Table B1

Intervention Components and Behavior Change Techniques in the Different Conditions for Both Studies

Senders				Network members			
Study 1		Study 2		Study 1		Study 2	
FVI posting	B&M posting	Public posting	Private posting	FVI posting	B&M posting	–	–
2.3 Self-monitoring of behaviour	2.3 Self-monitoring of behaviour	1.1 Goal setting (behaviour)	1.1 Goal setting (behaviour)	6.1 Demonstration of the behaviour	–	–	–
2.2 Feedback on behaviour		2.3 Self-monitoring of behaviour	2.3 Self-monitoring of behaviour	6.2 Social comparison	–	–	–
3.1 Social support (unspecified)		2.2 Feedback on behaviour		6.3 Information about others' approval	–	–	–
6.3 Information about others' approval		3.1 Social support (unspecified)		7.1 Prompts/cues	–	–	–
10.4 Social reward		6.3 Information about others' approval					
		10.4 Social reward					
		1.9 Commitment					

Note. Behavior change techniques were coded according to the Behavior Change Technique Taxonomy v1 (Michie et al., 2013). In Study 2, only senders were recruited. B&M = books and movies. FVI = fruit and vegetable intake.

Appendix C: Participant Flow Charts for Studies 1 and 2

Figure C1

Participant Flow Chart (Study 1)

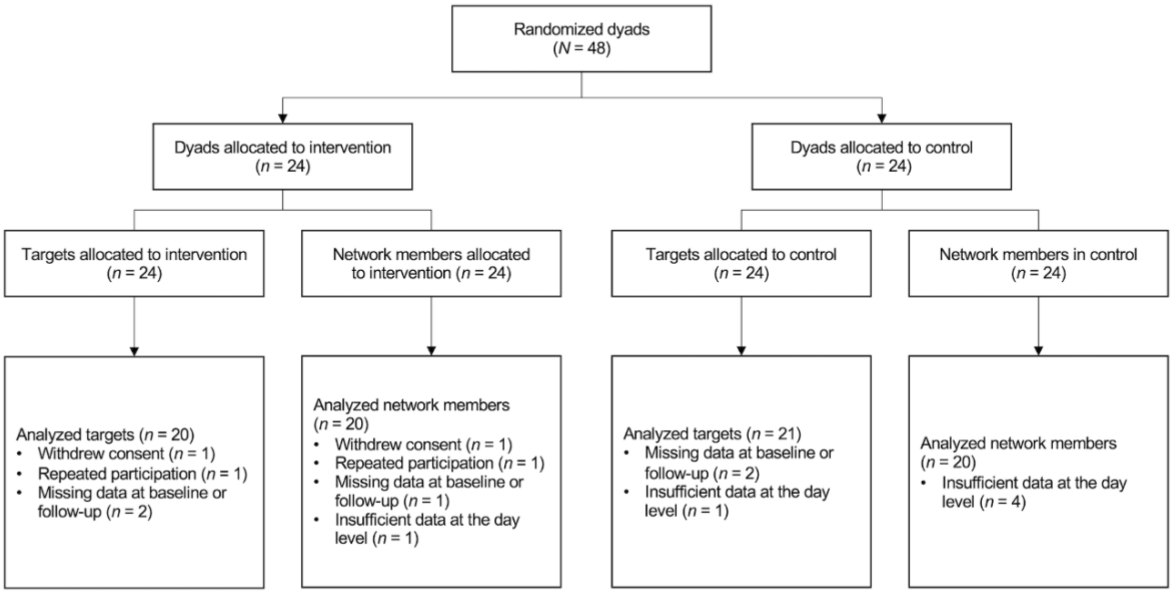
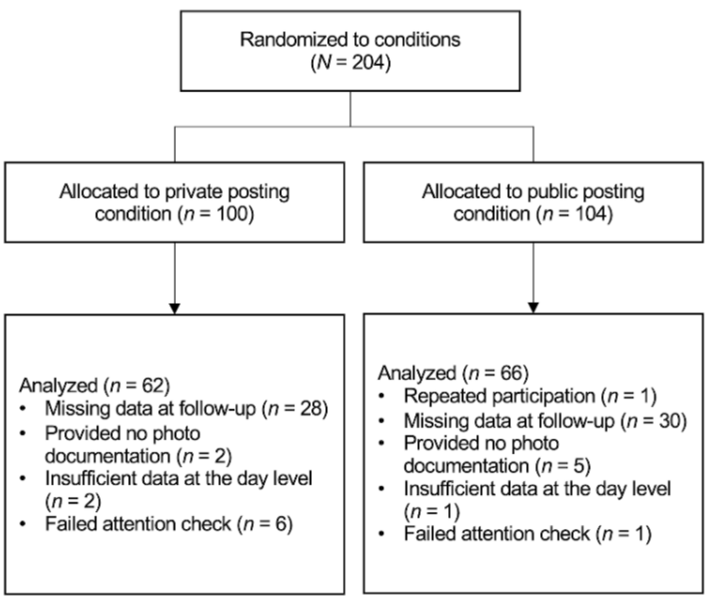


Figure C2

Participant Flow Chart (Study 2)



Appendix D: Baseline Characteristics and Differences between Senders and Network Members (Study 1)

Table D1

Baseline Characteristics and Differences between the Intervention (FVI) and Control (B&M) Groups, Separately for Senders and Network Members (Study 1)

Variable	Senders			Network members		
	Posting about B&M (n = 21)	Posting about FVI (n = 20)	p	Posting about B&M (n = 20)	Posting about FVI (n = 20)	p
Age (years)	23.86 (8.16)	22.20 (2.91)	.390	24.15 (8.96)	21.40 (3.47)	.213
Female, n (%)	19 (90.48)	14 (70.00)	.130	14 (70.00)	13 (65.00)	> .999
BMI (kg/m^2)	21.78 (2.56)	22.78 (3.93)	.342	23.05 (4.16)	23.59 (6.45)	.756
Education level, n (%)			.545			.695
Low (ISCED 0–2)	0 (0.00)	1 (5.00)		0 (0.00)	1 (5.00)	
Medium (ISCED 3–4)	18 (85.71)	15 (75.00)		15 (75.00)	16 (80.00)	
High (ISCED 5–8)	3 (14.29)	4 (20.00)		5 (25.00)	3 (15.00)	
Occupation, n (%)			.999			.709
Student	16 (76.19)	16 (80.00)		16 (80.00)	13 (65.00)	
Working	3 (14.29)	3 (15.00)		4 (20.00)	5 (25.00)	
NA	2 (9.52)	1 (5.00)		0 (0.00)	2 (10.00)	
Number of FVI pictures (Facebook + EMA)	11.86 (6.56)	10.25 (4.19)	.354	—	—	
Facebook posting frequency (updates/day)	0.07 (0.22)	0.04 (0.06)	.532	0.08 (0.17)	0.01 (0.03)	.110
Currently on diet, n (%)	1 (4.76)	1 (5.00)		4 (20.00)	3 (15.00)	>.999
FVI	3.71 (2.88)	4.05 (3.59)	.740	3.55 (2.71)	2.61 (1.83)	.208
Perceived FVI-related social support	24.84 (8.54)	19.99 (7.86)	.066	23.04 (7.15)	25.32 (7.55)	.334

Variable	Senders			Network members		
	Posting about B&M (n = 21)	Posting about FVI (n = 20)	p	Posting about B&M (n = 20)	Posting about FVI (n = 20)	p
Perceived injunctive FVI norms	5.46 (0.66)	4.67 (1.06)	.008	4.87 (0.97)	5.39 (0.74)	.060
Perceived descriptive FVI norms	2.31 (0.34)	2.14 (0.41)	.157	2.27 (0.4)	2.38 (0.2)	.267
Autonomous motivation for FVI	3.73 (1.12)	4.08 (0.91)	.271	3.83 (0.76)	4.01 (0.54)	.378

Note. Data are means (*SD*) or *n* (%). Baseline characteristics were compared between the control and intervention groups separately for senders and network members using either Welch's two-sample *t* tests (for means) or Fisher's exact test (for proportions). B&M = Books and movies; BMI = body mass index; EMA = ecological momentary assessment; FVI = fruit and vegetable intake; ISCED = International Standard Classification of Education.

Appendix E: Mediation Analyses for Intervention Effects (Study 1)

Table E1

Results of the Mediation Analyses for the Indirect Effects of the Experimental Posting Manipulation in Senders and Network Members (Study 1)

Mediator	Path A (Posting → Δ Mediator)		Path B (Δ Mediator → Δ FVI)		Path C (Posting → Δ FVI)		Indirect effect	
	β (*SE*)	*p*	β (*SE*)	*p*	β_y (*SE*)	*p*	β (*SE*)	95% CI
Senders								
Perceived FVI-related social support	0.84 (0.28)	.003*	0.13 (0.15)	.375	0.21 (0.31)	.497	0.11 (0.13)	[−0.13, 0.37]
Perceived descriptive FVI norms	0.47 (0.31)	.130	−0.10 (0.20)	.610	0.37 (0.30)	.210	−0.05 (0.11)	[−0.29, 0.14]
Perceived injunctive FVI norms	0.56 (0.30)	.065†	0.02 (0.18)	.912	0.31 (0.35)	.374	0.01 (0.12)	[−0.26, 0.25]
Network members								
Perceived FVI-related social support	0.47 (0.31)	.123	0.12 (0.18)	.505	0.43 (0.36)	.232	0.06 (0.10)	[−0.14, 0.28]
Perceived descriptive FVI norms	−0.11 (0.32)	.726	0.09 (0.21)	.683	0.50 (0.31)	.106	−0.01 (0.07)	[−0.17, 0.11]
Perceived injunctive FVI norms	−0.30 (0.31)	.346	−0.12 (0.29)	.683	0.45 (0.28)	.110	0.03 (0.12)	[−0.15, 0.35]

Note. All paths are controlled for each other. Standard errors and 95% confidence intervals (CIs) are bootstrapped with 10,000 simulations. FVI = Fruit and vegetable intake. † $p < .100$. * $p < .050$.

Appendix F: Within-Person Associations of Daily Facebook Activities with Outcome Variables (Study 1)

Table F1

Within-Person Associations of Daily Facebook Activities with Daily Fruit and Vegetable Intake and Perceived Social Support (Senders)

Effect	FVI			Perceived FVI-related social support		
	β	95% CI	*p*	β	95% CI	*p*
Fixed effects						
(Intercept)	1.18	[0.75, 1.61]	< .001*	−0.27	[−1.00, 0.46]	.433
Study-related Facebook usage (CWC)	0.16	[−0.01, 0.32]	.059†	0.17	[0.06, 0.27]	.002*
Number of daily FVI-related Facebook postings (CWC)	0.05	[−0.09, 0.18]	.503	−0.06	[−0.15, 0.04]	.267
Time	0.13	[−0.04, 0.30]	.137	−0.04	[−0.15, 0.06]	.414
Number of daily surveys	0.14	[−0.11, 0.39]	.273	0.02	[−0.13, 0.18]	.777
Sex [1 = female]	0.54	[0.14, 0.94]	.008*	0.37	[−0.22, 0.97]	.197
Age (CGM)	0.12	[−0.27, 0.51]	.547	0.23	[−0.32, 0.79]	.383
Education level (ISCED)						
1 (low)	1.16	[0.10, 2.22]	.032*	0.48	[−1.05, 2.02]	.509
2 (medium)	−0.65	[−1.13, −0.17]	.009*	0.36	[−0.40, 1.12]	.324
General Facebook usage frequency (CGM)	0.27	[0.00, 0.53]	.052†	0.15	[−0.30, 0.59]	.483
BMI (kg/m^2; CGM)	−0.70	[−1.17, −0.23]	.003*	−0.11	[−0.68, 0.46]	.687
Random effects						
Residual variance	0.00			2.97		
Intercept variance	0.17			7.07		
ICC	1.00			0.70		
$N_{\text{participants}}$	20			20		
Observations	127			127		
Marginal R^2/Conditional R^2	0.862/1.000			0.259/0.781		

Note. BMI = Body mass index; CI = confidence interval; CGM = centered around the grand mean; CWC = centered within clusters (persons); FVI = fruit and vegetable intake; ICC = intraclass correlation coefficient; ISCED = International Standard Classification of Education; † p < .100. * p < .050.

Table F2

Within-Person Associations of Daily Facebook Activities with Daily Fruit and Vegetable Intake and Perceived Social Support (Network Members)

Effect	FVI			Perceived FVI-related social support		
	β	95% CI	*p*	β	95% CI	*p*
Fixed effects						
(Intercept)	1.14	[0.83, 1.45]	< .001*	0.04	[−0.88, 0.96]	.919
Study-related Facebook usage (CWC)	0.04	[−0.06, 0.14]	.449	0.08	[0.02, 0.14]	.007*
Number of daily FVI-related Facebook postings (CWC)	0.03	[−0.07, 0.14]	.543	0.00	[−0.06, 0.06]	.976
Time	0.09	[−0.02, 0.21]	.121	0.03	[−0.03, 0.09]	.315
Number of daily surveys	0.07	[−0.05, 0.20]	.238	0.02	[−0.05, 0.10]	.520
Sex [1 = female]	0.12	[−0.07, 0.32]	.211	−0.04	[−0.62, 0.54]	.883
Age (CGM)				−0.50	[−1.37, 0.37]	.235
Education level (ISCED)						
1 (low)	0.29	[−0.24, 0.82]	.280	−0.23	[−1.98, 1.53]	.783
2 (medium)	0.15	[−0.18, 0.49]	.373	−0.11	[−1.20, 0.99]	.835
General Facebook usage frequency (CGM)	0.10	[−0.10, 0.29]	.334	0.02	[−0.60, 0.63]	.956
BMI (kg/m^2; CGM)	−0.21	[−0.42, −0.01]	.042*	0.55	[−0.18, 1.27]	.126
Random effects						
Residual variance	0.00			1.99		
Intercept variance	0.08			19.68		
ICC	1.00			0.91		
$N_{\text{participants}}$	19			19		
Observations	122			122		
Marginal R^2/Conditional R^2	0.588/1 .000			0.206/0 .927		

Note. BMI = Body mass index; CI = confidence interval; CGM = centered around the grand mean; CWC = centered within clusters (persons); FVI = fruit and vegetable intake; ICC = intraclass correlation coefficient; ISCED = International Standard Classification of Education. † $p < .100$. * $p < .050$.

Appendix G: Baseline Characteristics and Differences between Experimental Conditions in Study 2

Table G1

Baseline Characteristics and Differences of Participants in the Public and Private Posting Conditions (Study 2)

Variable	All (*N* = 128)	Private posting condition (*n* = 62)	Public posting condition (*n* = 66)	*p*
Demographic characteristics				
Age (years), *M* (*SD*)	22.74 (4.66)	22.19 (3.59)	23.26 (5.46)	.193
Female, *n* (%)	114 (89.06)	56 (90.32%)	58 (87.88)	.474
Education level, *n* (%)				.609
Low (ISCED 0–2)	6 (4.69)	4 (6.45)	2 (3.02)	
Medium (ISCED 3–4)	95 (74.22)	46 (74.19)	49 (74.24)	
High (ISCED 5–8)	27 (21.09)	12 (19.35)	15 (22.73)	
FVI-related pictures				
FVI-related Instagram postings, *M* (*SD*)	7.81 (8.75)	0.14 (0.69)	14.56 (6.76)	< .001
FVI-related postings (public Instagram postings + private WhatsApp postings), *M* (*SD*)	15.98 (7.28)	17.23 (7.61)	14.80 (6.81)	.061
Instagram use				
Daily minutes of Instagram use, *M* (*SD*)	62.45 (44.50)	52.36 (37.65)	71.92 (48.48)	.012
Number of followed Instagram accounts, *M* (*SD*)	332.65 (291.18)	336.06 (322.48)	329.44 (260.85)	.899
Number of Instagram followers, *M* (*SD*)	272.59 (239.13)	268.06 (264.85)	276.83 (214.17)	.838
Interaction with healthy food pictures, *M* (*SD*)	3.27 (1.26)	3.20 (1.36)	3.32 (1.16)	.597
Interaction with unhealthy food pictures, *M* (*SD*)	2.53 (1.04)	2.46 (1.07)	2.60 (1.02)	.454
Percentage of food pictures in Instagram feed, *M* (*SD*)	28.94 (23.96)	27.35 (24.01)	30.42 (24.01)	.471
Outcomes				
FVI (portions), *M* (*SD*)	4.94 (2.59)	4.73 (2.76)	5.14 (2.43)	.370
Intention, *M* (*SD*)	4.09 (0.91)	4.12 (0.83)	4.06 (0.98)	.696
Experiential FVI attitude, *M* (*SD*)	5.84 (0.94)	5.87 (0.95)	5.81 (0.94)	.720
Instrumental FVI attitude, *M* (*SD*)	6.62 (0.53)	6.64 (0.49)	6.60 (0.56)	.655
Perceived descriptive FVI norms, *M* (*SD*)	2.96 (0.71)	2.84 (0.76)	3.08 (0.64)	.064
Perceived injunctive FVI norms, *M* (*SD*)	3.36 (0.92)	3.31 (0.97)	3.41 (0.88)	.548
FVI-related self-efficacy, *M* (*SD*)	3.96 (0.69)	3.84 (0.72)	4.06 (0.65)	.073
Perceived FVI-related social support, *M* (*SD*)	24.91 (6.57)	24.35 (6.66)	25.44 (6.49)	.353

Note. The private and public posting conditions were compared with Welch's two-sample *t* tests (means) or Fisher's exact tests (for proportions). FVI = Fruit and vegetable intake; ISCED = International Standard Classification of Education.

Appendix H: Scale Descriptions of the Daily Questionnaires of the Psychosocial Constructs in Study 2

Daily FVI on the questionnaire day was measured by asking participants to recall every consumed portion of fruit and vegetables that day to improve portion estimation and to answer the two open-ended questions “How many portions of fruit [vegetables] did you eat today (portions per day)?” (Chapman et al., 2009).

Daily FVI intentions were measures with three items (Chapman et al., 2009) adapted to the behavior of eating fruit and vegetables several times per day (example item: “I intend to eat fruit and vegetables several times a day”; Nested alpha = .56) on a 5-point Likert agreement-scale (from 1 = *strongly disagree* to 5 = *strongly agree*).

Daily perceived FVI-related social support from the Instagram community was measured with nine items from the Frequency subscale from the Child and Adolescent Social Support Scale for Healthy Behaviors (CASSS-HB; Menon & Demaray, 2013), adapted for the target behavior of eating fruit and vegetables (example item: “Today, I had the impression that my Instagram community encourages me to eat more fruit and vegetables”; nested alpha = .51) on a 5-point Likert agreement-scale (from 1 = *strongly disagree* to 5 = *strongly agree*). All responses were summed to obtain an overall social support score (Menon & Demaray, 2013).

Daily perceived descriptive and injunctive FVI norms were assessed with four items each in accordance with the measurement guidelines for social norm items (Fishbein & Ajzen, 2011) and adapted from the literature on FVI norms (Cullen et al, 2001; Cullen et al., 2015) to capture the perceived social norms of eating fruit and vegetables several times per day (example items: “Today, I had the impression that most members of my Instagram community eat fruit and vegetables several times a day” and “Today, I had the impression that most members of my Instagram community approve of me eating fruit and vegetables several times a day"; nested alphas = .11 and .25) on a 5-point Likert scale (from 1 = *strongly disagree* to 5 = *strongly agree*).

Daily instrumental and experiential FVI attitudes toward eating fruit and vegetables several times per day were assessed with five and four 7-point semantic differential scales, respectively (Conner et al., 2011). Example items are "Today I found eating fruit and vegetables several times a day... (useless–useful)" (Nested alpha = .69) and "Today I found eating fruit and vegetables several times a day ... (unpleasant–pleasant)" (nested alpha = .56).

Daily FVI-related self-efficacy for eating fruit and vegetables the next day when facing different barriers was assessed with seven items of the National Cancer Institute's Food Attitudes and Behaviors Survey's self-efficacy questionnaire (Erinosho et al., 2015) on a 5-point Likert scale (from 1 = *strongly disagree* to 5 = *strongly agree*). An example item is "Today I am confident that tomorrow I can eat healthy foods, such as fruit/vegetables, when there is junk food in my house" (Nested alpha = .51).

Daily goal commitment to the goal of increasing participants' own fruit and vegetable intake was assessed with five items that are recommended in the goal-striving literature to assess goal commitment (Klein et al., 2001). An example item is "Today I am strongly committed to pursuing this goal" (Nested alpha = .68).

Appendix I: Mediation Analyses for the Indirect Effects of Posting Publicly About FVI (Study 2)

Table I1

Results of the Mediation Analyses for the Indirect Effects of Posting Publicly About FVI on FVI (Study 2)

Mediator	Path A (Posting → Δ Mediator)		Path B (Δ Mediator → Δ FVI)		Path C (Posting → Δ FVI)		Indirect effect	
	β (SE)	*p*	β (SE)	*p*	β_y (SE)	*p*	β (SE)	95% CI
FVI intentions	0.31 (0.17)	.074	−0.18 (0.12)	.130	0.06 (0.16)	.714	−0.06 (0.06)	[−0.20, 0.01]
Perceived FVI-related social support	−0.14 (0.18)	.420	−0.02 (0.06)	.764	0.00 (0.18)	.996	0.00 (0.01)	[−0.03, 0.04]
Perceived descriptive FVI norms	−0.37 (0.18)	.037*	−0.17 (0.11)	.111	−0.06 (0.19)	.749	0.06 (0.06)	[−0.01, 0.20]
Perceived injunctive FVI norms	0.04 (0.18)	.806	−0.11 (0.09)	.198	0.01 (0.18)	.961	−0.01 (0.03)	[−0.07, 0.04]
Experiential FVI attitude	−0.14 (0.18)	.432	−0.01 (0.08)	.920	0.00 (0.18)	.989	0.00 (0.02)	[−0.03, 0.05]
Instrumental FVI attitude	−0.06 (0.17)	.714	−0.04 (0.07)	.624	0.00 (0.18)	.994	0.00 (0.02)	[−0.02, 0.04]
FVI-related self-efficacy	−0.01 (0.18)	.954	−0.12 (0.12)	.319	0.00 (0.18)	.990	0.00 (0.03)	[−0.08, 0.06]
Goal commitment[a]	0.05 (0.18)	.793	0.11 (0.08)	.197	−0.00 (0.18)	.994	0.01 (0.02)	[−0.05, 0.06]

Note. All paths are controlled for each other. Standard errors and 95% confidence intervals (CIs) are bootstrapped with 10,000 simulations. FVI = Fruit and vegetable intake.
* $p < .050$. [a]For the mediator goal commitment, values at follow-up were used instead of difference scores (not applicable).

Table I2

Results of the Mediation Analyses for the Indirect Effects of Posting Publicly About FVI on FVI Intentions (Study 2)

Mediator	Path A (Posting → Δ Mediator)		Path B (Δ Mediator → Δ FVI intentions)		Path C (Posting → Δ FVI intentions)		Indirect effect	
	β (SE)	*p*	β (SE)	*p*	β_y (SE)	*p*	β (SE)	95% CI
Perceived FVI-related social support	−0.14 (0.18)	.420	−0.05 (0.09)	.587	0.30 (0.18)	.084	0.01 (0.02)	[−0.03, 0.07]
Perceived descriptive FVI norms	−0.37 (0.18)	.037*	0.04 (0.10)	.666	0.33 (0.18)	.069	−0.02 (0.04)	[-0.11, 0.06]
Perceived injunctive FVI norms	0.04 (0.18)	.806	0.09 (0.09)	.291	0.31 (0.17)	.078	0.00 (0.02)	[−0.04, 0.06]
Experiential FVI attitude	−0.14 (0.18)	.432	0.12 (0.09)	.174	0.33 (0.17)	.059	−0.02 (0.03)	[−0.09, 0.03]
Instrumental FVI attitude	−0.06 (0.17)	.714	0.16 (0.10)	.121	0.32 (0.17)	.062	−0.01 (0.03)	[−0.07, 0.07]
FVI-related self-efficacy	−0.01 (0.18)	.954	0.37 (0.08)	< .001*	0.31 (0.16)	.055	−0.00 (0.07)	[−0.14, 0.13]
Goal commitment[a]	0.05 (0.18)	.793	0.22 (0.08)	.008*	0.30 (0.17)	.078	0.01 (0.04)	[−0.07, 0.10]

Note. All paths are controlled for each other. Standard errors and 95% confidence intervals (CIs) are bootstrapped with 10,000 simulations. FVI = Fruit and vegetable intake.
* $p < .050$. [a]For the mediator goal commitment, values at follow-up were used instead of difference scores (not applicable).

Appendix J: Within-Person Associations of Daily Instagram Activities and Outcome Variables (Study 2)

Table J1

Within-Person Associations of Daily Instagram Activities with Daily Fruit and Vegetable Intake, Intentions, and Perceived Norms

Effect	FVI			FVI intentions			Perceived descriptive FVI norms			Perceived injunctive FVI norms		
	β	95% CI	*p*	β	95% CI	*p*	β	95% CI	*p*	β	95% CI	*p*
Fixed effects												
(Intercept)	0.31	[−0.23, 0.85]	.252	−0.42	[−0.92, 0.08]	.097	−0.13	[−0.66, 0.40]	.617	−0.15	[−0.67, 0.37]	.563
FVI-related Instagram usage (CWC)	0.08	[0.02, 0.13]	.006*	0.04	[−0.03, 0.11]	.215	0.04	[−0.02, 0.11]	.197	0.03	[−0.03, 0.10]	.327
Number of daily FVI-related Instagram postings (CWC)	0.17	[0.11, 0.23]	< .001*	0.15	[0.07, 0.22]	< .001*	0.03	[−0.04, 0.10]	.454	0.05	[−0.02, 0.12]	.129
Time	−0.05	[−0.11, 0.01]	.088	−0.05	[−0.12, 0.03]	.203	−0.03	[−0.11, 0.04]	.332	−0.11	[−0.17, −0.04]	.002*
Sex [1 = female]	−0.09	[−0.44, 0.25]	.589	0.04	[−0.27, 0.36]	.782	0.25	[−0.09, 0.59]	.140	−0.11	[−0.45, 0.22]	.494
Age (CGM)	−0.10	[−0.34, 0.14]	.405	−0.10	[−0.31, 0.12]	.383	0.09	[−0.14, 0.32]	.438	−0.17	[−0.39, 0.06]	.152
Education level (ISCED)												
1 (low)	0.56	[−0.31, 1.44]	.203	−0.66	[−1.47, 0.15]	.107	0.12	[−0.74, 0.98]	.782	−0.60	[−1.44, 0.24]	.160
2 (medium)	−0.24	[−0.72, 0.24]	.316	0.44	[−0.01, 0.88]	.053	−0.01	[−0.48, 0.46]	.976	0.22	[−0.24, 0.68]	.342
Average duration of daily Instagram use (minutes; CGM)	0.13	[−0.09, 0.35]	.229	0.16	[−0.05, 0.36]	.128	0.06	[−0.15, 0.28]	.558	−0.08	[−0.30, 0.13]	.432
BMI (kg/m^2; CGM)	−0.14	[−0.37, 0.08]	.202	−0.01	[−0.22, 0.20]	.905	−0.00	[−0.22, 0.22]	.982	−0.06	[−0.27, 0.16]	.599
Random effects												
Residual variance	2.51			0.20			0.22			0.23		
Intercept variance	7.87			0.30			0.41			0.46		
ICC	0.76			0.60			0.66			0.66		
$N_{participants}$	66			66			66			66		
Observations	368			368			368			368		
Marginal R^2/Conditional R^2	0.132/0.790			0.096/0.640			0.039/0.669			0.078/0.689		

Note. BMI = Body mass index; CGM = centered around the grand mean; CWC = centered within clusters (persons); FVI = fruit and vegetable intake; ICC = intraclass correlation coefficient; ISCED = International Standard Classification of Education. * $p < .050$.

Table J2

Within-Person Associations of Daily Instagram Activities with Daily Self-Efficacy, Perceived Social Support, Attitudes, and Goal Commitment

Effect	FVI-related self-efficacy			Perceived FVI-related social support			Experiential FVI attitude			Instrumental FVI attitude			Goal commitment		
	β	95% CI	*p*	β	95% CI	*p*	β	95% CI	*p*	β	95% CI	*p*	β	95% CI	*p*
Fixed effects															
(Intercept)	0.06	[−0.43, 0.55]	.810	0.16	[−0.38, 0.70]	.557	0.05	[−0.46, 0.55]	.856	0.03	[−0.48, 0.54]	.904	−0.21	[−0.22, 0.15]	.373
FVI-related Instagram usage (CWC)	−0.08	[−0.15, −0.01]	.030*	0.09	[0.03, 0.14]	.004*	0.01	[−0.05, 0.08]	.705	-0.00	[−0.06, 0.06]	.947	0.09	[0.01, 0.16]	.022*
Number of daily FVI-related Instagram postings (CWC)	0.10	[0.02, 0.17]	.015*	0.01	[−0.06, 0.07]	.806	0.08	[0.01, 0.15]	.031*	0.10	[0.03, 0.16]	.003*	0.22	[0.14, 0.30]	< .001*
Time	−0.08	[−0.16, −0.01]	.029	−0.03	[−0.09, 0.04]	.401	−0.04	[−0.11, 0.03]	.257	−0.05	[−0.11, 0.01]	.115	−0.09	[−0.17, −0.01]	.028*
Sex [1 = female]	−0.29	[−0.60, 0.02]	.066	−0.22	[−0.56, 0.13]	.216	−0.04	[−0.37, 0.28]	.791	0.07	[−0.26, 0.40]	.675	−0.03	[−0.51, 0.68]	.856
Age (CGM)	−0.09	[−0.31, 0.12]	.387	−0.12	[−0.36, 0.12]	.314	−0.17	[−0.39, 0.05]	.126	−0.21	[−0.43, 0.02]	.071	−0.13	[−0.33, 0.07]	.200
Education level (ISCED)															
1 (low)	−0.39	[−1.18, 0.40]	.330	−0.20	[−1.08, 0.69]	.660	−0.06	[−0.70, 0.94]	.776	0.24	[−0.59, 1.07]	.567	−0.45	[−0.14, 0.25]	.236
2 (medium)	0.18	[−0.26, 0.61]	.420	−0.06	[−0.55, 0.42]	.799		[−0.43, 0.46]	.950	−0.08	[−0.54, 0.37]	.719	0.21		.304
Average duration of daily Instagram use (minutes; CGM)	0.11	[−0.09, 0.30]	.296	0.14	[−0.08, 0.36]	.221	0.01	[−0.20, 0.21]	.951	0.03	[−0.18, 0.24]	.746	−0.11	[−0.32, 0.06]	.236
BMI (kg/m^2; CGM)	−0.31	[−0.51, −0.10]	.004*	−0.04	[−0.27, 0.19]	.729	−0.33	[−0.54, −0.12]	.003*	−0.24	[−0.45, −0.02]	.030*	−0.04	[−0.23, 0.16]	.698
Random effects															
Residual variance	0.19			0.23			0.49			0.33			0.37		
Intercept variance	0.26			0.63			0.89			0.73			0.41		
ICC	0.57			0.73			0.64			0.69			0.53		
$N_{participants}$	66			66			66			66			66		
Observations	368			368			368			368			368		
Marginal R^2/Conditional R^2	0.129/ 0.628			0.060/ 0.745			0.155/ 0.700			0.139/ 0.732			0.135/ 0.591		

Note. BMI = Body mass index; CGM = centered around the grand mean; CWC = centered within clusters (persons); FVI = fruit and vegetable intake; ICC = intraclass correlation coefficient; ISCED = International Standard Classification of Education. * $p < .050$.

4. Manuscript 3: A Theory-Based Video Intervention to Enhance Communication and Engagement in Online Health Communities: Two Experiments

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Abstract

Background: Online communities and social networking sites have great potential for supporting health behavior change. However, interventions vary greatly in participants' engagement rates and, consequently, their effectiveness. Theory-based interventions in real-world contexts are needed to further increase engagement and effectiveness.

Methods: We experimentally tested whether a video intervention teaching Self-Determination-Theory-based communication strategies increases need-supportive communication strategy use over one week (Study 1, $N = 76$) and perceived need support, engagement, and goal attainment in a behavior change intervention supported by a forum-based online community (Study 2, $N = 537$). In Study 2, participants chose a goal (increasing either fruit or vegetable consumption or increasing moderate or vigorous physical activity) and joined an online community for 2 weeks. Data from both experiments were analyzed with mixed models and follow-up tests.

Results: In Study 1, participants in the intervention but not in the control group showed an increase in the number of need-supportive communication strategies used both immediately and one week after the intervention (condition*time interaction, *partial* $\eta^2 = 0.31$). In Study 2, participants who watched the intervention video had a higher number of postings and reported a higher subjective forum use frequency (but not a higher number of logins) compared to participants who watched the control video. However, the effect on the subjective forum visit frequency was not robust. There were no intervention effects on perceived need support, goal attainment, or secondary outcomes. The results might be explained by low application of need-supportive communication strategies.

Conclusion: A brief video intervention may be a suitable, low-cost intervention to promote need-supportive communication strategy use, benefitting both engagement and behavior change. Future studies should incorporate additional means to further improve communication strategy uptake and engagement in online communities.

Introduction

Background

Lifestyle behaviors, such as physical inactivity or a poorly balanced diet, are the main risk factors for premature mortality and disability caused by noncommunicable diseases (GBD 2017 Diet Collaborators, 2019; GBD 2019 Risk Factors Collaborators, 2020; I.-M. Lee et al., 2012). Worldwide, there is a high need for interventions tackling these lifestyle behaviors. An important medium for reaching a high proportion of the population with interventions is the internet. Across the globe, access to the internet has grown rapidly in the last decade (International Telecommunication Union, 2020; Roser et al., 2015). In 2020, the International Telecommunication Union estimated that in 2019, 51% of the world population used the internet—for example, 77% of individuals in the United States, 82% in Europe, and 29% in Africa (International Telecommunication Union, 2020). In 2020, 89% of the German population over age 14 used the internet occasionally, and 72% used it daily (Beisch & Schäfer, 2020). One attractive vehicle for delivering behavior change interventions on a large scale is online communities, such as those found on social networking sites, including Facebook, Instagram, Twitter, and Reddit. In 2021, most U.S. adults used social networking sites: 69% used Facebook, 40% Instagram, and 18% Reddit (Pew Research Center, 2021). In Germany in 2020, 37% of the population over 14 used Facebook and 25% Instagram (Beisch & Schäfer, 2020). Social networking sites provide the opportunity to connect people worldwide through person-to-person relationships or building online communities.

Social networking sites are increasingly being used for health behavior change interventions (Dahl et al., 2016; Hou et al., 2014; Maher et al., 2016; Petkovic et al., 2021), typically as a platform to disseminate intervention materials (e.g., Napolitano et al., 2013) or as an add-on in multicomponent interventions to provide a supportive environment for behavior change (e.g., Godino et al., 2016). Because these platforms are widely integrated into daily social life, they allow to easily reach a wide range of populations with evidence-based health behavior change interventions (Arigo et al., 2019; Petkovic et al., 2021). They also likely increase the dose of effective ingredients of behavioral interventions ("behavior change techniques"; Michie et al., 2013), as they are remotely and continuously accessible, and frequently used (Mata & Baumann, 2017). They also provide unique features for interacting with like-minded people in private online spaces such as private forums or Facebook groups, increasing social support and social influence (Dahl et al., 2016; J. Zhang et al., 2016). Findings are mixed but results of several meta-analyses suggest a small positive effect of interventions using social networking sites for health behavior change (Laranjo et al., 2015; Petkovic et al., 2021; Waring et al., 2018; Williams et al., 2014; Yang, 2017). Nevertheless, little is known about potential mechanisms underlying these effects because social networking sites' unique effects are rarely isolated, and hypothesized intermediate outcomes are hardly ever tested (Waring et al., 2018; Yang, 2017). There are also some challenges when using online communities and social networking sites as health behavior change interventions, such as privacy concerns (Arigo et al., 2019; Klassen et al., 2018), adapting intervention contents (Pagoto et al., 2016), or open questions regarding necessary levels of engagement and factors influencing engagement (Arigo et al., 2019; Miller et al., 2019; Short et al., 2018).

One of the biggest problems of these interventions is a typically low user engagement. There are different ways of measuring actual and perceived engagement with server data or self-report, such as the number of logins, the number of postings written, the number of posts viewed, or the number of provided reactions, which can be categorized into broader categories, e.g., frequency or intensity of engagement (Short et al., 2018). Engagement varies substantially between studies and typically declines over the intervention period (Arigo et al., 2018; Waring et al., 2018; Yang, 2017). Research shows that there is often a high number of non-users and passive users (lurkers), who do not or only rarely contribute to the interactions within online communities and social networking sites, and a low number of very active users (power users) who contribute most of the interactions (Carron-Arthur et al., 2015; Edelmann, 2016; Hampton et al., 2012). However, even in the most extreme form of lurking (i.e., never posting or contributing to online communities and in social networking sites), lurkers might still profit from silently using the platform and viewing the content (Edelmann, 2016). Engagement is positively related to intervention outcomes: For example, frequency and number of postings as well as the number of reactions predict weight loss success in social-networking-site-based weight loss interventions (Pagoto et al., 2018; Xu & Cavallo, 2021). Still, the optimal kind (e.g., actively posting vs. passively viewing content) and amount of engagement for intervention success in digital health behavior interventions is often unclear and could depend on person and/ or intervention characteristics (Miller et al., 2019; Short et al., 2018). Furthermore, the effects of different forms of engagement in online communities and social networking sites likely depend on the amount and actual content of the other users' postings and reactions (Xu & Cavallo, 2021). Since at least some level of engagement is necessary for intervention success, interventions should ensure that participants stay engaged through the intervention period. It should, however, be noted that in some cases sustained engagement may not be necessary. For example, when participants find effective behavior change techniques early in the intervention and can carry them out by themselves, thus, do not depend on the intervention context. Characteristics of a digital behavior change intervention, particularly the experience and interaction within online communities, can influence the engagement of participants (Perski et al., 2017). Providing a more supportive and helpful environment is a promising approach to increase participants' engagement within online communities. Given that engagement is essential for positive intervention outcomes, strategies for increasing engagement may be at least as important as the intervention itself. One way to simultaneously increase engagement and successful behavior change in interventions involving online communities and social networking sites is to target interpersonal communication, one of their core features. Self-Determination Theory (SDT;

Deci & Ryan, 2000; Ryan & Deci, 2017) can provide a theoretical framework to understand interpersonal communication in online communities.

Self-Determination Theory

SDT (Deci & Ryan, 2000; Ryan & Deci, 2017) is a well-established macrotheory on human motivation, according to which there are 3 basic psychological needs: need for autonomy, relatedness, and competence. The fulfilment of these needs is assumed to energize and foster human motivation (Deci & Ryan, 2000; Ryan & Deci, 2017), particularly a more autonomous form of motivation (Ng et al., 2012). Autonomous motivation is important for the long-term regulation of health behaviors (Kwasnicka et al., 2016), such as eating a healthy diet (Teixeira et al., 2011). Findings from interventions suggest that changes in perceived need support are associated with changes in autonomous motivation and successful behavior change (Ntoumanis et al., 2021). Importantly, a person's social environment can be need-supportive (often also referred to as autonomy supportive), thus supporting or undermining the fulfilment of the 3 basic psychological needs (Deci & Ryan, 2000; Ryan et al., 2008; Ryan & Deci, 2017).

In the last decade, efforts have been made to integrate motivational theories such as SDT and more traditional social cognition models such as the theory of planned behavior (TPB; Ajzen, 1991), a theory that has been successfully applied to predict health behavior (McEachan et al., 2011, 2016). This theoretical integration suggests that a relatively more autonomous motivation may influence behavior at least partly via attitudes, subjective norms, and perceived behavioral control (Hagger & Chatzisarantis, 2009). A more refined version of the theory of planned behavior, the reasoned action approach (Fishbein & Ajzen, 2011), further differentiates different sub-facets of these three constructs, namely experiential and instrumental attitudes, descriptive and injunctive norms, capacity (related to self-efficacy) and autonomy (Fishbein & Ajzen, 2011; McEachan et al., 2016).

An SDT-view on Interpersonal Communication

Health behavior change interventions can be more or less need-supportive (Gillison et al., 2019; Ryan et al., 2008; Silva et al., 2014); the interpersonal communication between users in digital social environments, the key feature of interventions involving online communities and social networking sites, therefore play a central role (e.g., Ntoumanis et al., 2017; Su & Reeve, 2011, for findings in sports and teaching). Compared to increasing engagement, which focuses on the *quantity* of social interactions in online communities and social networking sites (e.g., number of logins, postings, or reactions), increasing need-supportive communication focuses on the style and *quality* of social interactions. Need-supportive communication has been described as an empathetic and patient rather than pressuring communication style (Ntoumanis et al., 2017). In need-supportive communication, one acknowledges others' perspectives and feelings, provides meaningful rationales, offers choices, nurtures inner motivational resources, and uses noncontrolling language (Su & Reeve, 2011). Further, it is possible to learn to use a need-supportive communication style with others through training (Su & Reeve, 2011). Importantly, no such interventions have been developed and tested in the context of health behavior interventions involving online communities or social networking sites. This is an important lack of research as online communities are usually large, and interventions involving social networking sites that have the power to reach a wide range of people potentially are particularly promising.

Increasing Need-supportive Communication Influences Behavior Change and Engagement

Promoting a need-supportive communication style within online communities should contribute to need fulfilment and perceived need support, autonomous motivation, and successful behavior change (Gillison et al., 2019; Ntoumanis et al., 2021). Building on the integrated SDT-TPB model (Hagger & Chatzisarantis, 2009) and the advancement of the TPB to the reasoned action approach, we expect intervention effects on behavior change to be at least partially mediated by changes in autonomous (but not controlled) motivation (Ng et al., 2012; Ntoumanis et al., 2021), and by changes in attitudes, social norms, and self-efficacy (McEachan et al., 2016; Sheeran et al., 2016). Higher need fulfilment may further lead to higher perceived social support, one key mechanism of health behavior change, which is usually targeted with social-networking-site and online-community-based health behavior interventions (Dahl et al., 2016; Petkovic et al., 2021), because participants feel understood and supported. Increased need support could also positively impact engagement and participation within online communities by improving users' experiences, and in consequence make interventions more successful (Perski et al., 2017; Waring et al., 2018).

Aims and Overview

This paper describes 2 studies evaluating a brief SDT-based intervention with the goal of instructing participants about need-supportive communication strategies within online communities. In Study 1, we developed a brief intervention video and tested—in an experimental setting—how this intervention changed communication strategies. We expected an increased use of the six targeted SDT-based need-supportive communication strategies from baseline to follow-up in the intervention group, but not the control group. In Study 2, we tested the effects of the intervention video on goal attainment, perceived need support, and engagement (primary outcomes) in the context of a behavior change intervention supported by a forum-based online community. Additionally, we examined the effect of the intervention on the following secondary outcomes, which could explain a potential positive effect of the intervention on goal attainment: autonomous motivation, experiential and instrumental attitudes, self-efficacy, perceived descriptive and perceived injunctive norms, and perceived social support. For all outcomes, we expected positive effects of the intervention video, that is, higher values in the intervention group compared to the control group. Based on the existing literature, we did not expect a positive effect on controlled motivation.

Materials and Methods

Design and Procedure

In Study 1, participants were recruited online via the study management system of a German University as well as word-of-mouth recommendations. After providing baseline data, participants were given 3 fabricated Facebook postings that consisted of a problem description in the nutrition context. Participants were asked to write a response to each of the postings (pre-intervention time point). Subsequently, participants were randomized to watch either the intervention containing information about need-supportive communication strategies or the control video containing more general communication tips (see below for intervention development). Thereafter, they answered short questions about the video and received a written summary of the communication strategies to ensure that all participants remembered the strategies. They were then asked to respond to 3 similarly structured Facebook postings and to apply the newly learned communication strategies in their responses (post-intervention time point). After 1 week, participants responded to 3 additional Facebook postings, with the instruction to use the learned communication strategies, but without watching the video again (1-week follow-up time point). The study was conducted in accordance with the Declaration of Helsinki.

In Study 2, which was preregistered on the Open Science Framework (https://osf.io/x7uv2), participants were recruited in two recruitment phases via advertisements in offline and online media, as well as Facebook ads. The intervention content was coded using the behavior change technique (BCT) taxonomy v1 (Michie et al., 2013) and the motivation and behavior change techniques (MBCTs) taxonomy for interventions based on Self-Determination Theory (Teixeira et al., 2020). The study was advertised as a “health challenge” to change one’s eating or physical activity behavior for 2 weeks while participating in a forum-based online community. To increase adherence and decrease dropout from the study, we gave participants the choice between 4 different goals: increase fruit intake, increase vegetable intake, increase moderate physical activity, or increase vigorous physical activity. Participants could first choose the behavioral domain (physical activity vs. eating fruits and vegetables) after which they could choose the more specific goal (see Appendix A). Participants were encouraged to choose a behavior which they do not show frequently and want to increase. All participants received the goal to increase intake or activity by 33% (BCT 1.1 Goal setting (behaviour). The behavioral target (number of portions or minutes of activity) was automatically calculated in the baseline assessment by using the individual baseline values of the selected behavior. After completing baseline questionnaires, participants were randomized to watch either the intervention or the control video. Next, participants were invited to join the forum-based online community that was established for their behavioral goal and intervention type where they could support each other (BCT 3.1. Social support (unspecified)). Appendix A contains an overview of all self-selected decisions and randomizations. The online communities were created exclusively for the study participants. A screenshot of one of the online communities can be seen in Appendix B. Participants subsequently worked on their goals for 2 weeks, after which they were asked to complete the follow-up questionnaire to assess primary and secondary outcome variables. Links to the videos and written summaries of the communication strategies were placed as community rules at the top of the forums and were accessible during the intervention period. One moderator monitored the postings in the forums over the intervention period to answer technical questions and to detect potential hostile postings. The moderator did not provide any other additional advice to participants. Participants were sent up to 2 reminder e-mails to answer the follow-up questionnaire. The study was approved by the Institutional Review Board of the University of Mannheim (11/2020).

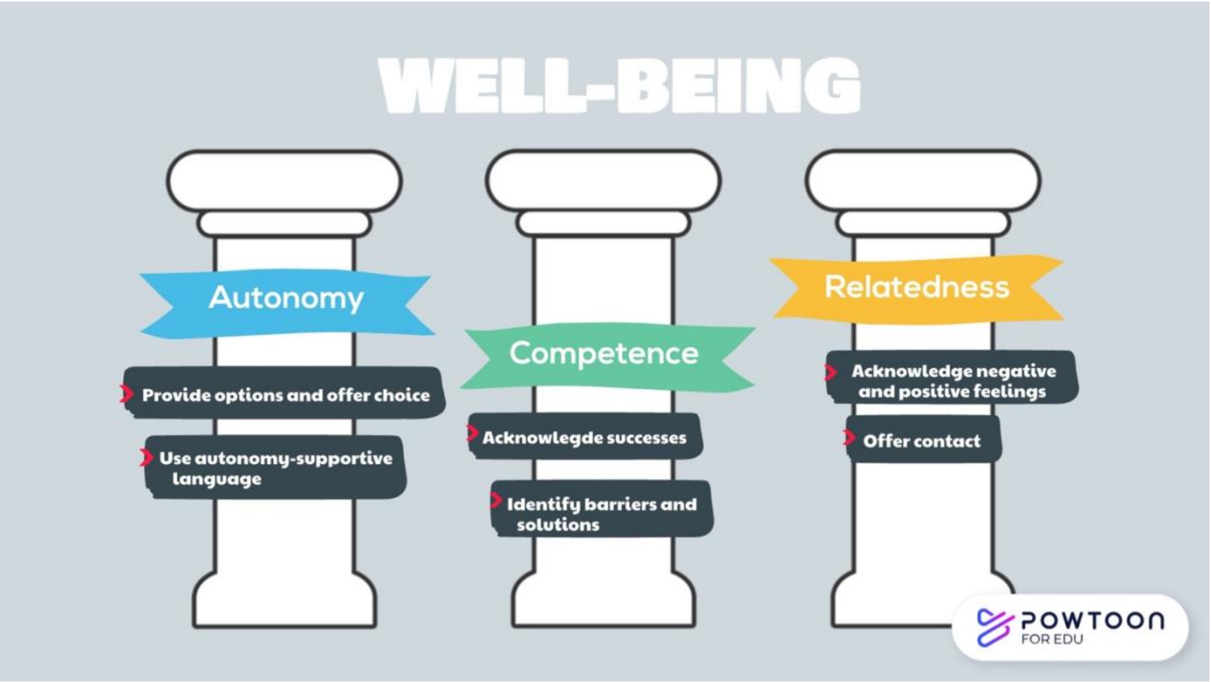
Intervention Development

We developed a brief educational video based on SDT (Deci & Ryan, 2000; Ryan & Deci, 2017) with 6 communication strategies to address need-supportive communication (see

Figure 1). Additionally, we created a control video with general netiquette rules. Netiquette means general tips and rules for respectfully interacting in online communities. Typical rules vary by platforms or even by sub-forums (e.g., in Reddit, every sub-reddit can create own community guidelines). For our control video, we included key rules which focus on the understandability of postings and a non-hostile community environment but did not overlap with the SDT-based need-supportive communication strategies. The included rules were “stay on topic”, “adapt to target audience”, “be respectful”, “avoid ambiguities and abbreviations”, and “pay attention to spelling and grammar”. The final videos have a duration of about 3 minutes and were created with the software Powtoon. Both videos were designed to be as similar as possible and consisted of a short introduction to social networking sites’ and online communities' advantages in supporting behavior change and goal attainment. Participants were then introduced to the different communication strategies, and the intervention video also contained brief information about the 3 basic psychological needs. Finally, both videos contained a written communication example with the application of the respective communication strategies (BCT 4.1 Instructions on how to perform the behaviour). Potential communication strategies were derived from 2 meta-analyses on SDT-based interventions (Gillison et al., 2019; Su & Reeve, 2011). The first author and 5 master’s students (in psychology) discussed possible communication strategies and their applicability in the context of written online communication. Two strategies for each basic psychological need were determined by joint discussion (MBCT 3. Use noncontrolling, informational language; MBCT 6. Provide choice; MBCT 8. Acknowledge and respect perspectives and feelings; MBCT 13. Providing opportunities for ongoing support; MBCT 15. Address obstacles for change; MBCT 18. Offer constructive, clear, and relevant feedback).

Figure 1

Screenshot of the Intervention Video With the Communication Strategies Based on Self-Determination Theory (Content Translated From German to English).



Measures

Study 1

Demographic characteristics included age, gender, and highest educational attainment. Educational attainment level was subsequently coded according to the International Standard Classification of Education (ISCED; UNESCO Institute for Statistics, 2012) and recommendations by Eurostat (Eurostat, 2021) as low (ISCED levels 0–2), medium (ISCED levels 3 and 4), and high (ISCED levels 5–8).

The first author and 5 Master's students who were involved in the development of the video intervention developed a first version for a coding scheme through joint discussions. Two trained Bachelor students in psychology blind to the experimental condition coded 20 responses separately. Both raters and the first author discussed the results, resolved disagreements, and refined the coding scheme. Subsequently, both raters coded 29%

(170/595) of the written responses (use of each of the 6 strategies; no = 0 vs. yes = 1) to estimate interrater reliability. Interrater agreement, calculated with ReCal OIR (Freelon, 2013), was adequate to good (percentage agreement = 76.5%-95.3%; Krippendorff's α = .51-.80; see Appendix C). In the next step, the coding scheme was further refined through discussions between the two raters and the first author; because of good inter-rater agreement, the final coding was conducted by one of the raters. Subsequently, the outcome variable need-supportive communication strategy use was calculated using the sum of the applied SDT-based communication strategies for every measurement time point (preintervention, postintervention, and 1-week follow-up). At every time point, participants wrote 3 responses to postings (3 responses with up to 6 need-supportive communication strategies used per posting; possible range: 0-18 uses).

Study 2

Demographic characteristics included age, gender, highest educational attainment, and highest professional degree, derived from the longitudinal German Internet Panel study (Blom et al., 2015, 2018). Educational attainment level was coded as in Study 1. Occupational skill level was coded according to the International Standard Classification of Occupations (ISCO; International Labour Office, 2012) as ISCO skill level 1 (low, e.g., unskilled worker), level 2 (medium, e.g., skilled worker), level 3 (high, e.g., higher skilled worker), and level 4 (very high, e.g., academic job). ISCO levels 3 and 4 were subsequently integrated into one category (high to very high).

Other control variables included if participants followed an omnivore diet (0 vs. 1) or a weight loss diet (0 vs. 1), if participants had a fructose intolerance (0 vs. 1), and the mean number of other active community members in the individual intervention period, which could have differed between the different online communities and recruitment phases.

Primary Outcomes. Perceived need support in the online community was measured with the 15-item Virtual Care Climate Questionnaire which is based on Self-Determination

Theory and other established questionnaires for assessing perceived autonomy-support (Smit et al., 2017; example item: 'The other forum users give me the feeling that I myself can choose a way to increase my TARGET BEHAVIOR by a third"; Cronbach's α = .92). The questionnaire assesses perceived autonomy/ need-support in virtual settings (e.g., Smit et al., 2017).

Goal attainment scores were calculated by dividing the *values of the self-reported behaviors* at follow-up (e.g., number of vegetable portions or weekly minutes of moderate physical activity) by the behavioral goal (i.e., baseline behavior increased by 33%). A value of 1.0 thus represents 100% goal attainment.

Physical activity was measured (in minutes per week) with 2 items each for moderate physical activity and vigorous physical activity derived from the International Physical Activity Questionnaire Short Form (Craig et al., 2003; Y. Kim et al., 2013). Example items for moderate physical activity include "During the last 7 days, on how many days did you do moderate physical activities (breathing and heartbeat are increased, speaking is still easy, but singing is no longer possible) like carrying light loads, riding a bicycle at normal speed, doing strenuous household chores, playing actively with children, or doing moderate-intensity sports and endurance sessions at home, in the gym, or out in the fresh air? Do not include walking" and "How much time did you usually spend doing moderate physical activities on one of those days?"

Fruit and vegetable intake was measured with the 2 open-ended questions "How many daily portions of fruits/vegetables did you eat on average in the last 7 days?" (cf. Chapman et al., 2009; Zhou et al., 2017) after receiving information about typical portion sizes according to the German Federal Centre for Nutrition and the "Five-a-Day" campaign (5 am Tag e.V., 2014; German Federal Centre for Nutrition, 2020).

Engagement was measured with 3 indicators. The subjective forum visit frequency was measured with the item "How often did you visit the online forum during the challenge period?" (response scale from 1 = not at all to 7 = multiple times daily). The number of logins and the number of postings within the 2-week intervention period were determined for each participant from the objective server data.

To examine whether the intervention had the hypothesized effect, we again calculated the need-supportive communication strategy use for every posting (possible range: 0-6) as an additional proximal outcome. Strategy use, along with other variables such as if a posting contained self-monitoring (0 vs. 1) or a problem description (0 vs. 1), was coded by 2 trained raters who also initially extended the coding manual of Study 1 in joint discussions. The raters were blind to the experimental condition. After coding and comparing 50 postings and the refinement of the initial coding manual, 10.24% (166/1621) of the postings were coded by both raters to calculate interrater agreement, which was good (percentage agreement = 91.0%-98.2%; Krippendorff's α = .27-.92; see Appendix C). The rest of the postings were divided among the 2 raters who each coded half of the postings.

Secondary Outcomes. Perceived social support was measured with 9 items adapted from the Child and Adolescent Social Support Scale for Healthy Behaviors (Menon & Demaray, 2013), for example, "The other forum users encourage me to maintain or increase my current TARGET BEHAVIOR"; Cronbach's α = .92.

Instrumental and experiential attitude were measured with 5 and 4 semantic differential scales, respectively, (Conner et al., 2011; Lawton et al., 2009). Items include "For me, maintaining or increasing my TARGET BEHAVIOR would be: useless–useful" and "For me, maintaining or increasing my TARGET BEHAVIOR would be: unpleasant–pleasant"; Cronbach's α = .87 for each.

Self-efficacy was measured with 4 items adapted from the preaction and maintenance self-efficacy scales of the Health Action Process Approach measures (Schwarzer, 2007; Sniehotta et al., 2005), for example, "I am sure I can maintain or increase my TARGET BEHAVIOR, even if I do not see success at once"; Cronbach's α = .78.

Perceived descriptive and injunctive norms were measured with 3 items for each construct following the recommendations for social norm items of the Reasoned Action Approach (Fishbein & Ajzen, 2011), such as "I think most forum members intend to maintain or increase their TARGET BEHAVIOR" and "I think most forum members expect me to maintain or increase my TARGET BEHAVIOR"; Cronbach's α = .92 and .95. Autonomous motivation and controlled motivation were measured with 10 items adapted from the Behavioral Regulation Sports Questionnaire (Lonsdale et al., 2008). Specifically, for each behavioral regulation form, two items with the highest item loadings were chosen and adapted to fit the target behavior. Subsequently, intrinsic motivation, integrated motivation, and identified motivation scores were combined to measure autonomous motivation; introjected motivation and external motivation scores were combined to measure controlled motivation. Example items include "I intend to maintain or increase my TARGET BEHAVIOR because it's fun" and "I intend to maintain or increase my TARGET BEHAVIOR because I feel pressure from other people to do so"; Cronbach's α =. 78 and .67.

Statistical Analyses

Analyses of both studies were conducted with study completers (available follow-up data) using R version 4.0.1. To test the effects of the condition and time variables, lmerTest was used to estimate linear mixed models, and glmmADMB and glmmTMB were used to estimate nonlinear mixed models. The R package emmeans was used to conduct Tukey-corrected post hoc contrasts with estimated marginal means. The R package performance was used to test for overdispersion and zero inflation in the nonlinear mixed models. The R package compareGroups was used to compare the different subgroups of the sample.

Study 1

The condition variable (intervention vs. control) and the time variable (preintervention vs. postintervention vs. follow-up) were effect-coded, so main and interaction effects can be interpreted independently. The intervention condition's and time variable's effects on need-supportive communication strategy use were tested with a linear mixed model with the different measurement time points nested within persons and a random intercept on the person level. Analysis of variance type III tables were calculated with the R package car.

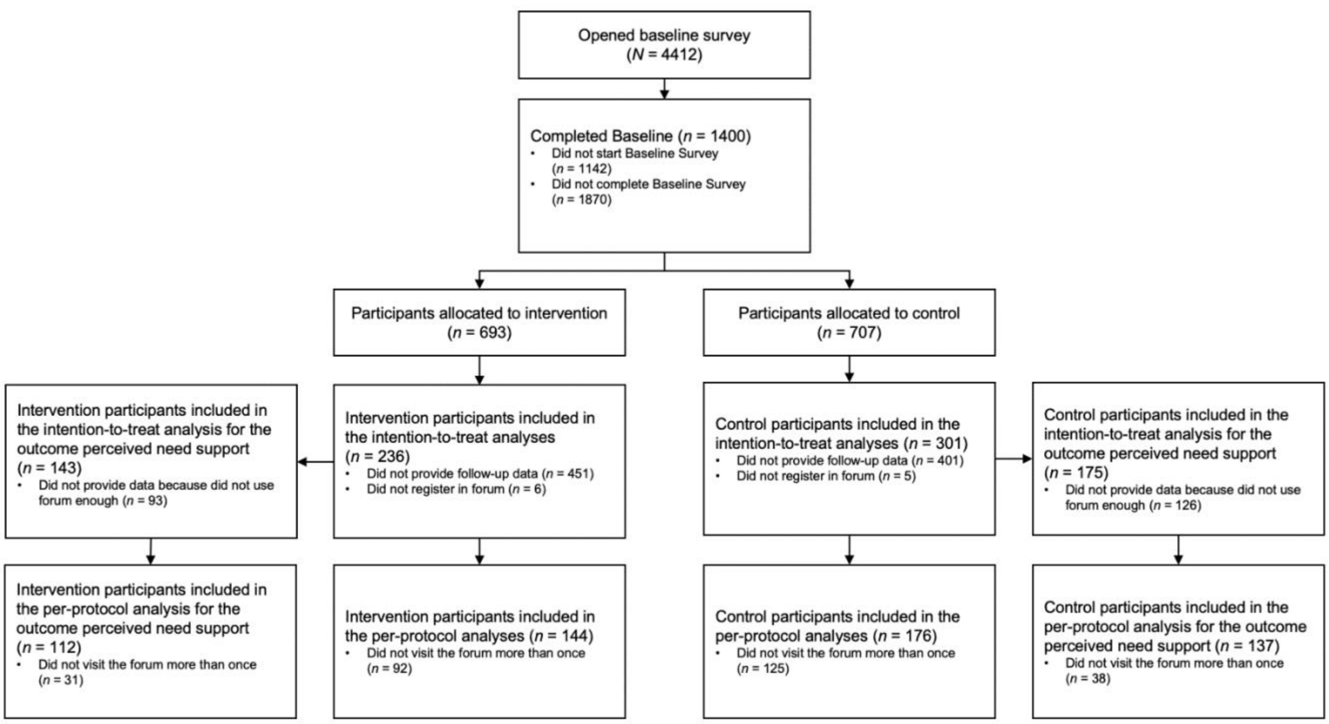
Study 2

The condition variable was dummy coded in Study 2 to compare the two groups at follow-up directly. Outliers were handled using winsorization based on 3 times the median absolute deviation (Leys et al., 2013) and including them in the analyses for most outcomes to preserve statistical power (Leys et al., 2019). We used the raw values for the count variables number of logins and number of postings because the data were highly skewed to the right and represented objective data points (see below for statistical models applied). All analyses were conducted twice, once using winsorized values and once excluding outliers. Instead of analyzing the engagement descriptively via the number of forum entries/ threads and number of responses per entry (as preregistered) we chose a more finely grained approach and analyzed the effect of the condition on the number of postings at the person level as an intensity measure of engagement (see also Short et al., 2018 for similar approaches). This decision was made to 1) increase the sample size for the analyses (there were only few entries, but many responses to entries) and to 2) account for the clustering of postings within participants and participants within the different forums. Additionally, we analyzed the number of logins and the subjective forum visit frequency as engagement measure. The number of logins can be seen as a frequency measure of engagement (Short et al., 2018) which we use as an indicator of the engagement of lurkers who do not post in the forums but may still benefit by passively viewing the content (Edelmann, 2016). We additionally analyzed the subjective forum visit frequency to see if the results for this more indirect form of engagement match in measures of both actual and perceived engagement. The intervention condition's effects on the outcomes were tested with linear mixed models for all primary and secondary outcome variables except for the number of logins and postings. The effect on the number of logins and postings was tested with negative-binomial-distributed mixed models because the variables represented counts and the presence of substantial overdispersion (Gelman & Hill, 2006). Additionally, we modeled zero inflation if detected (Gelman & Hill, 2006). As an additional proximal outcome, we estimated the intervention condition's effect on the coded need-supportive communication strategy use on the posting level with a Poisson-distributed mixed model. The mixed models contained the maximal random effect structure justified by design to maximize generalizability and control type-I error rate (Barr et al., 2013; Musca et al., 2011). That is, for the number of need-supportive communication strategies, we included random intercepts and random slopes (predictor: condition) for participants and forums to account for potential systematic differences in mean levels (random intercepts) and intervention-effects (random slopes) between participants and in the different forums because the observations (Level 1) were clustered within participants (Level 2) and forums (Level 3). For all other outcomes (e.g., number of logins and goal attainment), we included random intercepts and slopes (predictor: condition) for the cluster variable forum to account for potential systematic differences in mean levels (random intercepts) and intervention-effects (random slopes) in the different forums because participants (Level 1) were clustered within forums (Level 2). For most outcomes, the models did converge. We only excluded the random slope in the models for the outcomes perceived need-support and experiential attitude because of non-convergence. All models further included control variables (only variables where systematic differences between the two conditions or between the self-selected goal types were detected) and baseline values of the dependent variables (when available). To check the robustness of our results, the analyses were conducted with all participants who registered in the forum and provided follow-up data, regardless of whether they used the forum (following the intention-to-treat principle), as well as with participants who visited the forum more than once (per-protocol analyses; see the flowchart in Figure 2). With the per-protocol analyses we aimed to exploratorily examine if potential intervention effects would replicate in the smaller but less noisy sample of actual users of the online communities. The results of the intention-to-treat analyses with winsorized values are reported in the main text, tables, and figures, if not stated otherwise. We refrained from testing the expected indirect effects of the intervention video on behavior change because we did not find any effects on the expected mediators in the first place.

For sample size estimation in Study 2, we relied on previous short-term intervention studies targeting the provision of need support that suggested a medium to strong effect size on average; however, the lower level bound of the confidence interval implies that the effect size could also be small (Su & Reeve, 2011). We therefore conservatively estimated a required sample size of $N = 292$ ($n = 146$ in each experimental group) to detect small effect sizes with a power of .80 at an α level of .05 (see preregistration).

Figure 2

Participant Flowchart for Study 2



Results

Study 1

Participants and Descriptive Statistics

A total of 99 participants completed the baseline questionnaire, of whom 77% (76/99) also completed the follow-up questionnaire after 1 week. There were no significant baseline differences in demographic characteristics between completers and noncompleters. Participants in the final data set were mostly female (59/99, 78%), had a mean age of M = 25.2 years (SD = 11.4 years), and had medium to high educational attainment. There were no significant baseline differences in demographic characteristics and need-supportive communication strategy use preintervention between the two experimental conditions (see Table 1).

Need-Supportive Communication Strategy Use

For the outcome need-supportive communication strategy use, there was a significant main effect of condition ($F(1,$ 72.92) = 14.91; p < .001; *partial* η^2 = 0.17), a significant main effect of time ($F(2,$ 148.17) = 23.75; p < .001; *partial* η^2 = 0.24), and a significant interaction effect of condition and time ($F(2,$ 148.17) = 33.75; p < .001; *partial* η^2 = 0.31). Post hoc contrasts with Tukey adjustment showed that the number of need-supportive communication strategies used in the written responses increased in the intervention condition from preintervention to postintervention (estimate = –4.71, SE = 0.50; t(148) = –9.45; p < .001; Cohen's d = –2.16, 95% CI [-2.91 to –1.41]) and from preintervention to follow-up (estimate = –4.58, SE = 0.50; t(148) = –9.27; p < .001; Cohen's d = –2.10, 95% CI [–2.61 to –1.59]), but there were no significant changes in the control condition (all ps > .240). There was no difference in the mean number of need-supportive communication strategies used between the two groups at baseline (estimate = 0.83, SE = 0.78; t(132) = 1.07; p = .288; Cohen's d = 0.38, 95% CI [–0.33-1.09]), but the intervention condition had a higher mean number of need-supportive communication strategies used postintervention (estimate = –4.71, SE = 0.78;

$t(133) = –6.05$; $p < .001$; Cohen's $d = –2.16$, 95% CI [–2.96 to –1.37]) and at 1-week follow-up (estimate = –3.72, $SE = 0.78$; $t(132) = –4.80$; $p < .001$; Cohen's $d = –1.71$, 95% CI [–2.47 to –0.95]; for all means and standard errors, see Figure 3).

Table 1

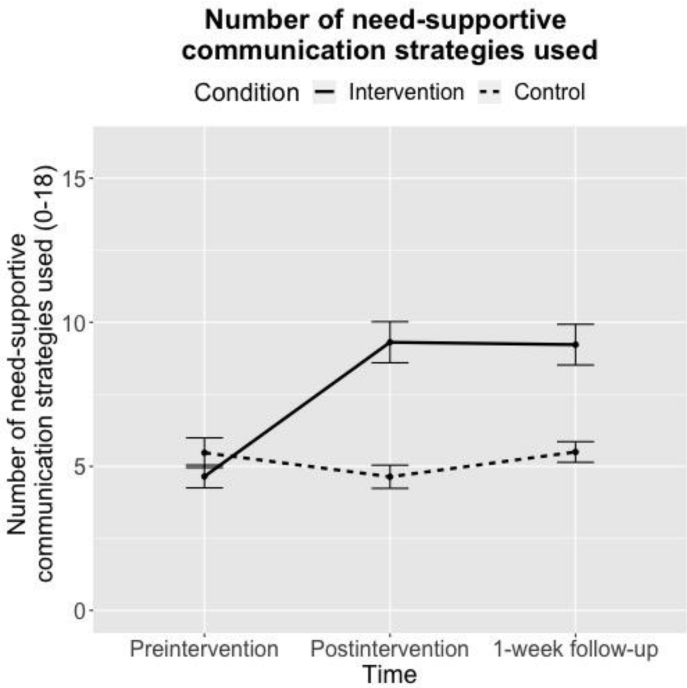
Baseline Characteristics and Participant Differences in the Control and Intervention Conditions (Study 1)

Variable	Control group (n = 36)	Intervention group (n = 40)	p
Demographic characteristics			
Age (years), *M* (*SD*)	26.00 (13.30)	24.52 (9.53)	.584
Female, *n* (%)	29 (81)	30 (75)	.594
Educational attainment, *n* (%)			
Low (ISCED 0–2)	0 (0)	0 (0)	.881
Medium (ISCED 3 & 4)	28 (78)	32 (80)	
High (ISCED 5–8)	7 (19)	8 (20)	
Other	1 (3)	0 (0)	
Outcome (preintervention)			
Need-supportive communication strategy use (number of need-supportive communication strategies), *M* (*SD*)	5.47 (3.1)	4.65 (2.51)	.211

Note. The control and intervention groups were compared with Welch's two-sample *t* tests (means) or Fisher's exact tests (proportions) whereby *p* shows the significance level of the comparisons. ISCED = International Standard Classification of Education.

Figure 3

Mean Number of Need-Supportive Communication Strategies Used (Study 1)



Note. Means and standard errors (error bars) for the number of need-supportive communication strategies used in the responses to fictive online postings, by measurement time and experimental condition.

Study 2

Participants and Descriptive Statistics

A total of 1400 participants completed the baseline assessment. After study dropout (lost to follow-up) and exclusion of 11 participants because they did not register in the forum, $n = 537$ participants could be included in the intention-to-treat analyses for most outcomes (537/1400, 38.36%). $N = 320$ participants could be included in the per-protocol analyses after excluding participants who did not log in more than once (320/1400, 22.86%; see participant flowchart in Figure 2).

There was a higher dropout in the intervention condition compared to the control condition (*OR* 0.70, 95% CI [0.56-0.87]; $p = .001$). Furthermore, study completers made on average more postings ($t(637.95) = –8.48$; $p <. 001$; Cohen's $d = 0.55$, 95% CI [0.43-0.66]), logged in more often ($t(648.01) = –8.64$; $p < .001$; Cohen's $d = 0.56$, 95% CI [0.44-0.67]), and had a lower fruit intake at baseline ($t(1169.10) = 2.04$; $p = .041$; Cohen's $d = –0.11$, 95% CI [–0.22-0.00]). There were no significant baseline differences in participant characteristics between the control and intervention group besides a lower vegetable intake at baseline in intervention participants, $t(526.86) = 1.94$; $p = .048$; Cohen's $d = –0.17$, 95% CI [–0.34-0.00] (see Table 2). As would be expected, we found baseline differences between participants who had self-selected different behavioral goals. Therefore, we included these variables as control variables in the mixed models (see Appendix D for a detailed overview of baseline differences between the different goal-type conditions).

In the two-week intervention period, there were $N = 1130$ postings in total in the forums. Participants created on average $M = 2.07$ ($SD = 3.88$) postings. One half of participants (273/537, 50.8%) posted at least once, and 31.7% (170/537) posted more than once (273/1400, 19.5% and 170/1400, 12.1% of initially randomized participants). Among all postings, 25.22% (285/1130) were categorized as self-monitoring postings, 32.57% (368/1130) contained a problem description by participants, 27.88% (315/1130) contained goal setting, and 17.96% (203/1130) contained a personal introduction. Participants logged in $M = 3.54$ ($SD = 4.97$) times on average. Most participants who registered in the forums (503/537, 93.67%) logged in at least once and around two third (320/537, 59.59%) logged in more than once.

Table 2

Baseline Characteristics and Participant Differences in the Control and Intervention Group (Study 2)

Variable	Control group (n = 301)	Intervention group (n = 236)	p
Demographic characteristics			
Age (years), M (SD)	42.02 (11.64)	43.46 (11.30)	.150
Body mass index (kg/m^2), M (SD)	28.52 (6.52)	28.57 (6.69)	.939
Female, n (%)	294 (97.7)	231 (97.9)	.999
Educational attainment, n (%)			.999
Low (ISCED 0–2)	3 (1.0)	2 (0.9)	
Medium (ISCED 3 & 4)	138 (45.9)	108 (45.8)	
High (ISCED 5–8)	159 (52.8)	126 (53.4)	
NA	1 (0.3)	0 (0.0)	
Occupational skill level, n (%)			.942
Low (ISCO skill level 1, e.g., unskilled worker)	24 (8.0)	16 (6.8)	
Medium (ISCO skill level 2, e.g., skilled worker)	117 (38.9)	92 (39.0)	
High (ISCO skill levels 3 & 4, e.g., higher skilled worker/academic job)	159 (52.8)	127 (53.8)	
NA	1 (0.3)	1 (0.4)	
Professional position, n (%)			.300
Full-time employees	152 (50.5)	108 (45.8)	
Part-time employees	74 (24.6)	73 (30.9)	
Students (higher education)	25 (8.3)	23 (9.8)	
Other	50 (16.6)	32 (13.6)	
Goal type, n (%)			.695
Fruit intake	20 (6.6)	15 (6.4)	
Vegetable intake	84 (27.9)	56 (23.7)	
Moderate physical activity	84 (27.9)	67 (28.4)	
Vigorous physical activity	113 (37.5)	98 (41.5)	
Outcomes (baseline)			
Fruit intake (no. portions), M (SD)	1.51 (1.01)	1.50 (0.94)	.957
Vegetable intake (no. portions), M (SD)	2.05 (1.41)	1.83 (1.25)	.048
Moderate physical activity (min/week), M (SD)	214.70 (193.09)	203.23 (192.77)	.494
Vigorous physical activity (min/week), M (SD)	33.19 (35.72)	32.56 (35.51)	.837
Autonomous motivation, M (SD)	3.94 (1.00)	3.85 (0.92)	.311
Controlled motivation, M (SD)	4.12 (1.52)	4.17 (1.51)	.720
Instrumental attitude, M (SD)	7.00 (0.00)	7.00 (0.00)	N/A[a]
Experiential attitude, M (SD)	5.50 (1.14)	5.55 (1.14)	.593
Self-efficacy, M (SD)	3.82 (0.67)	3.78 (0.68)	.582
Perceived descriptive norms, M (SD)	3.88 (0.68)	3.95 (0.68)	.219
Perceived injunctive norms, M (SD)	3.94 (0.78)	4.01 (0.80)	.271

Table 2

Baseline Characteristics and Participant Differences in the Control and Intervention Group (Study 2)

Variable	Control group (n = 301)	Intervention group (n = 236)	p
Other			
Number of other active forum members, M (SD)	165.92 (93.77)	167.57 (95.09)	.841
Omnivore diet, n (%)	185 (61.5)	153 (64.8)	.472
Weight loss diet, n (%)	70 (23.3)	53 (22.5)	.837
Fructose intolerance, n (%)	288 (95.7)	226 (95.8)	.999

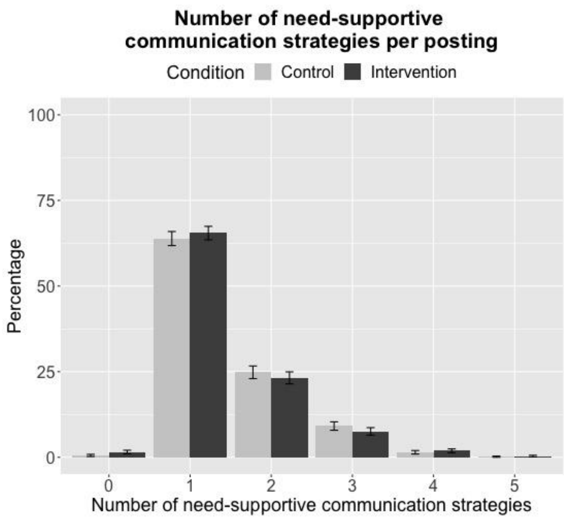
Note. The control and intervention groups were compared with Welch's two-sample t tests (means) or Fisher's exact tests (proportions), whereby p shows the significance of the comparisons. The outcomes goal attainment, perceived need support, perceived social support, number of logins, number of postings, and subjective forum use frequency are only available at follow-up. ISCED = International Standard Classification of Education. ISCO = International Standard Classification of Occupations. NA = Missing values. N/A = Not applicable.
[a]Not applicable because the distribution of the variable was highly skewed and there was little variance; after winsorization, all participants scored the highest value on the scale (7).

Proximal Outcome: Need-supportive Communication Strategy Use

To examine whether our manipulation (i.e., watching the intervention or the control video) influenced the use of need-supportive communication strategies, we descriptively analyzed the proportion of postings with a specific number of strategies used per posting (maximum of 6 strategies per posting) in the N = 1130 included postings, separated by condition. As shown in Figure 4, most postings (63.87% (350/548) of participants' postings in the control condition, 65.46% (381/582) of participants' postings in the intervention condition) contained only one need-supportive communication strategy. Additionally, in the mixed model, there was no significant effect of condition on the number of applied strategies on the posting level (B = –0.01, SE = 0.05; z = –0.28; p = .778). This means that participants in the intervention condition did not use need-supportive communication strategies more frequently than participants in the control condition ($M_{\text{Intervention}}$ = 1.44, $SD_{\text{Intervention}}$ = 0.76; M_{Control} = 1.48, SD_{Control} = 0.74). There were no intercept and slope variances (see Appendix E1), meaning that there were no differences in the mean levels of need-supportive communication strategy use between participants and the different forums. The effect of the video intervention did also not vary by participants and forums. The results did not change in the model with participants who visited the forum more than once.

Figure 4

Percentage of Postings With a Specific Number of Need-Supportive Communication Strategies Based on Self-Determination Theory by Experimental Condition (Study 2)



Note. The maximum possible number of strategies per posting is 6. Error bars represent 95% confidence intervals.

Primary Outcomes

Not in line with the preregistered hypotheses, there were no statistically significant effects of the intervention video on perceived need support, goal attainment, and most of the engagement variables (see Table 3 for all primary and secondary outcomes). There was only a statistically significant effect of the intervention video on the number of postings (B = 0.31, SE = 0.15; z = 1.99; p = .046), as expected. More specifically, participants who watched the intervention video tended to have a higher number of postings compared to participants who watched the control video (see Table 3). Overall, there was little evidence for substantial slope variances for the effect of the video intervention on the primary outcomes (see Appendix E1), meaning that the effects did not vary between forums. For the outcomes “goal attainment" and "subjective forum visit frequency" there were also no substantial intercept variances, meaning that there were no systematic differences in the mean-levels of the outcome variables in the different forums. Most of the results did not change after excluding outliers based on the median absolute deviation or with participants who visited the forum more than once. One exception (when excluding outliers instead of winsorization) was a statistically significant effect of the intervention video on the subjective forum visit frequency (B = 0.28, SE = 0.10; $t(514)$ = 2.71; p = .007). However, in participants visiting the forum more than once, the effect on subjective forum visit frequency was not statistically significant anymore (independent of the type of outlier handling). We also report sub-group analyses for the different health behaviors and goal types in Appendix F.

Secondary Outcomes

There were no statistically significant effects of the intervention video on autonomous motivation, controlled motivation, self-efficacy, perceived social support, experiential attitude, instrumental attitude, descriptive behavioral norms, or injunctive behavioral norms (see Table 3), which again was not in line the preregistered hypotheses. Overall, there were small to non-existent intercept and slope variances (see Appendix E2), meaning that the effect of the video intervention did not vary between the different forums, and that there were no systematic differences in the mean-levels of the outcome variables in the different forums. The results did not change when outliers were excluded based on median absolute deviation or in models including only participants who visited the forum more than once.

Table 3

Intervention Effects and Estimated Marginal Means for Intervention and Control Condition From Mixed Models (Study 2)

Variable	Estimated marginal mean (*SE*)		Intervention effect estimate *B* (*SE*)[a]	*p*
	Control group (*n* = 301)	Intervention group (*n* = 236)		
Proximal outcomes				
Number of need-supportive communication strategies[b]	1.48 (0.03)	1.44 (0.03)	-0.01 (0.05)	.778
Primary outcomes				
Perceived need support	3.03 (0.16)	3.08 (0.17)	0.05 (0.22)	.840
Goal attainment	1.12 (0.07)	1.22 (0.07)	0.11 (0.09)	.260
Number of postings[b]	1.81 (0.20)	2.42 (0.28)	0.31 (0.15)	.046
Number of logins[b]	3.51 (0.33)	3.59 (0.25)	0.10 (0.08)	.250
Subjective forum visit frequency	2.47 (0.10)	2.71 (0.10)	0.24 (0.13)	.101
Secondary outcomes				
Autonomous motivation	3.99 (0.06)	3.96 (0.09)	-0.03 (0.10)	.795
Controlled motivation	4.20 (0.10)	4.09 (0.11)	–0.11 (0.13)	.384
Self-efficacy	3.39 (0.04)	3.39 (0.05)	–0.01 (0.06)	.915
Experiential attitude	5.13 (0.11)	5.20 (0.12)	0.07 (0.16)	.669
Instrumental attitude	6.58 (0.03)	6.64 (0.04)	0.06 (0.05)	.319
Perceived descriptive norms	3.77 (0.09)	3.77 (0.05)	0.00 (0.10)	.977
Perceived injunctive norms	3.38 (0.08)	3.47 (0.08)	0.09 (0.10)	.389
Perceived social support	3.23 (0.18)	3.28 (0.15)	0.05 (0.22)	.813

Note. Analyses were conducted with winsorized values and the effect of the intervention condition (dummy coded) is controlled for baseline values of the outcome, variables with baseline differences between completers and noncompleters, and between the 4 self-selected goal types, that is age, fruit intake, vegetable intake, moderate physical activity, vigorous physical activity, body mass index, perceived descriptive norms, perceived injunctive norms, and the mean number of active forum users. The raw values were used for the poisson-distributed count variables number of need-supportive communication strategies, number of logins and number of postings.

[a]Differences between estimated marginal means and estimates originate from rounding.

[b]For the number of postings and the number of logins, the intervention's effect is multiplicative ($e^{estimate}$) rather than additive since the models use a log-link-function for the count data. *M* (*SE*) represents the raw values because estimated marginal means could not be derived for nonlinear mixed models.

Discussion

Principal Results

Consistent with our hypothesis, young adults who watched the intervention video with need-supportive communication strategies almost doubled their strategy use in written responses to fictive online postings immediately after watching the video and at 1-week follow-up in Study 1. In contrast, participants who watched a control video on netiquette rules showed no such increase directly after the intervention or at follow-up. These results suggest that a 3-minute educational video is sufficient to learn need-supportive communication strategies and apply them, at least for 1 week.

In Study 2, we tested whether this effect translates to a real-world online community, improving communication climate and perceived need support, using the same intervention videos. Not in line with our preregistered hypotheses, we found that participants in the intervention condition reported neither higher perceived need support from the other community members nor higher goal attainment compared to participants in the control condition. Goal attainment was generally very high: In both groups, participants reached on average more than 100% of their individual goals at the end of the intervention. We did only find mixed evidence regarding higher engagement in participants in the intervention condition. More specifically, they tended to have a higher perceived forum use (subjective forum visit frequency), but not actual forum use (number of logins); however, this effect was only inconsistent and not robust. Importantly, in line with our hypothesis, participants in the intervention condition showed a higher number of postings, compared to participants in the control condition. Not in line with our hypotheses, we did not find statistically significant differences between the two conditions at follow-up regarding behavior-related self-efficacy, experiential or instrumental attitudes, perceived descriptive or injunctive norms, perceived social support, or autonomous or controlled motivation. These findings are not surprising given that we expected the effects on our secondary outcomes to be mediated by changes in perceived need support (Hagger & Chatzisarantis, 2009), which we did not find in the first place. The results can be explained by a missing effect of the video intervention on the proximal outcome need-supportive communication strategy use.

Why did the strong increase in need-supportive communication strategy use not transfer from an experimental setting (Study 1) to a real-world setting (Study 2)? Regarding statistical power, we recruited an even higher sample size than preregistered (preregistered: $N = 292$ vs. final sample size: $N = 537$). This was the case because we conducted a community-based experiment where all participants had to start together. Participants had the chance to register for the study until two days before the intervention began; everyone who registered within this time window was allowed into the study. We did not shorten the envisioned time window to ensure enough participants at follow-up because we expected substantial study dropout (cf. Eysenbach, 2005). The larger sample size allowed us to detect small effects of the video intervention in Study 2 with a higher statistical power than initially targeted (.80 at an α level of .05). This was beneficial for our analyses because the effect size for our intervention had to be estimated on several theoretical assumption, because no similar intervention existed that could have informed this estimate. Additionally, Study 1 showed strong effects of the video intervention on need-supportive communication strategy use, suggesting that other reasons might underly the missing effects in Study 2. One reason could be that the strategies were not applicable to posting types that frequently occurred in the online communities. There was a substantial number of self-monitoring postings in which participants mainly tracked their goal progress without substantial or meaningful social interaction with other participants. The strategies, in contrast, aim to support other individuals who struggle with behavior change by fulfilling the basic psychological needs and enhancing the development of autonomous forms of motivation (Teixeira et al., 2020). Therefore, they are not applicable in self-monitoring posting. Further, all fictive online postings in Study 1 contained descriptions of barriers to a healthy diet, for which communication strategies such as "identifying problems and solutions," as explained in the intervention video, were easily applicable. In contrast, less than a third of postings in Study 2 contained a problem description by participants to which all need-supportive communication strategies could theoretically be applied.

Additionally, goal attainment was very high in both groups, which is somewhat surprising because there is typically a so-called intention-behavior gap and people struggle with translating their intentions into behavior (Sheeran, 2002; Sheeran & Webb, 2016). Why might participants have been so successful in reaching their goals? There are at least two reasons which might explain the finding. First, our overall intervention contained effective BCTs (goal setting, provision of social support via forum) in both experimental groups, which supports the enaction of intentions into behavior. Furthermore, participants also used effective BCTs by themselves (e.g., self-monitoring, which was a frequently occurring posting type). Eating and physical activity interventions that include self-monitoring and other BCTs from control theory (e.g., goal setting) have been shown to be more effective than interventions who do not use them (Michie et al., 2009). Second, the goals for participants were individualized, which make them more effective (Kwasnicka et al., 2021). Participants could choose their target behavior and the goal was adapted to the baseline level of the specific behavior. Research shows that goals are more effective when they are specific, personally relevant, and pursued for autonomous reasons (Kwasnicka et al., 2021). Because the intervention already included effective BCTs, participants might have not been in a high need for support by the other participants for very *specific* problems in the behavior change process – which was also reflected in the low number of postings containing a problem description. Taken together, the already successful behavior changes and high goal attainment in both groups may also partially explain the infrequent application of the need-supportive communication strategies, as they aim at supporting others who struggle with behavior change (Teixeira et al., 2020).

Lastly, another potential explanation for why the SDT-based video intervention did not produce the expected effects could be the generally low engagement in the online communities. Among participants who registered in the online community and provided follow-up data, one half contributed at least one post, around one third posted more than one. One reason for this could be that around half of the participants were also registered in at least one other online forum and around one third even actively participated – via reading and/or posting content – in other health-related online forums. This likely results in less time for using our study forum and might also reduce the need of participants to use our forum for the exchange and support with other people with shared goals. The relatively low engagement rate limits the impact of the need-supportive communication strategies on our hypothesized outcomes because they may simply not be applied frequently enough to change the perceived communication climate. Research suggests that a "critical mass" is necessary to stimulate natural interaction within online communities and on social networking sites in general, which—despite some interaction among participants—may have been too low. There are usually many passive users or lurkers within online communities and on social networking sites (Carron-Arthur et al., 2015; Edelmann, 2016). Additionally, engagement rates in social-networking-site-based interventions typically vary substantially (Klassen et al., 2018; Waring et al., 2018; Williams et al., 2014). Research suggests that only about 10–20% of users in online communities are actively contributing (Edelmann, 2016). This means that general engagement rates in our study at around 30% of our follow-up sample posting more than once, and around 60% logging in more than once were still comparably high. In addition, having few very active users is also important: One study estimated that removing the 1% of very active superusers in two large online communities about asthma—who contributed about 32% and 49% of the postings—would cause the communities to collapse (Joglekar et al., 2018). Therefore, superusers keep online communities thriving. As discussed earlier, passive participation is not equal to nonuse or nonengagement. Lurkers may still profit from online communities and interventions by silently using the platform (Edelmann, 2016).

To sum up, high levels of goal attainment, low engagement, and low applicability of the need-supportive communication strategies to frequently occurring posting types might explain the missing effect of the intervention video on need-supportive communication strategy use. We expect that the effects of the video intervention might have been more pronounced had participants shown stronger engagement and applied the need-supportive communication strategies more frequently in the interpersonal interactions. Interestingly, we found some evidence for an increase in engagement in participants watching the intervention video, even without increased need-supportive communication strategy use (increased number of postings). One possible explanation for this finding could be that the mere expectation of an improved communication climate in the online community stimulated engagement. Nevertheless, the effects were comparably small and might have been stronger and more reliable if the need-supportive communication strategies were applied more frequently in the interpersonal interactions.

Theoretical and Practical Implications

According to SDT (Deci & Ryan, 2000; Ryan et al., 2008; Ryan & Deci, 2017), a more need-supportive communication climate should lead to more autonomous and self-determined motivation, which should, in turn, lead to more effective behavior change. Additionally, it should positively influence behavior-related attitudes, perceived social norms, and self-efficacy, according to the integrated SDT model (Hagger & Chatzisarantis, 2009). Today, there is little research on need support in online communities and social networking sites. However, the results of previous offline randomized controlled trials show that health behavior interventions based on SDT can change perceived need support (Gillison et al., 2019; Ntoumanis et al., 2021). For example, in one SDT-based weight loss trial (Silva et al., 2008), providing a need-supportive environment led to higher perceived need support, autonomous motivation, behavior change, and weight loss, compared to a control group receiving a general health education curriculum (Silva et al., 2010, 2011). Interestingly, increased autonomous motivation for physical activity even spilled over to eating behavior regulation (Mata et al., 2009). Thus, increasing need support may even benefit health behaviors that are not directly targeted in an intervention. A recent meta-analysis showed that interventions to improve the provision of need support to others can be successful across different domains (Su & Reeve, 2011). It is important that future research further examines whether improving perceived need support in online communities and social networking sites leads to successful behavior change.

While short interventions can improve the provision of need support (Su & Reeve, 2011) and a short intervention format is generally promising for intervention delivery to large numbers of people (as typically found in online communities), short videos may not be intense enough to change a person's communication style in a long-term field context. Therefore, future studies could test whether the incorporation of regular refreshers of intervention materials, such as watching the video again or short reminders about the key points, increases the expected effects. Yet another way to improve need-supportive communication strategy uptake and need-supportive communication could be to incentivize a proportion of the users for using the need-supportive communication strategies in their postings, making them peer role models. Relatedly, incentivizing participants for postings has been shown to increase engagement in a Facebook-delivered weight loss intervention (Pagoto et al., 2017). In addition, superusers or content moderators of online communities could receive more intense SDT-based training in need-supportive communication. For example, Inauen et al. (2017) trained and instructed confederate moderators in smartphone-based eating-related social support groups to model and ensure the provision of social support to participants by responding to every posting with supportive messages and posting daily questions.

Strengths and Limitations

One limitation of Study 1 was the highly controlled experimental setting and a relatively homogeneous sample. While this can impact the ecological validity and generalizability of the findings, this controlled setting allowed us to test whether a short intervention video can change communication strategies under ideal conditions.

To address limitations inherent in a controlled experiment, we tested whether effects also applied in a real-world setting with a more heterogeneous sample (Study 2). While mostly women responded to our recruitment ads (e.g., print advertisement and Facebook ads), other characteristics such as age and body mass index substantially varied. Ecological validity was further increased by allowing participants to select their behavioral goals. This better reflects reality, where people usually choose to change a specific behavior, and it ensured that participants selected behavioral domains with room for improvement. The self-selection resulted on the other hand in unbalanced cell sizes for each behavior. In the analyses, we circumvented possible resulting power problems by pooling participants and focusing on goal attainment instead of the behavior itself in separate analyses. Nevertheless, this design feature also resulted in a different number of other active participants in the different forums. To account for this, we controlled for the mean number of other forum members in all analyses. To avoid such disbalance, future studies could focus on one behavior at a time (e.g., physical activity or vegetable intake) or include participants who choose different behaviors in the same forum. A more rigorous approach might be to randomize participants to the different goal behaviors. However, this could undermine participants' motivation.

Study 2 participants had a comparably high rate of dropout to follow-up (863/1400, 61.6%). Surprisingly, there was a higher dropout in the intervention group compared to the control group. One potential reason for this is that it might have been more difficult for participants to apply the need-supportive communication strategies (compared to the more general netiquette rules) in the interpersonal communication, resulting in frustration and study dropout. This idea is indirectly supported by the fact that the use of need-supportive communication strategies was generally very low. While high dropout rates in general are not unusual for internet-based interventions (Eysenbach, 2005; Kelders et al., 2012), the dropout in this study may have been influenced by a low adherence-motivating structure (e.g., without face-to-face appointments, reminders, or content moderators), no delivery of intervention content via the online communities, and the lack of a monetary incentive for study participation. Nevertheless, we recruited even more participants than preregistered, as discussed earlier. Because our intervention also aimed to increase engagement in the context of a mere community-support intervention, we did not include any additional strategies to target engagement. However, since engagement is typically low but important for intervention outcomes, the following strategies for enhancing engagement in interventions involving online communities or social networking sites in general could be helpful: including content moderators or (peer) role models (Inauen et al., 2017; Pagoto et al., 2017), increasing posting frequency, using call-to-actions in postings (Pagoto et al., 2016; Waring et al., 2018), using a combination of text, pictures, and videos in postings (Cavallo et al., 2020; Waring et al., 2018), dependent on the possibilities of the specific platform, and also creating a positive and supportive communication climate, as we intended with our intervention.

One further limitation of Study 2 was the use of self-report questionnaires for fruit and vegetable intake and physical activity. For physical activity, assessments with questionnaires can result in lower reliability or validity and lead to systematic overestimation (Helmerhorst et al., 2012; Prince et al., 2008) or underestimation of physical activity (Prince et al., 2008). Yet, self-reports with validated measures such as in our study are efficient, affordable, and can be easily administered in online forums. While accelerometers are not subject to recall bias, they can be very costly (Lee & Shiroma, 2013), not equally suitable for all kinds of activity (e.g., swimming, bicycling), and can produce different results depending on the model or how they are worn. Thus, they are difficult to use in an online-recruited study such as ours. Assessments of eating behavior such as food frequency questionnaires or 24-hour recall methods often rely on subjective measures that can lead to recall bias (Naska et al., 2017). To improve reliability of the fruit and vegetable intake assessment in our study, we provided written examples of portion sizes and pictures. Importantly, self-report is the most feasible method in online studies. Nevertheless, future studies could consider new assessment methods such as photo-based recording (König et al., 2021) that may increase usability and reduce participant burden. Importantly, while absolute levels of target behaviors may be biased in our study, the goal attainment scores are informative, because both scores were measured with the same method within the same person, resulting in the same bias (e.g., systematic over- or underestimation) at every measurement point.

For Study 2, we created new online communities explicitly for our participants. Additional analyses, however, suggested that most participants who completed the follow-up questionnaire would prefer to join a private Facebook group (vs. a forum). When conducting interventions involving social networking sites, one of the big questions is whether to create a social networking site and online community from scratch or to use already established ones such as Facebook, Instagram, Twitter, or Reddit. In this decision, there is usually a trade-off between privacy and usability. Creating a social networking site from scratch for research purposes has the huge advantage that the data belongs to the researchers. There is no third-party company involved whose privacy guidelines must be applied. Furthermore, there is always full access to the necessary data. In addition, there are several challenges in using commercial applications for research (Arigo et al., 2019; Pagoto et al., 2016). For example, collected data typically belongs to the company and can be used for other purposes such as advertisement. It is essential to inform participants about the existing privacy guidelines and who has access to what data. Another challenge is limited data access for researchers, which could even change during the project because application programming interface permissions and restrictions frequently change. Advantages of commercial social networking site applications include their high usability, wide distribution, and integration into smartphones, thus allowing them to conveniently reach a large proportion of the population (Arigo et al., 2019). In line with this, one systematic review showed that interventions using private Facebook groups had the highest levels of engagement and acceptance (Klassen et al., 2018). Fortunately, there have been efforts to develop ethical standards for social networking site and social media research to protect user privacy, although they are still mostly uncoordinated (Arigo et al., 2019; Pagoto & Nebeker, 2019).

Conclusions

Social networking sites and online communities have a huge potential for supporting behavior change, but user engagement is typically low, and the quality of interpersonal communication and interaction needs to be improved to maximize effects. According to SDT, promoting need-supportive communication could positively influence both user engagement and behavior change. A brief video intervention could serve as a low-cost intervention to improve need-supportive communication. However, its applicability and effectiveness in more ecologically valid contexts need further evaluation. Complementary strategies such as training super-users or content moderators in need-supportive communication may improve strategy uptake and intervention effects. Future intervention studies should incorporate additional strategies for improving user engagement to further stimulate natural interpersonal interaction among users.

Abbreviations

ISCED: International Standard Classification of Education

ISCO: International Standard Classification of Occupations

SDT: Self-Determination Theory

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Disclosure Statement

The authors report no conflict of interest.

Ethics Statement

Study 1 was conducted in accordance with the Declaration of Helsinki. Study 2 was approved by the Institutional Review Board of the University of Mannheim (11/2020).

CRediT Author Statement

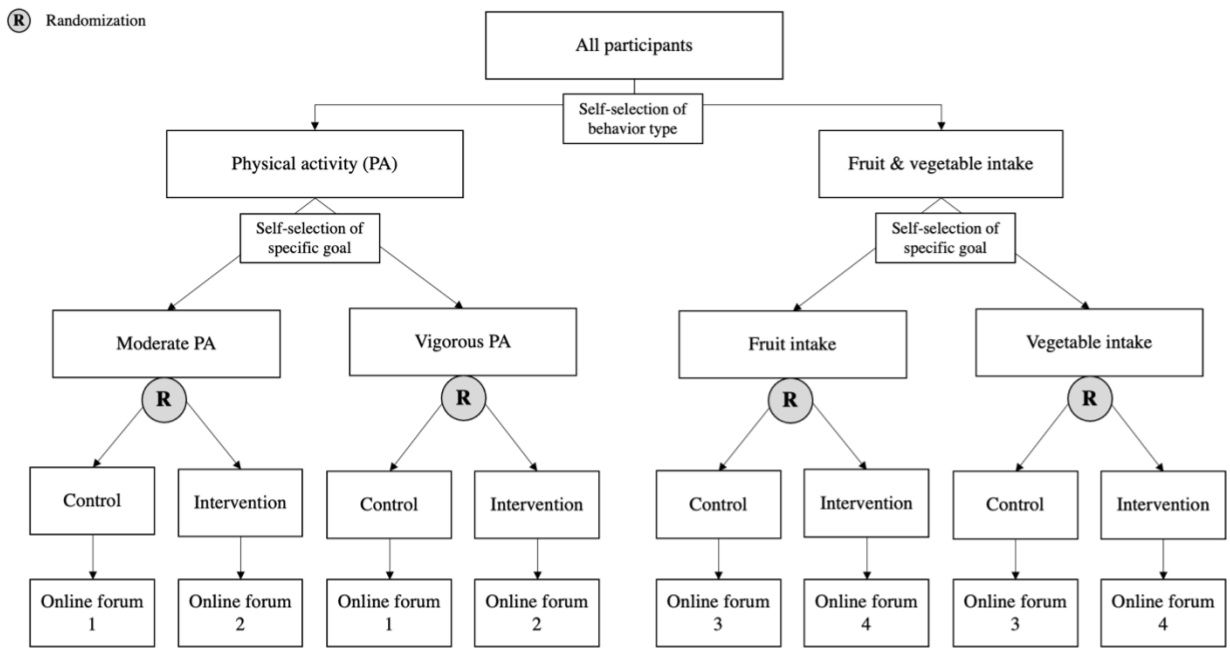
Michael Kilb: Conceptualization, Methodology, Investigation, Formal analysis, Visualization, Data curation, Project administration, Writing - Original draft preparation, Reviewing, and Editing. **Oliver Dickhäuser:** Conceptualization, Writing - Reviewing and Editing. **Jutta Mata:** Conceptualization, Methodology, Resources, Funding acquisition, Project administration, Writing – Reviewing and Editing, Supervision.

Data Availability Statement

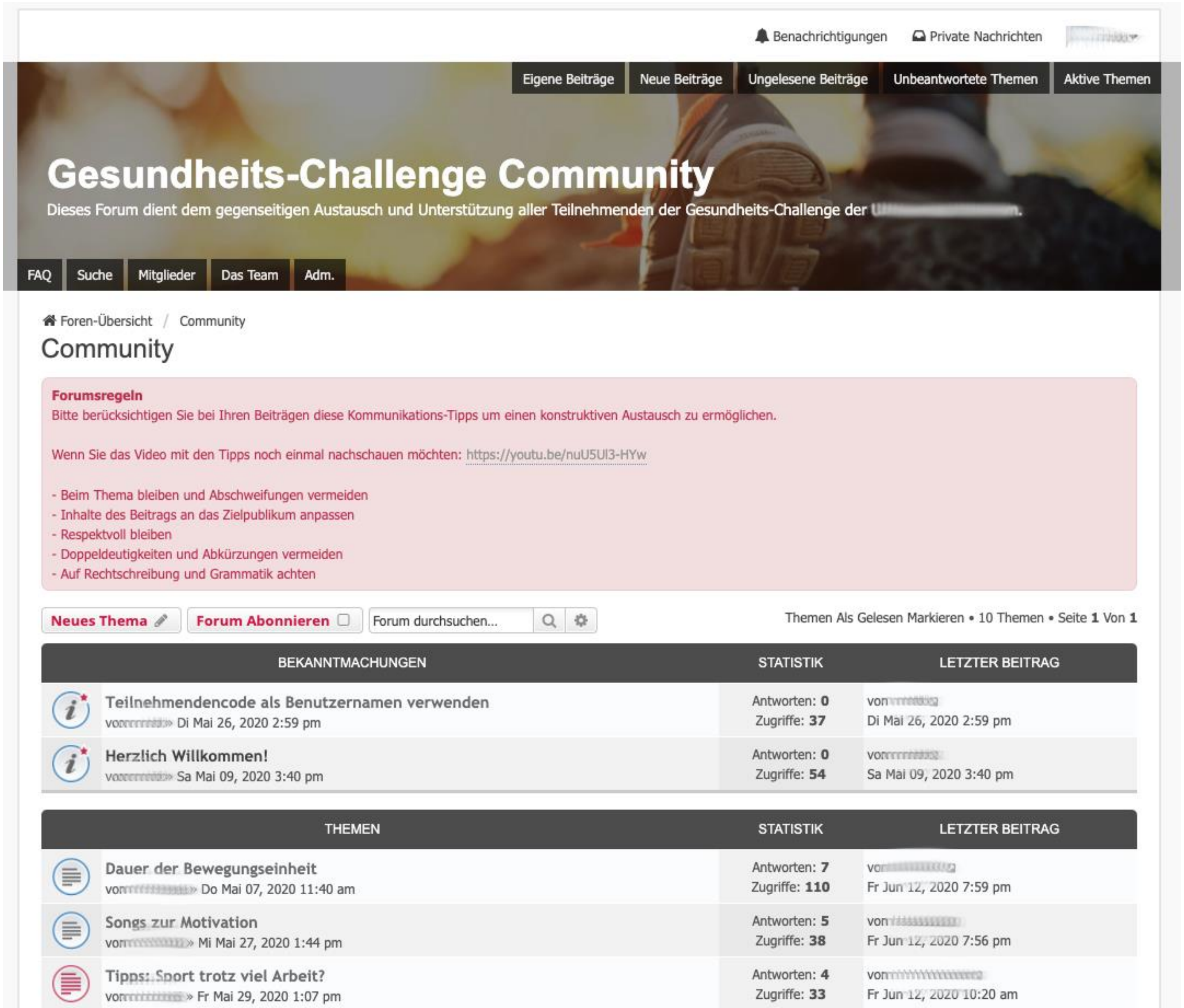
The data that support the findings of this study are openly available in the Open Science Framework at https://osf.io/xsb2e/.

Appendix

Appendix A: Randomization Scheme and Forum Structure of the 4 Online Communities in Study 2.



Appendix B: Screenshot of 1 of the 4 Online Communities (Physical Activity Behavior and Control Condition) in Study 2.



Appendix C: Interrater Agreement for Variables in Study 1 and Study 2

Table C1

Interrater Agreement for Variables Coded in Written Responses (Study 1) and Postings of Participants in the Online Communities (Study 2)

Variable	Agreement (%)	Krippendorff's α[a]	*N*
Study 1			
Providing options and offering choices	90.6	0.80	170
Using autonomy-supportive language	76.5	0.51	170
Acknowledging successes	95.3	0.77	170
Identifying barriers and solutions	88.8	0.76	170
Acknowledging negative and positive feelings	78.2	0.56	170
Offering contact	94.1	0.79	170
Study 2			
Providing options and offering choices	96.4	0.80	166
Using autonomy-supportive language	93.4	0.39	166
Acknowledging successes	95.8	0.74	166
Identifying barriers and solutions	97.0	0.27	166
Acknowledging negative and positive feelings	94.0	0.82	166
Offering contact	96.4	0.77	166
Providing solutions	94.6	0.83	166
Reference to other posting	86.1	0.77	166
Self-monitoring of behavior in posting	94.6	0.87	166
Goal setting in posting	92.2	0.80	166
Organizational posting	98.2	0.74	166
Introduction in posting	97.0	0.92	166
Problem description in posting	91.0	0.81	166

Note. N denotes the number of postings in the calculation of the interrater agreement.

[a]Estimated population rate of observations (e.g., 1) based on the coded data influences Krippendorff α estimates, whereby higher rates punish Krippendorff's α calculations because more agreements could be due to chance, which can lead to high percentage agreement but lower Krippendorff's α estimates.

Appendix D: Baseline Characteristics and Participant Differences in the Different Self-Selected Goal Types (Study 2).

Table D1

Baseline Characteristics and Participant Differences in the Different Self-Selected Goal Types (Study 2)

Variable	Goal type				p	Differences[a]
	Fruit intake (FI; n = 35)	Vegetable intake (VI; n = 140)	Moderate physical activity (MPA; n = 151)	Vigorous physical activity (VPA; n = 211)		
Demographic characteristics						
Age (years), M (SD)	43.11 (12.11)	45.22 (10.51)	44.10 (11.63)	39.84 (11.41)	<.001	VI > VPA MPA > VPA
Body mass index (kg/m^2), M (SD)	27.89 (6.53)	29.05 (6.29)	30.63 (7.28)	26.82 (5.79)	<.001	VI > VPA MPA > VPA
Female, n (%)	35 (100.0)	136 (97.1)	147 (97.4)	207 (98.1)	.383	
Educational attainment, n (%)					.518	
Low (ISCED 0–2)	0 (0.0)	2 (1.4)	0 (0.0)	3 (1.4)		
Medium (ISCED 3 & 4)	18 (51.4)	60 (42.9)	78 (51.7)	90 (42.7)		
High (ISCED 5–8)	17 (48.6)	78 (55.7)	73 (48.3)	117 (55.5)		
NA	0 (0.0)	0 (0.0)	0 (0.0)	1 (0.5)		
Occupational skill level, n (%)					N/A[b]	
Low (ISCO skill level 1, e.g., unskilled worker)	2 (5.7)	4 (2.9)	15 (9.9)	19 (9.0)		
Medium (ISCO skill level 2, e.g., skilled worker)	16 (45.7)	58 (41.4)	62 (41.1)	73 (34.6)		
High (ISCO skill level 3 & 4, e.g., higher skilled worker/academic job)	17 (48.6)	78 (55.7)	73 (48.3)	118 (55.9)		
NA	0 (0.0)	0 (0.0)	1 (0.7)	1 (0.5)		
Professional position, n (%)					N/A[b]	
Full-time employment	15 (42.9)	68 (48.6)	77 (51.0)	100 (47.4)		

Table D1

Baseline Characteristics and Participant Differences in the Different Self-Selected Goal Types (Study 2)

Variable	Goal type				*p*	Differences[a]
	Fruit intake (FI; *n* = 35)	Vegetable intake (VI; *n* = 140)	Moderate physical activity (MPA; *n* = 151)	Vigorous physical activity (VPA; *n* = 211)		
Part-time employment	10 (28.6)	41 (29.3)	36 (23.8)	60 (28.4)		
Students (higher education)	5 (14.3)	9 (6.4)	11 (7.3)	23 (10.9)		
Other	5 (14.3)	22 (15.7)	27 (17.9)	28 (13.3)		
Outcomes (baseline)						
Fruit intake (no. portions), *M* (*SD*)	0.91 (0.82)	1.37 (0.90)	1.54 (0.96)	1.67 (1.02)	<.001	FI < MPA
						FI < VPA
						VI < VPA
Vegetable intake (no. portions), *M* (*SD*)	1.48 (1.17)	1.49 (1.13)	2.15 (1.49)	2.20 (1.31)	<.001	FI < MPA
						FI < VPA
						VI < MPA
						VI < VPA
Moderate physical activity (min/week), *M* (*SD*)	203.89 (209.06)	255.13 (199.84)	144.59 (146.67)	227.01 (203.29)	<.001	VI >MPA
						MPA < VPA
Vigorous physical activity (min/week), *M* (*SD*)	34.90 (38.83)	37.43 (36.81)	22.71 (32.75)	36.89 (34.95)	.001	VI > MPA
						MPA < VPA
Autonomous motivation, *M* (*SD*)	3.76 (0.92)	4.01 (0.87)	3.91 (0.94)	3.85 (1.05)	.350	
Controlled motivation, *M* (*SD*)	3.98 (1.82)	4.30 (1.61)	4.01 (1.35)	4.15 (1.51)	.385	
Instrumental attitude, *M* (*SD*)	7.00 (0.00)	7.00 (0.00)	7.00 (0.00)	7.00 (0.00)	N/A[c]	
Experiential attitude, *M* (*SD*)	5.63 (1.07)	5.67 (1.05)	5.46 (1.23)	5.44 (1.13)	.267	
Self-efficacy, *M* (*SD*)	3.84 (0.73)	3.86 (0.68)	3.76 (0.67)	3.78 (0.67)	.583	

Table D1

Baseline Characteristics and Participant Differences in the Different Self-Selected Goal Types (Study 2)

Variable	Goal type				*p*	Differences[a]
	Fruit intake (FI; *n* = 35)	Vegetable intake (VI; *n* = 140)	Moderate physical activity (MPA; *n* = 151)	Vigorous physical activity (VPA; *n* = 211)		
Perceived descriptive norms, *M* (*SD*)	3.76 (0.68)	3.95 (0.68)	4.03 (0.69)	3.83 (0.66)	.015	MPA > VPA
Perceived injunctive norms, *M* (*SD*)	3.87 (0.75)	4.02 (0.83)	4.11 (0.79)	3.85 (0.76)	.012	MPA > VPA
Other						
Number of other active community members, *M* (*SD*)	94.47 (48.10)	98.77 (44.88)	198.45 (94.46)	200.89 (93.56)	<.001	FI < MPA FI < VPA VI < MPA VI < VPA
Omnivore diet, *n* (%)	27 (77.1)	95 (67.9)	85 (56.3)	131 (62.1)	.060	
Weight-loss diet, *n* (%)	4 (11.4)	36 (25.7)	42 (27.8)	41 (19.4)	.080	
Fructose intolerance, *n* (%)	0 (0.0)	6 (4.3)	10 (6.6)	7 (3.3)	.309	

Note. The 4 self-selected goal type conditions were compared with analyses of variance (means) or Fisher's exact tests (proportions), whereby *P* shows the overall significance of the comparisons. ISCED = International Standard Classification of Education. ISCO = International Standard Classification of Occupations. NA = Missing values. N/A = Not applicable.

[a]The column Differences shows the statistically significant Tukey-adjusted pairwise contrasts.

[b]Not applicable because test statistic could not be calculated.

[c]Not applicable because the distribution of the variable was highly skewed and there was little variance; after winsorization, all participants scored the highest value on the scale (7).

Appendix E: Full Mixed Models for the Outcome Variables in Study 2

Table E1

Mixed Models for the Primary Outcomes of Study 2 at Follow-Up

Effects	Number of need-supportive communication strategies[a]			Perceived need-support			Goal attainment			Subjective forum visit frequency			Number of postings[a]			Number of logins[a]		
	B	*SE*	*p*	*B*	*SE*	*p*	*B*	*SE*	*p*	*B*	*SE*	*p*	*B*	*SE*	*p*	*B*	*SE*	*p*
Fixed effects																		
(Intercept)	0.41	0.21	.056	2.65	0.44	<.001	1.43	0.32	<.001	2.19	0.47	<.001	-0.34	0.65	.599	0.70	0.34	.040
Condition (intervention)	-0.01	0.05	.778	0.05	0.22	.840	0.11	0.09	.260	0.24	0.13	.101	0.31	0.15	.046	0.10	0.08	.250
Age	-0.01	0.00	.035	-0.01	0.00	.045	-0.00	0.00	.320	-0.00	0.01	.857	0.01	0.01	.328	0.00	0.00	.962
Body mass index	-0.00	0.00	.861	-0.01	0.01	.250	-0.00	0.01	.538	0.01	0.01	.285	-0.01	0.01	.691	0.00	0.01	.880
Fruit intake (baseline)	0.01	0.03	.831	-0.02	0.06	.706	0.04	0.04	.369	0.00	0.07	.998	0.01	0.08	.915	0.08	0.05	.101
Vegetable intake (baseline)	0.01	0.02	.514	-0.04	0.04	.373	0.04	0.03	.169	-0.05	0.05	.314	-0.01	0.06	.899	-0.05	0.04	.167
Moderate physical activity	-0.00	0.00	.895	-0.00	0.00	.411	-0.00	0.00	.380	0.00	0.00	.587	0.00	0.00	.716	-0.00	0.00	.603
Vigorous physical activity (baseline)	0.00	0.00	.108	0.00	0.00	.138	-0.00	0.00	.439	0.00	0.00	.409	0.00	0.00	.398	0.00	0.00	.068
Descriptive norms (baseline)	0.03	0.05	.591	0.18	0.10	.081	-0.08	0.07	.266	-0.18	0.11	.099	-0.22	0.16	.162	-0.03	0.08	.725
Injunctive norms (baseline)	-0.01	0.05	.765	0.02	0.09	.863	0.05	0.06	.464	0.09	0.09	.339	0.23	0.15	.111	0.04	0.07	.566
Number of other active forum members	0.00	0.00	.142	0.00	0.00	.169	-0.00	0.00	.961	0.00	0.00	.003	0.00	0.00	<.001	0.00	0.00	<.001
Random effects																		
Residual variance σ^2				0.74			0.77			1.70								
Intercept variance $_{participant}$	0.00			-			-			-			-			-		

Intercept variance $_{forum}$	0.00	0.08	0.00	0.01	0.00	0.00
Slope variance (condition) $_{forum}$	0.00	N/A[b]	0.00	0.01	0.00	0.00
Slope variance (condition) $_{participant}$	0.00	-	-	-	-	-
n $_{forum}$	8	8	8	8	8	8
n $_{participant}$	274	318	537	537	537	537
N	1130	318	537	537	537	537

Note. Analyses were conducted with winsorized values and the effect of the intervention condition (dummy coded) is controlled for baseline values of the outcome, variables with baseline differences between completers and noncompleters, and between the 4 self-selected goal types, that is age, fruit intake, vegetable intake, moderate physical activity, vigorous physical activity, body mass index, perceived descriptive norms, perceived injunctive norms, and the mean number of active forum users. The raw values were used for the poisson-distributed count variables number of logins and number of postings.

[a]For the number of need-supportive communication strategies, number of postings and the number of logins, the intervention's effect is multiplicative ($e^{estimate}$) rather than additive since the models use a log-link-function for the count data. *M* (*SE*) represents the raw values because estimated marginal means could not be derived for nonlinear mixed models.

[b]N/A = not applicable (random effect could not be specified because of convergence problems). NA = not applicable.

Table E2

Mixed Models for the Secondary Outcomes of Study 2 at Follow-Up

Effects	Autonomous motivation			Controlled motivation			Self-efficacy			Experiential attitude			Instrumental attitude			Perceived descriptive norms			Perceived injunctive norms			Perceived social support		
	B	*SE*	*p*	*B*	*SE*	*p*	*B*	*SE*	*p*	*B*	*SE*	*p*	*B*	*SE*	*p*	*B*	*SE*	*p*	*B*	*SE*	*p*	*B*	*SE*	*p*
Fixed effects																								
(Intercept)	2.17	0.36	<.001	2.72	0.56	<.001	0.72	0.26	.007	1.92	0.43	<.001	6.09	0.16	<.001	3.50	0.26	<.001	2.56	0.36	<.001	2.81	0.50	<.001
Condition (intervention)	-0.03	0.10	.795	-0.11	0.13	.384	-0.01	0.06	.915	0.07	0.16	.669	0.06	0.05	.319	0.00	0.10	.977	0.09	0.10	.389	0.05	0.22	.813
Age	-0.00	0.00	.226	0.00	0.01	.512	0.00	0.00	.642	-0.01	0.00	.239	0.00	0.00	.040	-0.00	0.00	.416	-0.01	0.00	.024	-0.01	0.01	.018
Body mass index	-0.01	0.01	.300	-0.02	0.01	.100	0.01	0.00	.029	-0.00	0.01	.610	-0.00	0.00	.414	-0.00	0.00	.661	0.01	0.01	.186	-0.01	0.01	.342
Fruit intake (baseline)	-0.00	0.05	.918	0.05	0.07	.548	-0.01	0.03	.672	0.07	0.05	.196	0.00	0.02	.897	0.05	0.04	.168	0.02	0.05	.745	-0.02	0.07	.763
Vegetable intake (baseline)	0.01	0.04	.678	0.00	0.06	.999	0.05	0.03	.041	0.04	0.04	.328	0.02	0.02	.273	-0.03	0.03	.196	0.04	0.04	.285	-0.01	0.05	.853
Moderate physical activity (baseline)	-0.00	0.00	.126	-0.00	0.00	.562	0.00	0.00	.471	0.00	0.00	.320	-0.00	0.00	.478	-0.00	0.00	.073	-0.00	0.00	.797	-0.00	0.00	.424
Vigorous physical activity (baseline)	0.00	0.00	.434	0.00	0.00	.132	0.00	0.00	<.001	0.01	0.00	<.001	0.00	0.00	.018	0.00	0.00	.447	0.00	0.00	.137	0.00	0.00	.291
Perceived descriptive norms (baseline)	0.20	0.08	.015	-0.09	0.13	.477	0.04	0.06	.536	0.03	0.09	.755	0.05	0.04	.166	0.02	0.06	.690	-0.12	0.09	.180	0.15	0.11	.179
Perceived injunctive norms (baseline)	-0.02	0.07	.763	0.05	0.11	.623	0.06	0.05	.213	-0.01	0.08	.932	0.04	0.03	.218	0.11	0.05	.026	0.34	0.07	<.001	0.05	0.10	.614
Number of other active forum members	-0.00	0.00	.917	-0.00	0.00	.706	-0.00	0.00	.554	-0.00	0.00	.204	-0.00	0.00	.529	-0.00	0.00	.211	-0.00	0.00	.180	0.00	0.00	.101
Autonomous motivation (baseline)	0.40	0.04	<.001																					
Controlled motivation (baseline)				0.45	0.04	<.001																		
Self-efficacy (baseline)							0.46	0.05	<.001															
Experiential attitude (baseline)										0.58	0.04	<.001												
Instrumental attitude (baseline)													NA[b]											
Random effects																								

Residual variance σ2	0.91	2.24	0.46	1.12	0.20	0.49	1.03	0.88
Intercept variance $_{forum}$	0.00	0.00	0.00	0.03	0.00	0.02	0.01	0.09
Slope variance (condition) $_{forum}$	0.01	0.00	0.00	N/A[a]	0.00	0.02	0.01	0.06
n $_{forum}$	8	8	8	8	8	8	8	8
N	537	537	537	537	537	537	537	290

Note. Analyses were conducted with winsorized values and the effect of the intervention condition (dummy coded) is controlled for baseline values of the outcome, variables with baseline differences between completers and noncompleters, and between the 4 self-selected goal types, that is age, fruit intake, vegetable intake, moderate physical activity, vigorous physical activity, body mass index, perceived descriptive norms, perceived injunctive norms, and the mean number of active forum users. The raw values were used for the poisson-distributed count variables number of need-supportive communication strategies, number of logins and number of postings.

[a]N/A = not applicable (random effect could not be specified because of convergence problems).

[b]NA = not available because predictor was dropped from the model because of rank deficiency.

Appendix F: Intervention Effects on the Different Health Behaviors Separately for the Different Goal Types

Table F1

Intervention Effects on Health Behaviors and Estimated Marginal Means for the Intervention and Control Condition From Mixed Models (Study 2)

Variable	Estimated marginal mean (*SE*)		Intervention effect estimate *B* (*SE*)[a]	*p*
	Control group	Intervention group		
Health behavior				
Fruit intake, no. of portions (*n* = 35)	1.67 (0.31)	2.39 (0.89)	0.72 (0.94)	.564
Vegetable intake, no. of portions (*n* = 140)	1.95 (0.13)	2.37 (0.14)	0.42 (0.15)	.005
Moderate physical activity, min/week (*n* = 151)	204.40 (24.08)	214.79 (22.09)	10.39 (31.41)	.760
Vigorous physical activity, min/week (*n* = 211)	105.21 (8.62)	105.10 (9.26)	-0.11 (11.67)	.993

Note. Analyses were conducted with winsorized values and the effect of the intervention condition (dummy coded) is controlled for baseline values of the outcome and variables with baseline differences between both conditions, that is controlled motivation for fruit intake and moderate physical activity, and perceived descriptive and perceived injunctive norms for moderate physical activity.

[a]Differences between estimated marginal means and estimates originate from rounding.

Table F2

Mixed Models for Different Health Behaviors at Follow-Up Separately by Goal Type (Sub-Group Analysis)

Effects	Fruit intake			Vegetable intake			Moderate physical activity			Vigorous physical activity		
	B	*SE*	*p*	*B*	*SE*	*p*	*B*	*SE*	*p*	*B*	*SE*	*p*
Fixed effects												
(Intercept)	0.09	0.54	.869	1.03	0.13	<.001	108.66	94.66	.254	54.04	9.99	<.001
Condition (intervention)	0.72	0.94	.564	0.42	0.15	.005	10.39	31.41	.760	-0.11	11.67	.993
Fruit intake (baseline)	0.80	0.17	<.001									
Vegetable intake (baseline)				0.62	0.07	<.001						
Moderate physical activity (baseline)							0.75	0.09	<.001			
Vigorous physical activity (baseline)										1.39	0.17	<.001
Controlled motivation (baseline)	0.22	0.09	.021				2.92	10.55	.782			
Perceived descriptive norms (baseline)							-13.36	24.86	.592			
Perceived injunctive norms (baseline)							7.27	21.60	.737			
Random effects												
Residual variance σ^2	0.67			0.73			28487.9			7142		
Intercept variance $_{\text{forum}}$	0.08			0.00			274.2			0.00		
Slope variance (condition) $_{\text{forum}}$	0.94			0.00			274.2			N/A[a]		
n_{forum}	4			4			4			4		
N	35			140			151			211		

Note. Analyses were conducted with winsorized values and the effect of the intervention condition (dummy coded) is controlled for baseline values of the outcome and variables with baseline differences between both conditions, that is controlled motivation for fruit intake and moderate physical activity, and perceived descriptive and perceived injunctive norms for moderate physical activity. [a]N/A = not applicable (random effect could not be specified because of convergence problems).

5. General Discussion

In the following, I will provide an overview of the main results of the three manuscripts and integrate the implications from the theoretical perspective and the results from the four conducted studies. Furthermore, I discuss the theoretical implications and integrate them into the existing literature. Subsequently, I will discuss the strengths and limitations of the three manuscripts and outline implications for future research and practice. I end with a general conclusion that can be drawn from this dissertation.

5.1. Summary of Results

In Manuscript 1 (section 2), my co-author and I outlined a conceptual framework for a better understanding of health-related social media effects. We suggest that social media use can be described on four factors essential for determining mechanisms of action in health-related social media effects: (1) the social media *communication features* used (e.g., one-click-reactions, comments, postings, or messages), (2) the *contents* which are communicated via those features (e.g., postings of food pictures, postings about barriers for behavior change), the *directionality of interaction* (e.g., active contribution to postings vs. passive exposure to postings) and (4) *engagement* (e.g., total amount or intensity of social media use). Those factors cannot be considered entirely independent from each other as social media communication is highly interactive (Valkenburg, 2017; Valkenburg et al., 2016). For example, when people actively post about a specific topic (e.g., their consumed foods in the form of pictures), they are also passively exposed to social feedback in the form of one-click reactions and comments in response to these postings. The combination of features, contents, and involvement determines which behavior change techniques (Knittle et al., 2020; Michie et al., 2013; Teixeira et al., 2020) might be enacted or triggered when using social media. Behavior change techniques are the active ingredients in (social media-based) health behavior interventions (Michie et al., 2013; Simeon et al., 2020), and we suggest that they are also the active ingredients in naturally occurring health behavior-related social media use (cf. Myneni et al., 2016). Drawing on research from the behavior change literature, particularly the experimental medicine approach to health behavior change (Nielsen et al., 2018; Sheeran et al., 2017), we argued that the enacted or triggered behavior change techniques influence health behavior change via changes in psychosocial determinants of health behaviors. For example, the technique “information about other’s approval” could change perceived injunctive social norms (Fishbein & Ajzen, 2011; Higgs & Thomas, 2016), and “social support” and “social reward” provided through likes and comments could change perceived social-support (de la Peña & Quintanilla, 2015). Some theoretical constructs and meanings and how we share, access, and process information are assumed to differ in online and offline environments (Marsh & Rajaram, 2019; McFarland & Ployhart, 2015). However, it is unclear how this impacts how health behavior-related social media effects might differ from offline social influences on health behaviors. We argued that underlying mechanisms of action are likely comparable and complex. Instead, social media increases the total amount of social influences on health behaviors and intensifies them. Potential reasons discussed are the omnipresence of social media, the fast adaptability of social media environments in response to user behavior and curation algorithms, reinforcing echo chambers, and homophile networks and social identification processes.

In Manuscript 2 (section 3), my colleagues and I experimentally examined the causal effects of healthy eating-related postings (regarding fruit and vegetable intake) on the eating behavior of both senders and receivers without a behavior change goal (Study 1) and of senders with an eating behavior change goal (Study 2), as well as different psychosocial determinants of eating behavior. We compared the effects of public posting about fruit and vegetable intake (representing a form of public self-monitoring of intake) to the effects of public posting about a control topic (Study 1) and private self-monitoring of intake (both studies). We also examined the temporal dynamics of eating-related social media effects. The conducted studies and examined determinants are based on the reasoned action approach (Fishbein & Ajzen, 2011), including a normative approach to social influences on eating behavior (Higgs & Thomas, 2016), and an extension by the literature on social media-based health behavior interventions (Petkovic et al., 2021; Simeon et al., 2020). Eating-related posting benefitted senders' and network members' healthy eating (Study 1): Senders who posted about their fruit and vegetable intake maintained their intake (compared to a decrease in senders who posted about a control topic and simultaneously privately self-monitored intake). Furthermore, network members (receivers) whose study partners posted about fruit and vegetable intake increased their intake (compared to no change in the control group). However, these trends only emerged in the post-hoc comparisons, potentially due to low power caused by the relatively small sample size (cf. Lakens & Evers, 2014). Additionally, public posting about fruit and vegetable intake via social media supported the increase of intake in senders with an intake increase goal but not more strongly than "private posting", that is, private picture-based self-monitoring of intake (Study 2). Intentions to eat fruit and vegetables tended to increase more strongly in senders who posted publicly (compared to privately) about their intake via social media (Study 2). Furthermore, there was an increase in perceived social support of senders who publicly posted about their fruit and vegetable intake (but not in senders who posted about a control topic) in Study 1. In contrast, there was no stronger increase in perceived social support in senders who posted publicly about their fruit and vegetable intake in Study 2. Across both studies, there was little evidence for the expected stronger increases in the other examined psychosocial determinants of eating behavior (i.e., attitudes, perceived social norms, self-efficacy, and goal commitment). There were also no indirect effects of publicly posting about fruit and vegetable intake on intake via changes in the psychosocial determinants in both studies. Regarding the temporal dynamics of eating-related social media effects, there were some of the expected positive dose-response relationships between *intra*individual variations in daily eating-related social media activities and daily eating behavior and psychosocial determinants. More specifically, we found in both studies that on days on which senders used social media more than usual, they reported higher fruit and vegetable intake (even when controlling for the daily number of postings). Furthermore, on days on which senders and network members used social media more than usual for communication related to senders' postings, they reported higher perceived social support (both studies). In Study 2, we found a comparable positive dose-response relationship with daily goal commitment (but also an unexpected negative association with self-efficacy). Additionally, there were the expected positive dose-response relationships between the daily number of intake-related postings with daily fruit and vegetable intake and intentions, instrumental and experiential attitudes, goal commitment, and self-efficacy. That is, on days on which senders posted more intake-related postings than usual, they reported higher intake, intentions, goal commitment, self-efficacy, and more positive instrumental and experiential attitudes. In sum, we found initial but mixed evidence for causal effects of eating-related social media postings on eating behavior and perceived social support but not on the other examined mechanisms. The examined psychosocial determinants did not explain the potential effects on eating behavior change (see section 5.2.4. for possible reasons). Daily eating-related social media activities were associated with daily eating behavior and psychosocial determinants within-person.

In Manuscript 3 (section 4), my colleagues and I examined the importance of communication *quality* (operationalized as need-support provision; Ntoumanis et al., 2017) in social media communication via social media postings for health behavior change. We experimentally tested whether the effectiveness of a social media-based health behavior change intervention (utilizing a forum-based online support community) could be increased through a short video intervention based on self-determination theory (Deci & Ryan, 2000). The intervention video contained information about need-supportive communication strategies (2 strategies addressing each of the three basic needs for autonomy, relatedness, and competence) that can be applied in social media communication. The study and the underlying theoretical model are based on self-determination theory (Deci & Ryan, 2000; Ryan et al., 2008) and the integrated model of self-determination theory and the reasoned action approach (Hagger & Chatzisarantis, 2009, 2012). As expected, the use of need-supportive communication strategies in written responses to fictive social media postings increased in participants who viewed the intervention video (but not in participants who viewed the control video about general netiquette rules) both immediately and one week after viewing the video (Study 1). We further experimentally tested whether these positive effects would translate to need-supportive communication strategy use in social media postings in a real-world setting (Study 2). We expected a successful application of the strategies in the postings and, in turn, higher perceived need-support, goal attainment (regarding health behavior change), and participant engagement in participants who viewed the intervention video (compared to participants who viewed the control video). Additionally, we expected higher autonomous motivation, self-efficacy, perceived social support, and more positive perceived social norms and attitudes. The results did not support most of the hypotheses: There were no effects on goal attainment, perceived need-support, autonomous motivation, perceived social norms, attitudes, and self-efficacy. We found effects on participant engagement (higher objective number of postings and subjective forum visit frequency, but not a higher objective number of logins). The null effects on goal attainment, perceived need-support, autonomous motivation, perceived social norms, attitudes, and self-efficacy could be explained by a missing effect on the use of need-supportive communication strategies in the forum postings in the first place. This could be due to the (a) already high goal attainment of both groups (as the need-supportive communication strategies aimed at supporting participants with behavior change struggles), a (b) misfit of the strategies to some posting types (e.g., mere self-monitoring postings without further meaningful interaction with other participants which represented one-fourth of postings), and (c) a generally low engagement in the forum. Because we did not find effects on the most proximal outcomes, need-supportive communication strategy use and perceived-need-support, we did not test the complete path model assuming indirect effects (cf. Hagger & Chatzisarantis, 2009) of the video intervention on goal attainment via perceived need-support, autonomous motivation, and the constructs from the reasoned action approach. In a nutshell, we found persistent effects of the developed video intervention on need-supportive communication strategy use in a laboratory setting. Still, the effects did not translate in a real-world setting.

5.2. Integration of Results and Theoretical Implications

I investigated health-related social media effects from different but complementary perspectives in the three manuscripts. In Manuscript 1 (see section 2), I provided a theoretical perspective on *when* and *how* health-related social media effects might occur by outlining an integrative conceptual framework for a better understanding of these effects based on psychological and behavioral theories and a detailed look at social media use. Manuscripts 2 and 3 (see sections 3 and 4) complement this theoretical approach by empirically examining the causal effects of specific types of health-related social media use on health behavior change and psychosocial determinants of health behaviors that might mediate effects on behavior. Within the two empirical manuscripts, I referred to the developed framework and relied on empirically supported (Chan et al., 2020; McEachan et al., 2016; Ntoumanis et al., 2021; Sheeran et al., 2016) health behavior theories and models. The three manuscripts work hand in hand to close several research gaps in the literature on health-related social media effects and provide a comprehensive understanding of *whether*, *when*, and *how* health-related social media use might influence health behaviors.

5.2.1. Whether, When, and How Social Media Use Influences Health Behaviors – Moving Beyond Active and Passive Social Media Use

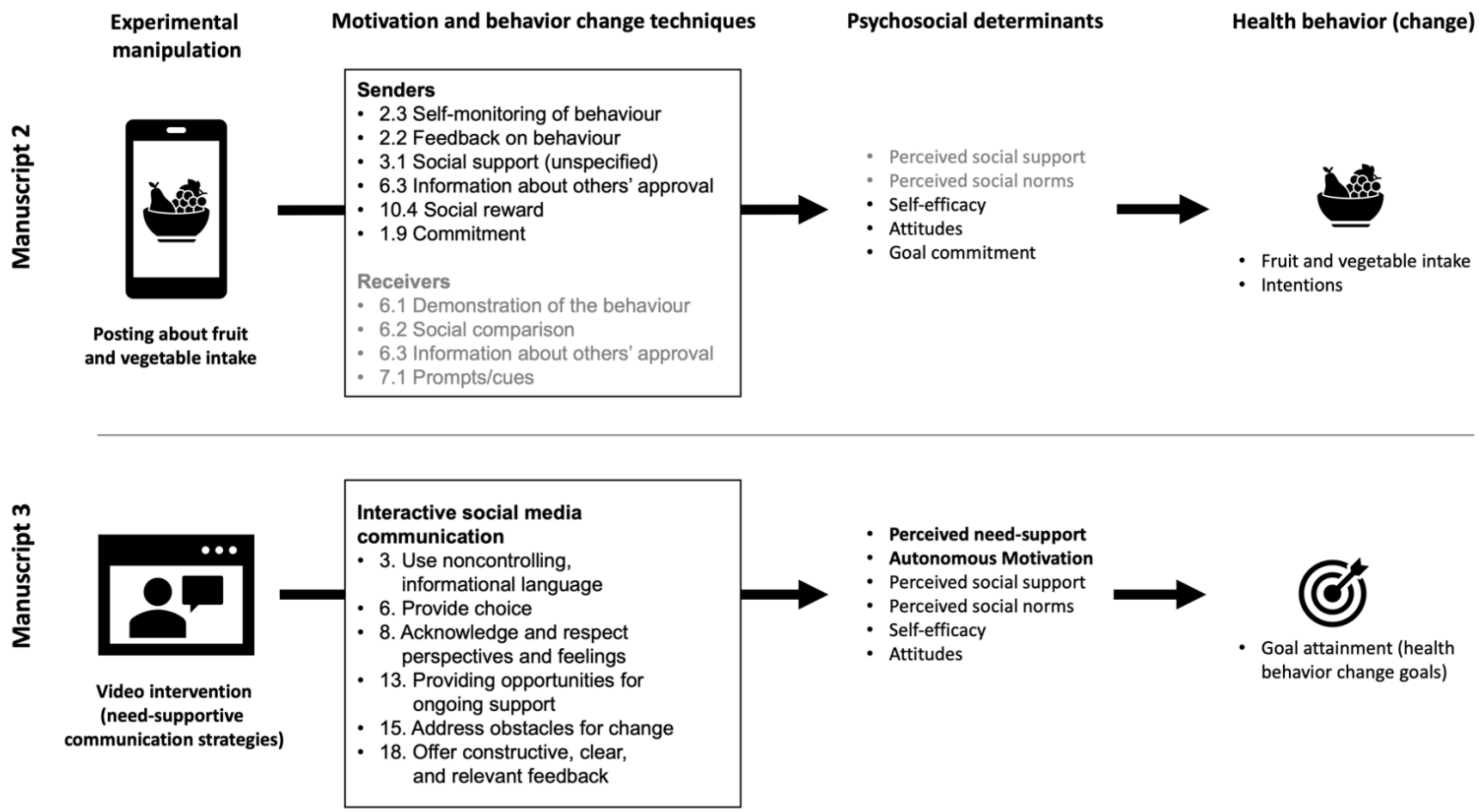
The first aim of this dissertation was to develop an integrative conceptual framework to understand health-related social media effects. In a nutshell, health-related social media effects are relatively complex and interdependent. We argue (see section 2) that four different factors of social media use should be considered to understand *whether*, *when*, and *how* social media use influences health behaviors: (1) social media communication features, (2) communicated contents, the (3) directionality of interaction, and (4) a person's engagement. The combination of those four factors is assumed to determine whether health-related effects occur, which behavior change techniques might be contained or triggered and thus be the active ingredients, and which psychosocial determinants may be responsible for causing changes in health behaviors.

Drawing on this framework, I examined the causal effects of different types of interaction directionality (active posting and exposure to postings) relating to one specific type of social media feature, postings (Manuscript 2; see section 3). I simultaneously focused on one very popular social media content and topic: Eating-related social media postings in the form of food pictures (Hu et al., 2014; Mejova et al., 2015). I also coded contained and hypothesized behavior change techniques at work (see Michie et al., 2013 for the utilized taxonomy). Publicly posting about the own healthy eating likely contains the following techniques: "2.3 Self-monitoring of behaviour", "2.2 Feedback on behaviour", "3.1 Social support (unspecified)", "6.3 Information about others' approval", "10.4 Social reward", and "1.9 Commitment" for senders (see Figure 3). The postings could also trigger the enactment of other behavior change techniques through the responses of receivers of these postings (e.g., "15.1 Verbal persuasion about capability"). However, this depends on the reactions' actual content, which we could not control in our studies. The results of the conducted studies suggest that social media postings about healthy food may influence the healthy eating of senders by serving as a public form of self-monitoring (Harkin et al., 2016) with additional simultaneously working behavior change techniques (e.g., social feedback or support) due to the publicness of postings. Supporting this idea, we found additional benefits (beyond mere self-monitoring effects) of public eating-related social media postings in senders who did not have eating behavior change goals (Study 1). We also found that these postings can support eating behavior change of senders who have current eating behavior change goals (Study 2). However, not in line with our hypothesis, public posting (containing additional behavior change techniques present in social media environments such as receiving social feedback from the own social media network) was not more effective than private self-monitoring in supporting eating behavior change goals. Thus, self-monitoring of behavior may be the most active behavior change technique in eating-related social media postings, explaining most of its effects regarding the support of eating behavior change goals. Current eating behavior change goals may also reduce the additional effects of eating-related social media postings beyond mere self-monitoring (e.g., the effects of social feedback and received information about others' approval) because goal setting is itself an effective behavior change technique (Epton et al., 2017). Importantly, effects on behavior are highly dependent on the *actual enactment* of behavior change techniques (see Hankonen, 2021 for a discussion on the importance of participants' enactment of behavior change techniques in behavioral interventions). Thus, another explanation could be that senders might have received too little social feedback from their network to cause an additional effect on behavior change. For network members ("receivers") exposed to healthy eating-related postings, the behavior change techniques "6.1 Demonstration of the behaviour", "6.2 Social comparison", "6.3 Information about others' approval", and "7.1 Prompts/cues" might cause changes in psychosocial determinants of eating behavior and ultimately eating behavior itself. The results of Study 1 suggest that the exposure to healthy eating-related social media postings likely benefits the healthy eating of receivers, too (Study 1).

Furthermore, I examined the relevance of *how* people communicate with each other via social media postings, that is, the relevance of need-support provision in social media postings for health behavior change (Manuscript 3; see section 4). The communication strategies described in the developed video intervention represent self-determination theory-related motivation and behavior change techniques (Teixeira et al., 2020). Thus, if successfully applied, the following motivation and behavior change techniques might cause changes in psychosocial mechanisms (particularly perceived need-support) and, ultimately health behaviors (see also Figure 3): “Use noncontrolling, informational language”, “Provide choice”, “Acknowledge and respect perspectives and feelings”, “Providing opportunities for ongoing support”, “Address obstacles for change”, and “Offer constructive, clear, and relevant feedback” (Teixeira et al., 2020). Exposure to social media communication containing these strategies could effectively support health behavior change via increasing perceived need-support (Ntoumanis et al., 2017; Ryan et al., 2008; Silva et al., 2011). We showed that people can learn and apply a need-supportive communication style in written social media postings (Study 1). However, this only held true in a laboratory setting but not a real-world setting of a health behavior change intervention with an online support community delivered via forums. Because there were no differences in the actual enactment of those strategies between the two experimental groups, we did not find effects on perceived need-support of forum members and, ultimately goal attainment (cf. Hankonen, 2021). Overall, participants showed low use of these six need-supportive communication strategies in the postings across both experimental groups. Additional exploratory analyses of posting content showed that participants also naturally used other behavior change techniques in their postings, for example, daily goal setting (“6.1 Goal setting (behaviour)) and self-monitoring (“2.3 Self-monitoring of behaviour”). As outlined above, the social responses to these postings may contain additional behavior change techniques (e.g., “3.1 Social support (unspecified)”).

Figure 3

Overview about Assumed Mechanisms of Action in the Experimental Conditions in Manuscripts 2 and 3



Note. Assumed mechanisms of action in the applied studies (Study 1 and 2 in Manuscript 2; Study 2 in Manuscript 3) include hypothesized motivation and behavior change techniques and psychosocial determinants. Techniques were coded with established taxonomies, the Behavior Change Techniques Taxonomy (Michie et al., 2013) in Manuscript 2, and a taxonomy referring to self-determination theory (Teixeira et al., 2020) in Manuscript 3. In receivers (Manuscript 2, Study 1), only greyly colored psychosocial determinants were examined. Bolded psychosocial determinants are expected to be the most proximal outcomes affected by the experimental manipulation.

To sum up, in addition to theoretically outlining a framework of how health-related social media effects might work, I empirically examined specific types of health-related social media use, their active ingredients as operationalized by different motivation and behavior change techniques, and the respective psychosocial determinants (e.g., perceived need-support, perceived social norms) that might cause changes in health behaviors. As – to the best of my knowledge – no research to date has experimentally addressed how eating-related postings in the form of food pictures, and need-provision in social media communication, could influence health behavior change (see Hawks et al., 2020; Ntoumanis et al., 2021; Petkovic et al., 2021; Sina et al., 2022, for recent reviews), the two manuscripts provide significant empirical contributions to the literature.

5.2.2. Causality of Health-Related Social Media Effects

The second aim of this dissertation was to provide causal evidence for the effects of very specific types of health-related social media use on psychosocial determinants of health behaviors and real-world health behaviors. In the following, I treat the *intention to perform a behavior* as an additional proxy of behavior, even though it is typically operationalized as one of the most proximal psychosocial determinants of behavior (Fishbein & Ajzen, 2011; Sheeran et al., 2017). Research also shows a substantial intention-behavior gap: People often do not translate their intentions into behavior (Sheeran, 2002; Sheeran & Webb, 2016). Nevertheless, I use this categorization because many psychosocial determinants, particularly perceived social norms, attitudes, and self-efficacy, are seen as determinants of intentions but not behavior per se (Fishbein & Ajzen, 2011).

The results of the second manuscript provide the first causal and experimental evidence that healthy eating-related postings likely benefit the daily eating behavior of both senders and receivers (Study 1). The results also show that postings can serve as a form of public self-monitoring of eating behavior, supporting eating behavior change of senders (Study 2). However, this form seems to be not more effective compared to private, non-public self-monitoring. Notably, the results regarding eating intentions showed the expected pattern of a stronger increase in senders who publicly posted about their eating behavior (compared to senders who privately self-monitored their eating behavior). We aimed to isolate the causal effects of unique elements of the social media environment, that is, the anticipated and received social responses of other users, from mere self-monitoring with our experimental conditions. Therefore, it is not possible to make statements regarding the effect of picture-based food postings compared to no self-monitoring. The two studies contribute to closing important research gaps in the literature, namely a lack of research on (eating-related) sender effects and a strong focus on cross-sectional (e.g., Hawkins et al., 2020; Qutteina et al., 2022) or artificial experimental laboratory study designs (e.g., Coates et al., 2019b; Hawkins et al., 2021). The two conducted studies complement the existing literature and fit into other research showing potentially positive effects of social media use related to healthy eating (e.g., Qutteina et al., 2022). As sender effects have been strongly neglected in research (cf. Hawks et al., 2020; Sina et al., 2022), the two studies provide some of the first causal evidence that postings of healthy food pictures can benefit the eating behavior of senders both with and without healthy eating goals. Self-monitoring of behavior (Harkin et al., 2016) might be the most active behavior change technique, but only for senders without eating behavior change goals.

I further examined the causal effects of increasing need-support in written social media postings in a peer-based online support community within a health behavior change intervention in the third manuscript. As no research so far has examined the effects of increasing need-support in written social media communication (postings) on health behavior change, the two conducted studies provide important contributions to the literature. In Study 1, my colleagues and I found causal evidence that a short video intervention can increase need-supportive communication strategy use in written responses to fictive social media postings. These effects also persist one week after the intervention. However, this effect did not translate into a real-world setting in Study 2 (number of need-supportive communication strategies used in postings in a forum-based health behavior intervention with peer support and goal setting. Therefore, we could not test the causal effects of increasing need-support in social media postings on health behavior change, participant engagement, and underlying psychosocial determinants. Most probably for this reason, we did not find the expected positive effects on goal attainment and the examined determinants. The two studies represent the first studies (cf. Gillison et al., 2019; Ntoumanis et al., 2021; Su & Reeve, 2011) that (a) look at health-related social media effects and social media communication in general, from the lens of self-determination theory, (b) developed an intervention directly targeting individuals participating in health behavior change interventions instead of intervention providers, as typically done, and (c) rigorously test the effects of the intervention both in a laboratory and a real-world setting. Our approach seems promising due to its solid theory base and the initial results that need-supportive communication strategies can be learned and applied under specific circumstances. Future studies should further examine the potential and effects of increasing need-support in social media communication on health behavior change.

5.2.3. Temporal Dynamics of Health-Related Social Media Effects

The third aim of this dissertation was to provide the first examination of the temporal dynamics of eating-related social media effects. I addressed this goal in the second manuscript by examining dose-response relationships of *intra*individual variations in daily eating-related social media activities with eating behavior and psychosocial determinants of eating behavior. The differentiation of between- and within-person effects can help to refine behavioral theories (Dunton et al., 2021) and to understand temporal dynamics in health behavior change (Scholz, 2019). There also has been a call for a differentiation between both effect types in the media and communications studies literature (Thomas et al., 2021). However, up to date, no research has examined *intra*individual and day-level associations between social media use and eating behavior (cf. Hawks et al., 2020; Sina et al., 2022). This also holds true for other (health-related) social media effects, except for recent research on alcohol-related social media effects (Hendriks et al., 2021; Kurten et al., 2022) and social media use and well-being (Valkenburg et al., 2022). Therefore, the two studies of this dissertation address a current research gap and provide important contributions regarding a better understanding of temporal dynamics and within-person effects in the literature on eating-related (and more generally, health-related) social media effects. My co-authors and I found positive dose-response associations between *intra*individual variations in the subjective eating-related social media usage and eating behavior of senders in both studies. That is, on days on which senders used social media more than usual for communication regarding their study-related postings containing pictures of consumed fruits and vegetables, they ate more fruits and vegetables. Furthermore, there were comparable positive associations between *intra*individual variations in the number of daily study-related postings containing pictures of consumed fruits and vegetables with daily intake and intentions, but only in senders with eating behavior change goals (Study 2). Although not examining the effects of postings and eating behavior, the results of a recent study also suggest the existence of sender effects on the day level for alcohol consumption, that is, daily associations of liking alcohol content and daily drinking behavior (Kurten et al., 2022). In contrast, we found no effects of the number of daily eating-related postings in senders without eating behavior change goals on their eating behavior (Study 1). Furthermore, there was no comparable association in receivers (i.e., of the number of postings they were exposed to). This finding is not in line with a recent study showing that the daily number of alcohol-related postings college students were exposed to was associated with their drinking probability and quantity on the day level (Hendriks et al., 2021). The differing results may be explained due to different behavior types (health vs. risk behavior). Supporting this claim, the exposure to unhealthy (vs. healthy) eating content also tends to have a stronger or more consistent effect on eating behavior (Sina et al., 2022). Furthermore, Hendriks et al. (2021) did not examine *intra*individual associations and disentangle between-and within-person variance through centering (cf. Enders & Tofighi, 2007), as we did. In our studies, we also found positive dose-response associations between both types of eating-related social media activities and examined psychosocial determinants of eating behavior (see also section 5.2.4.). Examining both between- and within-person effects is also crucial because effects on the different levels can diverge and sometimes be contradictory (e.g., Inauen et al., 2016). This is also what we somehow found in our studies. There were only few changes of the examined constructs in response to posting on the group level (e.g., no differential effects on eating behavior between both posting conditions in Study 2). However, there were positive dose-response relationships between eating-related social media use and our outcomes (e.g., daily eating behavior). Thus, some effects might be more transient and only present in timely proximity to actual social media use. Taken together, the two studies address an important research gap in the literature on eating-related (and more generally health-related) social media effects, namely a lack of research on within-person effects in both senders and receivers of eating-related social media postings.

5.2.4. Psychosocial Mechanisms Underlying Health-Related Social Media Effects

The fourth aim of this dissertation was to examine psychosocial determinants of health behaviors that might change in response to health-related social media use and thus explain health behavior change. Therefore, I rigorously tested potentially underlying psychosocial determinants throughout the four empirical studies. Based on an extended version of the reasoned action approach (Fishbein & Ajzen, 2011), I examined increases in perceived social support, perceived social norms, attitudes, self-efficacy, and goal commitment as potentially involved psychosocial determinants that might change is response to eating-related social media postings. Drawing on the integrated model of the reasoned action approach and self-determination theory (Hagger & Chatzisarantis, 2009, 2012), I also examined changes in these determinants in response to an intervention aiming to improve health behavior-related need-support in written social media postings. Additionally, I examined increases in perceived need-support and autonomous motivation in response to the intervention as key determinants derived from self-determination theory (Deci & Ryan, 2000; Ntoumanis et al., 2017; Ryan et al., 2008). Need-supportive communication strategy use and perceived-need-support are assumed to be the most proximal outcomes affected by the video intervention. We did not find effects of the intervention on these outcomes. Therefore, we could not test the assumed causal effects of improving need-support in social media communication on the other psychosocial determinants (for which we also did not find any effects of the video intervention). In the following, I only discuss the results of the two studies that examined psychosocial determinants regarding eating-related social media effects (both studies of Manuscript 2; see section 3) and integrate them into the literature. Nevertheless, I also discuss the key determinant from self-determination theory, perceived need-support, from a theoretical point of view.

Perceived social support is one psychosocial determinant that might change in response to eating-related social media use (de la Peña & Quintanilla, 2015; Simeon et al., 2020). We found increases in perceived eating-related social support of senders who publicly posted about healthy eating via social media and got *intentionally supported* by a study partner and network member and their general social media network ("receivers"). That is, study partners were instructed and incentivized to respond with positive one-click reactions and comments to senders' postings (Manuscript 3, Study 1). There was no such increase in senders supported only by their general social media network, which may have resulted in less control about potential reactions of the social media network (Manuscript 3, Study 2). We also found a trend that perceived eating-related social support might increase in receivers, too (Study 1), although this trend only emerged in the post-hoc comparisons. Furthermore, on days on which both senders and network members used social media more than usual related to communication about senders' food postings, they reported higher perceived social support in both studies. Research supports these findings as social media use and postings have been shown to be associated with increased social support (D. Liu et al., 2018; Lu & Hampton, 2017). Although the provision of social support is the most prevalent behavior change technique (Simeon et al., 2020), the results of a recent meta-analysis show a non-significant overall effect of social media-based interventions on social support due to substantial heterogeneity (Petkovic et al., 2021). No study specifically examined the effects on eating-related social support. Descriptive and qualitative research suggests benefits of social media for eating-related social support (e.g., de la Peña & Quintanilla, 2015; Turner-McGrievy & Tate, 2013) but little research has examined the change of perceived social support in response to eating-related social media use (see Sina et al., 2022 for a recent review). Thereby, the results of the two studies provide an important contribution to the literature. Importantly, we isolated the effects of one specific type of social media activity, (eating-related) postings, and social media use in response to these postings. However, even though there were increases in perceived social support in Study 1, these increases were not related to eating behavior change in our studies, which is in contrast to earlier studies (e.g., Cavallo et al., 2014; Turner-McGrievy & Tate, 2013). A possible reason is the missing eating behavior change goal in Study 1, as social support primarily assists successful goal striving (Fitzsimons & Finkel, 2010). To sum up, the results of both studies suggest that perceived social support might increase when provided by significant others (Study 1) but not the general social network (Study 2). The effects could also be more temporary and in timely proximity to actual social media use. Although perceived social support might increase in response to healthy eating-related postings and related social media use, it may not necessarily explain changes in eating behavior for social media users *without* eating behavior change goals.

Perceived descriptive and injunctive norm (Cialdini et al., 1991; Rimal & Lapinski, 2015) changes could also explain the effects of eating-related social media use on eating behavior. Throughout the two studies, my co-authors and I found little evidence for changes in perceived social norms in response to eating-related postings (Manuscript 2). It is important to note that there were increases in perceived injunctive norms in senders *intentionally receiving social feedback* via social media from a study partner and network member, which might be necessary for effects to occur (Manuscript 2, Study 1). This finding is in line with assumptions of social norm theories that the received social feedback (behavior change techniques: “2.2 Feedback on behaviour”, “6.3 Information about others’ approval”, and “10.4 Social reward”) changes the perceived social approval of the depicted behavior (Higgs & Thomas, 2016; Rimal & Lapinski, 2015). The social feedback can be communicated already very quickly via likes (Simeon et al., 2020). Perceived descriptive norms of senders, in contrast, might only change if the social network also communicates about consumed foods in response to these postings via comments or messages (Higgs & Thomas, 2016). Senders might have received negative or too little social feedback from their network, maybe because many social media users do not actively contribute to social media communication but only passively view content (Edelmann, 2016; Hampton et al., 2012). Thereby, a lot of social information and social feedback regarding the own social media network is missing. It remains unclear why we did not find effects on network members’ perceived descriptive social norms, as the picture-based food postings depicted the actual eating behavior of senders (Higgs & Thomas, 2016). The cross-sectional results in the literature are somewhat mixed, showing more consistent associations for unhealthy and risky behaviors (e.g., Geusens et al., 2020; Qutteina et al., 2022), and our results fit this picture. However, the cross-sectional studies in the literature should be cautiously interpreted because they do not allow conclusions regarding causality. Homophily processes (Centola & van de Rijt, 2015; McPherson et al., 2001) and a resulting majority illusion (Bunker & Varnum, 2021; Lerman et al., 2016) could also partially explain and inflate the observed associations between social media use and norm perceptions. The two field experiments thus provide an important empirical contribution to the literature by experimentally showing that posting and viewing eating-related social media postings does not causally influence perceived social norms. One alternative explanation for the results could be that our experimental manipulation was not intense enough (i.e., we could not manipulate the whole social media feed and all social responses). The only observed change in perceived social norms that was as expected (an increase of perceived injunctive norms of senders in Study 1 who posted about their eating behavior) did not predict changes in eating behavior. The finding supports evidence suggesting that perceived injunctive norms only play a minor role in explaining eating behavior change (McEachan et al., 2016; Robinson, Fleming, et al., 2014; Stok, de Ridder, et al., 2014). One other reason might be *low identification* with the social media community as a whole, as identification is an important moderating factor (Higgs & Thomas, 2016; Stok et al., 2016) and social media users also follow and interact with people they do not necessarily want to emulate (D. Liu et al., 2016). Finally, many social media users are mainly digitally connected with each other in daily life. Therefore, the absence of the norm referents (other social media users) in the moment of consumption, or no association between a specific eating situation and the social media community at all, might also explain the missing association (Stok et al., 2016). In a nutshell, our results suggest that changes in perceived social norms might only occur in response to social media use when examining perceptions regarding referent groups who actually provide information about their eating behaviors and the social approval of eating behaviors (e.g., via postings, comments, or one-click reactions). This is the case for more specific referent groups that *actively* use social media (and not the whole social media network). Perceived social norms might only influence eating behavior when assessed regarding the perceived behavior (not social approval) of other social media users, in cases of high identification or similarity with other social media users, and when specific eating situations are associated with these users.

Self-efficacy (Bandura, 1997) changes could be another psychosocial determinant of eating behavior that might change in response to eating-related social media use. We found no stronger increases in the self-efficacy of senders who publicly posted about their eating behavior change (compared to private self-monitoring of eating behavior). Existing research in the literature is mixed (Petkovic et al., 2021; Yang, 2020) and does not focus on eating-related self-efficacy changes. As already discussed earlier, social media effects are relatively complex and likely depend on the engagement level (e.g., the number of postings), the actual content of postings (e.g., depicting personal successes vs. communicating about failures), and received social responses (e.g., whether senders get verbally persuaded regarding their capabilities in social media comments). These factors ultimately determine, if mastery experiences or verbal persuasion take place (Bandura, 1997). In line with this argument, senders reported higher self-efficacy on days on which they posted more than usual about their healthy eating (Manuscript 2, Study 2). Relatedly, the number of contributed social media interactions in a social media-based weight loss intervention tended to predict self-efficacy increases (Xu & Cavallo, 2021). Furthermore, the number of received comments predicted self-efficacy increases and indirectly weight loss (Xu & Cavallo, 2021). Surprisingly, we found that senders reported lower self-efficacy on days on which they used social media more than usual for communication regarding their eating-related postings (Manuscript 2, Study 2). However, the reverse pathway may also be plausible due to the cross-sectional nature: Senders may have used social media more intensely on days on which they experienced lower self-efficacy to compensate for this drop. Furthermore, as already discussed, between- and within-level effects can sometimes diverge and result in opposing effects which is also true for health-related effects of self-efficacy (Beauchamp et al., 2019). For example, self-efficacy can have a negative within-person association with performance due to an overestimation of self-efficacy beliefs (Beauchamp et al., 2019). Therefore, future studies should examine the associations of different types of eating- and health-related social media use more generally, in a longitudinal manner, and more detail, for example, with additional moderators such as the number of positive reactions received (see also implications for future research, section 5.4.). The conducted study provides important contributions to the literature by experimentally testing whether senders' self-efficacy changes in response to eating-related postings and by examining dose-response associations between daily social media use related to the postings and daily self-efficacy. In summary, self-efficacy did not increase in senders who started to publicly post about their healthy eating behavior changes (Manuscript 2, Study 2). There were dose-response relationships between *intra*individual variations in daily eating-related social media activities and self-efficacy. Still, the associations were mixed in their direction (negative for subjective eating-related social media usage and positive for the number of eating-related postings).

Attitude changes might also explain effects of eating-related social media use on eating behavior change. We experimentally examined the effects of posting about the own healthy eating on attitude changes in senders in the context of an eating behavior change goal. There was no increase in experiential and even a decline in instrumental attitude (i.e., more negative attitudes; Manuscript 2, Study 2). This is not in line with cross-sectional and longitudinal studies showing that sharing alcohol references is positively associated with alcohol-related attitudes (Geusens et al., 2020; Geusens & Beullens, 2019). However, because of their correlational nature, conclusions regarding the causality of these effects are again limited. We found that senders reported higher instrumental and experiential attitudes on days on which they posted more eating-related postings than usual (but not on days on which they used social media more than usual related to these postings). One possible reason for the mixed results may be that postings probably better capture the active ingredients of self-persuasion effects (Valkenburg, 2017). The number of postings can be seen as an indicator for the frequency of behavioral self-monitoring, which is likely more relevant than active and passive use related to these postings (e.g., viewing received likes and comments). To sum up, our findings suggest dose-response relationships in self-persuasion effects via social media postings (cf. Aronson, 1999; Valkenburg, 2017) and, again, more temporary effects but not general effects of the modality (publicness) of self-monitoring of behavior on attitude change.

Goal commitment might be a different mechanism for senders with eating behavior change goals who post about their eating behavior change on social media. We found no higher goal commitment in senders who publicly posted about their eating behavior change via social media compared to private self-monitoring of eating behavior (Manuscript 2, Study 2). This is in contrast to empirical findings that publicness of goals increases goal commitment (Klein et al., 1999, 2020). Indeed, there were positive dose-response relationships of *intra*individual variations in the daily eating-related social media activities with daily goal commitment. That is, on days on which senders posted more eating-related postings than usual and used social media more than usual related to communication about these postings, they reported higher goal commitment. The results again suggest that effects on goal commitment might be more transient and in temporal proximity to actual social media use (see also the discussion in section 5.2.3.).

Need support provided via interpersonal social media communication could be another mechanism of action for supporting long-term health behavior change (Ntoumanis et al., 2017; Ryan et al., 2008). We aimed to increase need-support provision in written social media communication via postings with a short, educational video intervention based on self-determination theory (Deci & Ryan, 2000; Ryan & Deci, 2017); see section 4. Unfortunately, the positive effects of the video intervention on need-supportive communication strategy use in a laboratory setting (Study 1) did not translate into a real-world environment (Study 2). Thus, we did not find positive effects on perceived need-support and, in turn, could not test indirect effects on goal attainment and the other psychosocial determinants (e.g., autonomous motivation, self-efficacy). However, because there are strong theoretical and empirical arguments for the assumed causal pathway, future research should continue to examine changes in perceived need-support concerning the enactment of health behaviors as a potential underlying mechanism. It already has been shown that perceived autonomy- and need-support are important for long-term health behavior change (Ng et al., 2012; Ntoumanis et al., 2021) and that how people communicate can influence need fulfillment or thwarting (Martela et al., 2021; Ntoumanis et al., 2017). Furthermore, the provision of need-support through social agents can be trained (Su & Reeve, 2011) and can increase perceived need-support (Gillison et al., 2019). However, as – to the best of my knowledge - no research to date has addressed interpersonal communication in social media through the lens of self-determination theory, especially regarding the effects on health behavior change. Therefore, the two conducted studies provide significant theoretical and empirical contributions to the literature on self-determination theory-based health behavior interventions and psychosocial mechanisms underlying health-related social media effects.

Taken together, I examined changes in several psychosocial determinants of health behaviors as potential mechanisms of action. Perceived need-support is a promising determinant that should be examined in future studies, even though it could not be increased in our study (Manuscript 3, Study 2) because the use of need-supportive communication strategies in the intervention group was low and did not increase through the video intervention. Most of the other examined psychosocial determinants (including perceived social support) did not explain eating behavior change. There were more effects on the day level, suggesting rather transient effects in timely proximity to social media use. However, due to the cross-sectional nature of the day-level analyses, it is not possible to causally interpret these associations. Theoretical arguments and other empirical evidence support the relevance of the examined determinants based on the reasoned action approach (Fishbein & Ajzen, 2011) and self-determination theory (Deci & Ryan, 2000; Ryan & Deci, 2017). Therefore, future research should continue to examine their causal role in sender and receiver effects. Researchers should aim to identify potential moderators (e.g., amount and valence of received network reactions) of health-related sender and receiver effects in future studies, as they are likely complex and interdependent (Valkenburg, 2017; Valkenburg et al., 2016). The theoretical predictions of the theory of planned behavior and the reasoned action approach are empirically supported (McEachan et al., 2011, 2016; Sheeran et al., 2016). However, it is important to note that there is an ongoing debate about the usefulness of the theory of planned behavior to understand health behavior change (Ajzen, 2015; Conner, 2015; Hagger, 2015; Sniehotta et al., 2014). Critique relates to the small amount of explained variance in health behaviors (Sniehotta et al., 2014) and the lack of volitional constructs (e.g., planning) that, among others, might help to bridge the earlier mentioned intention-behavior gap (Sheeran, 2002; Sheeran & Webb, 2016). Proponents suggest the extension of the theory (Conner, 2015), as already partially done through the advancement to the reasoned action approach. Future studies should also utilize other health behavior theories, for example theories containing volitional constructs such as planning or action control (e.g., Schwarzer, 2008) or other social processes such as social identity (Tajfel & Turner, 1979), that might also help to understand underlying mechanisms in health-related social media effects.

5.2.5. Social Media as an Intervention Tool

I also aimed to examine how social media could be used and optimized as an intervention tool to support health behavior change. Most interventions typically combine several components and are delivered in groups (Petkovic et al., 2021). I found that eating-related social media posting can serve as a public form of self-monitoring of eating behavior, support eating behavior change of *individuals* with behavior change goals (Manuscript 2, Study 2). Thereby, I show the potential of social media (1) as a standalone intervention tool for improving the eating behavior of (2) individuals (instead of groups) by posting to their private social media networks. Public social media posting was not more effective than non-public self-monitoring of behavior, as we had expected due to the publicness of monitoring and behavioral goals (cf. Epton et al., 2017; Harkin et al., 2016). In contrast, other studies show benefits of group vs. individual tracking of eating behavior (Meng et al., 2017) and group-based support for reaching eating behavior goals (Inauen et al., 2017). However, as already mentioned, these studies are delivered with either other participants sharing the same behavioral goals (Inauen et al., 2017) or confederates (Meng et al., 2017). Furthermore, we specifically examined the additional unique effects of public (compared to private) self-monitoring. The results suggest that self-monitoring of behavior may be the most relevant behavior change technique contained in behavior-related social media postings that cause changes of the respective health behavior. Furthermore, I examined how social media-based interventions could be optimized by increasing need-support in social media communication with a short educational video (Manuscript 3, Study 2). Unfortunately, need-supportive communication among forum members and, in turn, goal attainment could not be increased with the video intervention. Still, theoretical arguments strongly support the aim of increasing need-support in social media-based interventions. Therefore, future research should identify populations (e.g., with substantial behavior change difficulties) and conditions under which these strategies can be applied. Furthermore, researchers could boost the application of need-supportive communication strategies by considering additional means such as using content moderators or peers as role models and training them more intensely in need-supportive communication (Inauen et al., 2017; Pagoto et al., 2017).

5.3. Strengths and Limitations

The three independent manuscripts and the whole dissertation have several strengths and some limitations that should be considered when interpreting the results. A significant strength of this dissertation is the comprehensive approach to understanding health-related social media effects by combining both theoretical and empirical work. I outlined a conceptual framework for examining health-related social media effects and, relying on this framework, experimentally tested the effects of specific types of health-related social media use on health behavior change and potential underlying mechanisms of action. Thus, I provided comprehensive explanations about *whether*, *when*, and *how* health-related social media use could influence health behaviors.

The second strength of this dissertation is a solid theoretical foundation of both the conceptual framework and the four conducted empirical studies by taking a psychological, social-cognitive perspective. I integrated research streams from different areas (media and communication studies and health psychology and behavioral sciences) and applied extensively tested health-psychological theories (Fishbein & Ajzen, 2011; Hagger & Chatzisarantis, 2009; Ryan & Deci, 2017) to test possible underlying mechanisms of action underlying health-related social media effects. The conducted studies provide one of the first experimental examinations of changes in perceived social support and social norms, frequently discussed candidates in the eating behavior domain, and further theoretically derived psychosocial determinants from the reasoned action approach (Fishbein & Ajzen, 2011). I also examined the provision of need-support (Deci & Ryan, 2000; Ryan & Deci, 2017)in social media communication as another mechanism of action.

The third major strength of this dissertation refers to the multimethod approach to examine health-related social media effects, resulting in several additional strengths of the conducted studies. Throughout the conducted empirical studies, I combined experimental designs (all four studies) with behavioral social media data (all three applied studies) and intensive longitudinal data (both studies in Manuscript 2). This approach allowed me to simultaneously address several research gaps in the literature: (a) an insufficient differentiation between different types of health-related social media use (Parry et al., 2022). Furthermore, a lack of (b) research with experimental designs and high ecological validity (capturing social media use and eating behavior in daily life) and (c) research on within-person effects and the temporal dynamics of effects (Sina et al., 2022; Strowger & Braitman, 2022). One strength, therefore, is that I experimentally tested the effects of specific types of social media use by isolating the assumed active ingredients (social media elements that contain or trigger different motivation and behavior change techniques). I used strong control groups (mere private self-monitoring in Manuscript 2; control video with general netiquette rules in Manuscript 3) to allow more valid conclusions regarding the causality of effects. Another strength is that I incorporated and linked both objective (coded behavioral social media data) and subjective aspects of social use (subjective questionnaire data) and thus reduced the probability of common method bias (Podsakoff et al., 2012) for some of the conducted analyses. A further strength is the use of experience sampling and daily diary methods (Shiffman et al., 2008; Trull & Ebner-Priemer, 2014). These methods allowed me to research health-related social media effects in participants' daily lives where social media use and eating behavior typically occur, reducing recall bias and increasing ecological validity (Shiffman et al., 2008). A further strength is the examination of dose-response relationships and within-person effects on the day level (Manuscript 2). I thereby shed light on *intra*personal associations of eating-related social media use, eating behavior, and potentially underlying mechanisms of action.

Finally, the fourth strength of this dissertation is the use of open science methods to examine the research questions of interest and deliver the results to the scientific community, addressing calls for improving current research practices (Shrout & Rodgers, 2018; van 't Veer & Giner-Sorolla, 2016). Where possible, research questions and hypotheses have been preregistered, the data supporting the main results and conclusions of the manuscripts have been or will be made publicly available, and the manuscripts have been or will be published in open access journals and openly available research directories.

The obtained results of this dissertation should be interpreted considering the following limitations: I primarily used subjective questionnaire data when examining the research questions of interest. The use of subjective measures can introduce common method bias (Podsakoff et al., 2012), and recalls of enacted behavior can be biased, leading to systematic under- or overestimation of the behavior of interest (Archer et al., 2013; Parry et al., 2021; Prince et al., 2008). However, subjective measures also have several strengths, such as being very affordable (cf. Lee & Shiroma, 2014), easily applicable (especially when conducting online studies), and individuals themselves often have the best available information about their behavior (McClung et al., 2018; Naska et al., 2017). Furthermore, subjective measures are still needed to assess very specific types of social media use, what I did (e.g., how intense participants used social media to *passively view* healthy food pictures and related communication without further interaction with the content), or subjective experiences (e.g., perceived need-support). I also aimed to reduce bias by combining subjective measures with more objective measures (coded content of participants' social media postings). Both objective and subjective measures should be combined in future research to profit from the strengths of both measure types (see also section 5.4.). One further limitation is the use of cross-sectional data for some research questions and respective analyses (particularly the examination of dose-response relationships in Manuscript 2). This does not allow conclusions regarding the direction of the effects, which could also be the other way around. Therefore, future studies should examine *lagged* within-person effects (Wickham & Knee, 2013), for example, the effect of higher than usual social media use on day x on eating behavior on day x + 1, to reduce the probability of reverse causation and further examine temporal dynamics. Nevertheless, I used person-mean centering for predictors (Enders & Tofighi, 2007) and controlled for several variables to rule out other alternative explanations for the obtained results (especially potential interindividual differences between persons). A further limitation, and the reason why I did not examine lagged effects, is the relatively small sample size of the two studies in Manuscript 2. Both studies were powered to detect the expected medium-sized experimental effects, not examining within-person associations. Thus, smaller effects of the experimental manipulations could not be estimated reliably (Lakens & Evers, 2014). Furthermore, the examination of within-person effects, especially in the case of small effect sizes and lagged effects (because missing values can drastically reduce the number of usable data points), requires a substantially higher sample size and number of measurements (see Arend & Schäfer, 2019 for recommendations for two-level models). Nevertheless, the results of the two studies provide initial evidence for dose-response relations between daily eating-related social media activities and daily eating behavior on the within-person level. Finally, the duration of the conducted interventions was relatively short (one week in Manuscript 2; two weeks in Manuscript 3), and the studies did not include a long-term follow-up. Some of the expected effects might take more time to unfold (e.g., attitude or self-efficacy changes) or might even strengthen over time (e.g., sustained higher intake of fruit and vegetables in the long term in the case of public self-monitoring via social media due to higher accountability and social rewards).

5.4. Implications for Future Research

Several implications for future research can be derived from this dissertation. First, the suggested conceptual framework offers a behavioral science lens to examine the causal pathways of different types of social media effects on health behaviors. Based on this framework, researchers should aim to identify and code the active ingredients of different types of social media use (i.e., the assumed behavior change techniques at work) using established taxonomies (e.g., Michie et al., 2013; Teixeira et al., 2020), and examine their effects on health behavior and psychosocial determinants that might mediate the effects on health behaviors (cf. Cavallo, Tate, et al., 2014; Myneni et al., 2016; Pappa et al., 2017). Furthermore, researchers should make greater use of experimental methods (Sheeran et al., 2017) to test the unique and causal effects of the assumed active ingredients on potential psychosocial determinants and health behavior change by using adequate control groups. For example, using private picture-based self-monitoring of intake as a control group for picture-based social media postings, as I have done. Social media also provide the opportunity to conduct large-scale field experiments (see Mosleh et al., 2021), for example, by randomizing participants to follow different social media accounts (Bail et al., 2018).

Second, future research should build on the research conducted in this dissertation and examine within-person effects and the temporal dynamics of health-related social media effects. Using intensive longitudinal data and disentangling between- and within-person variance and effects can advance the understanding of health behavior change (Dunton et al., 2021) and reciprocal communication dynamics in social media effects (Thomas et al., 2021). Only little research (e.g., Hendriks et al., 2021; Kurten et al., 2022; Valkenburg et al., 2022) has focused on within-person effects in this domain so far. Social media use is a very frequently occurring behavior (e.g., Ohme et al., 2021), and many health behaviors occur multiple times per day, too (e.g., eating or smoking). Therefore, researchers should also use more intense sampling strategies with multiple measurements per day (e.g., five times a day) to conduct more finely grained analyses of temporal dynamics. Researchers should also examine lagged effects (Wickham & Knee, 2013), ideally combined with the aforementioned smaller time lags between measurements. This can reduce same source bias (Ohly et al., 2010) and the probability of reverse causation as alternative explanations for the examined directions of action.

Third, future research should examine moderating factors of health-related social media use on health behaviors and psychosocial mechanisms, both at the between- and within-person level. Social media effects can be relatively complex (Xu & Cavallo, 2021) and interactive (Valkenburg, 2017). That is, sender effects might, for example, depend on receivers' reactions. Future studies should take this complexity into account. For example, the number of positive received social responses (i.e., likes and positive comments) is an interesting potential moderator of effects. It can be seen as a proxy for the amount of received social reward, the most frequently occurring active behavior change technique in interactive social media (Simeon et al., 2020). Furthermore, the type and extent of social comparison in the moment of social media use could moderate effects (e.g., Peng et al., 2019; Rheu et al., 2021). Effects of health-related social media use on health behaviors might also depend on interpersonal characteristics such as social comparison tendency (e.g., Y. Liu & Kashian, 2021) or social identification with the individuals who create social media content (e.g., Stok et al., 2016).

Fourth, future research should aim to use more objective measures. Even though subjective measures of social media use (compared to objective logs) can be substantially biased (Parry et al., 2021), they are still most frequently used in research (Parry et al., 2022). Researchers can code the content of people's individual social media feeds or their created postings and comments (such as we and others did, e.g., Hendriks et al., 2021). Although still developing, artificial intelligence and coding algorithms will likely advance the research field. They are way more efficient in processing huge data sets and can accurately code pictures or texts (e.g., McAllister et al., 2018; Zhang et al., 2015). However, using objective social media data for research can also be challenging due to access restrictions in application programming interfaces of social media platforms and ethical and data quality concerns (Tromble, 2021). Subjective measures are also needed to assess specific types of social media use (e.g., how long individuals use social media to view healthy food pictures and related communication *passively*) or to examine non-observable psychological processes (e.g., whether upward or downward social comparison occurs). There are objective measures for many types of health behaviors, too. For example, CO2-analyzer for smoking behavior (e.g., Lüscher et al., 2019), photo-based assessment of eating behavior with smartphones and automated analysis (König et al., 2021), or accelerometry for the assessment of physical activity (McClung et al., 2018). However, as for measures of social media use, researchers may benefit most from combining both objective and subjective measures of health behaviors because objective measures typically provide only little contextual information (Skender et al., 2016).

Fifth, as we only found little evidence for a causal role of the examined psychosocial determinants, future research should continue to explore these and other mechanisms and potential moderating factors that impact if specific determinants might play a role. For example, researchers could use stronger experimental manipulations such as creating social media applications and manipulating the whole social media feed (cf. Kurten et al., 2022) instead of only manipulating the posting behavior of one social media friend. Furthermore, researchers should use more extended intervention periods as some effects (e.g., attitude change) might need more time to unfold or strengthen over time. Additionally, several moderating factors likely influence if changes in determinants of health behaviors such as perceived injunctive social norms occur (e.g., the amount of received positive social feedback) or if they impact health behavior change (e.g., social identification processes). Finally, research should also examine additional potential psychosocial determinants, such as social identity (Geusens & Beullens, 2021), knowledge, or perceived susceptibility (Petkovic et al., 2021). As argued throughout this dissertation, if changes of specific psychosocial determinants occur likely depend on the actual type of social media use and the respective behavior change techniques.

5.5. Implications for Practice

The results of the dissertation have important implications for practice. Health behaviors represent important risk and protective factors for the most dominant causes of ill-health to date, non-communicable diseases (GBD 2019 Risk Factors Collaborators, 2020). Health behaviors are influenced by potentially interacting factors on the intrapersonal, interpersonal, and societal level (see, e.g., Sallis et al., 2006). The internet and social media represent a relatively new but rapidly growing and important part of today's information and decision environment regarding health behaviors (Granheim et al., 2022; Kozyreva et al., 2020). Especially for adolescents and young adults, the most frequent users of social media (Beisch & Schäfer, 2020; Pew Research Center, 2021), social media may even represent the most important source of information (Pew Research Center, 2018). Therefore, social media environments, similar to built environments (e.g., the availability of fast-food restaurants or outdoor exercise facilities in individuals' living spaces), need to be considered to understand and intervene on health behaviors (Abroms, 2019). The first set of practice implications thus refers to the potential of social media for improving both individual- and population-level health. Due to their wide distribution and frequent use, social media can be used in small-scale interventions targeting individuals (Petkovic et al., 2021) and large-scale interventions targeting large proportions of the population (e.g., Breza et al., 2021) to support human health. First, practitioners aiming to change the health behaviors of individuals should consider supporting health behavior change attempts with peer-based support via social media and online communities consisting of individuals with the same health behavior change goals. Second, individuals themselves can use social media to support their health behavior change attempts, for example, via self-monitoring behavior via social media postings. Third, social media can effectively reach large proportions of the population with health advice, for example, in the case of public health emergencies such as Covid-19 (e.g., Murthy et al., 2021).

Another implication of this dissertation is that *how* people and institutions communicate via social media could be essential for supporting health behavior change and other health and well-being outcomes. Self-determination theory has been successfully applied to different contexts, showing various benefits of need fulfillment for behavior change, human health, and well-being (Ryan & Deci, 2017). Relating to the aforementioned use case, how governments and health institutions communicate to the public via social media in times of public health crisis could promote the uptake of health advice and improve individuals' health and well-being (Martela et al., 2021). For example, communicating rules in a caring and autonomy-supportive way with guidance on adherence possibilities may increase the voluntary compliance with behavioral restrictions due to Covid-19 (Martela et al., 2021). Interventionists in social media-based interventions and content moderators in naturally formed online health communities should further aim to ensure communicating in a need-supportive way to support health behavior change in individuals.

In addition to using social media to support health behavior change in the direction of healthier behaviors, measures should be taken to reduce the potential adverse effects of social media use on health and risk behaviors. In this dissertation, I examined the positive role of social media in improving health behaviors – especially eating behavior. The results of the conducted studies and other studies show that both healthy and unhealthy eating behavior can increase in response to eating-related social media use (cf. Sina et al., 2022). Research shows that social media users are frequently exposed to unhealthy eating content (e.g., Cassidy et al., 2021; Qutteina et al., 2019). A recent research report by the British Office of Communications further shows that social media users continuously get younger – in fact, 33% of children in the age between 5 and 7 years and 60% in the age between 8 and 11 years report having at least one social media profile (Ofcom, 2022). Politicians worldwide should consider introducing or extending unhealthy food marketing regulations and restrictions (Breda et al., 2020) to social media environments to reduce potential negative impacts on children's and adolescents' eating behavior and, ultimately, health (Mc Carthy et al., 2022). This argument also translates to other risky behaviors, such as alcohol consumption and smoking, which can also increase in response to social media use.

5.6. General Conclusion

In this dissertation, I took a comprehensive look at the effects of health-related social media use on health behaviors and underlying psychosocial mechanisms. If, when, and how social media effects occur depends on the specific type of health-related social media use, which can be characterized by the utilized communication features (e.g., postings or comments), the contents communicated via these features (e.g., postings about healthy vs. unhealthy food), the directionality of interaction (e.g., active vs. passive use), and the engagement of participants (i.e., the amount of social media use). Eating-related social media postings and social media use concerning these postings can influence eating behavior and support eating behavior change. However, underlying psychosocial mechanisms remain mostly unclear. Some effects might be more temporary and in timely proximity to social media use. Furthermore, how social media users communicate with each other might play an essential role in supporting health behavior change. The rapid growth of social media use, especially in younger age groups, increases social influences on health behaviors and might intensify them due to the fast adaptability of social media environments, content algorithms, and echo chambers. Therefore, social media environments must be considered to understand and intervene on health behaviors and ultimately improve individual and population heal

References

5 am Tag e.V. (2014, September 11). *Was ist 5 am Tag*. https://www.5amtag.de/wissen/was-ist-5-am-tag/

Abbar, S., Mejova, Y., & Weber, I. (2015). You tweet what you eat: Studying food consumption through Twitter. *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, 3197–3206. https://doi.org/10.1145/2702123.2702153

Abroms, L. C. (2019). Public health in the era of social media. *American Journal of Public Health, 109*(S2), S130–S131. https://doi.org/10.2105/AJPH.2018.304947

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Ajzen, I. (2015). The theory of planned behaviour is alive and well, and not ready to retire: A commentary on Sniehotta, Presseau, and Araújo-Soares. *Health Psychology Review, 9*(2), 131–137. https://doi.org/10.1080/17437199.2014.883474

Aral, S., & Nicolaides, C. (2017). Exercise contagion in a global social network. *Nature Communications*, *8*(1), Article 14753. https://doi.org/10.1038/ncomms14753

Archer, E., Hand, G. A., & Blair, S. N. (2013). Validity of U.S. nutritional surveillance: National health and nutrition examination survey caloric energy intake data, 1971–2010. *PLoS ONE*, *8*(10), Article e76632. https://doi.org/10.1371/journal.pone.0076632

Arend, M. G., & Schäfer, T. (2019). Statistical power in two-level models: A tutorial based on Monte Carlo simulation. *Psychological Methods*, *24*(1), 1–19. https://doi.org/10.1037/met0000195

Arigo, D., Jake-Schoffman, D. E., Wolin, K., Beckjord, E., Hekler, E. B., & Pagoto, S. L. (2019). The history and future of digital health in the field of behavioral medicine. *Journal of Behavioral Medicine*, *42*(1), 67–83. https://doi.org/10.1007/s10865-018-9966-z

Arigo, D., Pagoto, S., Carter-Harris, L., Lillie, S. E., & Nebeker, C. (2018). Using social media for health research: Methodological and ethical considerations for recruitment and intervention delivery. *DIGITAL HEALTH*, *4*, Article 2055207618771757. https://doi.org/10.1177/2055207618771757

Aronson, E. (1999). The power of self-persuasion. *American Psychologist*, *54*(11), 875–884. https://doi.org/10.1037/h0088188

Bail, C. A., Argyle, L. P., Brown, T. W., Bumpus, J. P., Chen, H., Hunzaker, M. B. F., Lee, J., Mann, M., Merhout, F., & Volfovsky, A. (2018). Exposure to opposing views on social media can increase political polarization. *Proceedings of the National Academy of Sciences of the United States of America*, *115*(37), 9216–9221. https://doi.org/10.1073/pnas.1804840115

Bakshy, E., Messing, S., & Adamic, L. A. (2015). Exposure to ideologically diverse news and opinion on Facebook. *Science*, *348*(6239), 1130–1132. https://doi.org/10.1126/science.aaa1160

Bakshy, E., Rosenn, I., Marlow, C., & Adamic, L. (2012). The role of social networks in information diffusion. *Proceedings of the 21st International Conference on World Wide Web*, 519–528. https://doi.org/10.1145/2187836.2187907

Baldwin, H. J., Freeman, B., & Kelly, B. (2018). Like and share: Associations between social media engagement and dietary choices in children. *Public Health Nutrition*, *21*(17), 3210–3215. https://doi.org/10.1017/S1368980018001866

Bandura, A. (1997). *Self-efficacy: The exercise of control*. W. H. Freeman and Company.

Bandura, A. (1998). Health promotion from the perspective of social cognitive theory. *Psychology & Health*, *13*(4), 623–649. https://doi.org/10.1080/08870449808407422

Barr, D. J., Levy, R., Scheepers, C., & Tily, H. J. (2013). Random effects structure for confirmatory hypothesis testing: Keep it maximal. *Journal of Memory and Language*, *68*(3), 255–278. https://doi.org/10.1016/j.jml.2012.11.001

Bayer, J. B., Triệu, P., & Ellison, N. B. (2020). Social media elements, ecologies, and effects. *Annual Review of Psychology*, *71*(1), 471–497. https://doi.org/10.1146/annurev-psych-010419-050944

Beauchamp, M. R., Crawford, K. L., & Jackson, B. (2019). Social cognitive theory and physical activity: Mechanisms of behavior change, critique, and legacy. *Psychology of Sport and Exercise*, *42*, 110–117. https://doi.org/10.1016/j.psychsport.2018.11.009

Beisch, N., & Schäfer, C. (2020). Internetnutzung mit großer Dynamik: Medien, Kommunikation, Social Media. *Media Perspektiven*, *9*, 462–481. https://www.ard-werbung.de/media-perspektiven/fachzeitschrift/2020/detailseite-2020/internetnutzung-mit-grosser-dynamik-medien-kommunikation-social-media/

Bender, J. L., Jimenez-Marroquin, M.-C., & Jadad, A. R. (2011). Seeking support on Facebook: A content analysis of breast cancer groups. *Journal of Medical Internet Research*, *13*(1), Article e1560. https://doi.org/10.2196/jmir.1560

Berkman, L. F., Glass, T., Brissette, I., & Seeman, T. E. (2000). From social integration to health: Durkheim in the new millennium. *Social Science & Medicine*, *51*(6), 843–857. https://doi.org/10.1016/S0277-9536(00)00065-4

Berman, R., & Katona, Z. (2020). Curation algorithms and filter bubbles in social networks. *Marketing Science*, *39*(2), 296–316. https://doi.org/10.1287/mksc.2019.1208

Blom, A. G., Felderer, B., Höhne, J. K., Krieger, U., Rettig, T., & SFB 884 ´Political economy of reforms´, Universität Mannheim. (2018). *German Internet Panel, Wave 31—Core Study (September 2017)—Codebuch* - (1.0.0) [Data set]. GESIS Data Archive. https://doi.org/10.4232/1.13011

Blom, A. G., Gathmann, C., & Krieger, U. (2015). Setting up an online panel representative of the general population: The German Internet Panel. *Field Methods*, *27*(4), 391–408. https://doi.org/10.1177/1525822X15574494

Bond, R. M., Fariss, C. J., Jones, J. J., Kramer, A. D. I., Marlow, C., Settle, J. E., & Fowler, J. H. (2012). A 61-million-person experiment in social influence and political mobilization. *Nature*, *489*(7415), 295–298. https://doi.org/10.1038/nature11421

Borek, A. J., Abraham, C., Greaves, C. J., Gillison, F., Tarrant, M., Morgan-Trimmer, S., McCabe, R., & Smith, J. R. (2019). Identifying change processes in group-based health behaviour-change interventions: Development of the mechanisms of action in group-based interventions (MAGI) framework. *Health Psychology Review*, *13*(3), 227–247. https://doi.org/10.1080/17437199.2019.1625282

Boswell, R. G., & Kober, H. (2016). Food cue reactivity and craving predict eating and weight gain: A meta-analytic review. *Obesity Reviews*, *17*(2), 159–177. https://doi.org/10.1111/obr.12354

Breda, J., Castro, L. S. N., Whiting, S., Williams, J., Jewell, J., Engesveen, K., & Wickramasinghe, K. (2020). Towards better nutrition in Europe: Evaluating progress and defining future directions. *Food Policy*, *96*, 101887. https://doi.org/10.1016/j.foodpol.2020.101887

Breza, E., Stanford, F. C., Alsan, M., Alsan, B., Banerjee, A., Chandrasekhar, A. G., Eichmeyer, S., Glushko, T., Goldsmith-Pinkham, P., Holland, K., Hoppe, E., Karnani, M., Liegl, S., Loisel, T., Ogbu-Nwobodo, L., Olken, B. A., Torres, C., Vautrey, P.-L., Warner, E. T., … Duflo, E. (2021). Effects of a large-scale social media advertising campaign on holiday travel and COVID-19 infections: A cluster randomized controlled trial. *Nature Medicine*, *27*(9), 1622–1628. https://doi.org/10.1038/s41591-021-01487-3

Brugnoli, E., Cinelli, M., Quattrociocchi, W., & Scala, A. (2019). Recursive patterns in online echo chambers. *Scientific Reports*, *9*(1), Article 20118. https://doi.org/10.1038/s41598-019-56191-7

Bunker, C. J., & Varnum, M. E. W. (2021). How strong is the association between social media use and false consensus? *Computers in Human Behavior*, *125*, Article 106947. https://doi.org/10.1016/j.chb.2021.106947

Cane, J., O'Connor, D., & Michie, S. (2012). Validation of the theoretical domains framework for use in behaviour change and implementation research. *Implementation Science*, *7*(1), 37. https://doi.org/10.1186/1748-5908-7-37

Carey, R. N., Connell, L. E., Johnston, M., Rothman, A. J., de Bruin, M., Kelly, M. P., & Michie, S. (2019). Behavior change techniques and their mechanisms of action: A synthesis of links described in published intervention literature. *Annals of Behavioral Medicine*, *53*(8), 693–707. https://doi.org/10.1093/abm/kay078

Carr, C. T., & Hayes, R. A. (2015). Social media: Defining, developing, and divining. *Atlantic Journal of Communication*, *23*(1), 46–65. https://doi.org/10.1080/15456870.2015.972282

Carr, R. M., Prestwich, A., Kwasnicka, D., Thøgersen-Ntoumani, C., Gucciardi, D. F., Quested, E., Hall, L. H., & Ntoumanis, N. (2019). Dyadic interventions to promote physical activity and reduce sedentary behaviour: Systematic review and meta-analysis. *Health Psychology Review*, *13*(1), 91–109. https://doi.org/10.1080/17437199.2018.1532312

Carron-Arthur, B., Ali, K., Cunningham, J. A., & Griffiths, K. M. (2015). From help-seekers to influential users: A systematic review of participation styles in online health communities. *Journal of Medical Internet Research*, *17*(12), Article e271. https://doi.org/10.2196/jmir.4705

Cassidy, O., Shin, H. W., Song, E., Jiang, E., Harri, R., Cano, C., Vedanthan, R., Ogedegbe, G., & Bragg, M. (2021). Comparing McDonald's food marketing practices on official Instagram accounts across 15 countries. *BMJ Nutrition, Prevention & Health*, *4*(2). https://doi.org/10.1136/bmjnph-2021-000229

Cavallo, D. N., Brown, J. D., Tate, D. F., DeVellis, R. F., Zimmer, C., & Ammerman, A. S. (2014). The role of companionship, esteem, and informational support in explaining physical activity among young women in an online social network intervention. *Journal of Behavioral Medicine*, *37*(5), 955–966. https://doi.org/10.1007/s10865-013-9534-5

Cavallo, D. N., Martinez, R., Webb Hooper, M., & Flocke, S. (2020). Feasibility of a social media-based weight loss intervention designed for low-SES adults. *Translational Behavioral Medicine*, *11*(4), 981–992. https://doi.org/10.1093/tbm/ibaa070

Cavallo, D. N., Tate, D. F., Ward, D. S., DeVellis, R. F., Thayer, L. M., & Ammerman, A. S. (2014). Social support for physical activity—Role of Facebook with and without structured intervention. *Translational Behavioral Medicine*, *4*(4), 346–354. https://doi.org/10.1007/s13142-014-0269-9

Centola, D. (2011). An experimental study of homophily in the adoption of health behavior. *Science*, *334*(6060), 1269–1272. https://doi.org/10.1126/science.1207055

Centola, D., & van de Rijt, A. (2015). Choosing your network: Social preferences in an online health community. *Social Science & Medicine*, *125*, 19–31. https://doi.org/10.1016/j.socscimed.2014.05.019

Chan, D. K. C., Zhang, L., Lee, A. S. Y., & Hagger, M. S. (2020). Reciprocal relations between autonomous motivation from self-determination theory and social cognition constructs from the theory of planned behavior: A cross-lagged panel design in sport injury prevention. *Psychology of Sport and Exercise*, *48*, Article 101660. https://doi.org/10.1016/j.psychsport.2020.101660

Chapman, J., Armitage, C. J., & Norman, P. (2009). Comparing implementation intention interventions in relation to young adults' intake of fruit and vegetables. *Psychology & Health*, *24*(3), 317–332. https://doi.org/10.1080/08870440701864538

Chen, J., & Wang, Y. (2021). Social media use for health purposes: Systematic review. *Journal of Medical Internet Research*, *23*(5), Article e17917. https://doi.org/10.2196/17917

Chung, A., Vieira, D., Donley, T., Tan, N., Jean-Louis, G., Gouley, K. K., & Seixas, A. (2021). Adolescent peer influence on eating behaviors via social media: Scoping review. *Journal of Medical Internet Research*, *23*(6), Article e19697. https://doi.org/10.2196/19697

Chung, C.-F., Agapie, E., Schroeder, J., Mishra, S., Fogarty, J., & Munson, S. A. (2017). When personal tracking becomes social: Examining the use of Instagram for healthy eating. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems* (pp. 1674–1687). Association for Computing Machinery. https://doi.org/10.1145/3025453.3025747

Cialdini, R. B., Kallgren, C. A., & Reno, R. R. (1991). A focus theory of normative conduct: A theoretical refinement and reevaluation of the role of norms in human behavior. In M. P. Zanna (Ed.), *Advances in experimental social psychology* (Vol. 24, pp. 201–234). Academic Press. https://doi.org/10.1016/S0065-2601(08)60330-5

Cinelli, M., Brugnoli, E., Schmidt, A. L., Zollo, F., Quattrociocchi, W., & Scala, A. (2020). Selective exposure shapes the Facebook news diet. *PLoS ONE*, *15*(3), Article e0229129. https://doi.org/10.1371/journal.pone.0229129

Cinelli, M., De Francisci Morales, G., Galeazzi, A., Quattrociocchi, W., & Starnini, M. (2021). The echo chamber effect on social media. *Proceedings of the National Academy of Sciences of the United States of America*, *118*(9), Article e2023301118. https://doi.org/10.1073/pnas.2023301118

Cinelli, M., Quattrociocchi, W., Galeazzi, A., Valensise, C. M., Brugnoli, E., Schmidt, A. L., Zola, P., Zollo, F., & Scala, A. (2020). The COVID-19 social media infodemic. *Scientific Reports*, *10*(1), Article 16598. https://doi.org/10.1038/s41598-020-73510-5

Coates, A. E., Hardman, C. A., Halford, J. C. G., Christiansen, P., & Boyland, E. J. (2019a). Food and beverage cues featured in YouTube videos of social media influencers popular with children: An exploratory study. *Frontiers in Psychology*, *10*. https://www.frontiersin.org/article/10.3389/fpsyg.2019.02142

Coates, A. E., Hardman, C. A., Halford, J. C. G., Christiansen, P., & Boyland, E. J. (2019b). Social media influencer marketing and children's food intake: A randomized trial. *Pediatrics*, *143*(4), Article e20182554. https://doi.org/10.1542/peds.2018-2554

Conner, M. (2015). Extending not retiring the theory of planned behaviour: A commentary on Sniehotta, Presseau and Araújo-Soares. *Health Psychology Review*, *9*(2), 141–145. https://doi.org/10.1080/17437199.2014.899060

Conner, M., & Norman, P. (2015). *Predicting and changing health behaviour: A social cognition approach*. Open University Press.

Conner, M., Rhodes, R. E., Morris, B., McEachan, R., & Lawton, R. (2011). Changing exercise through targeting affective or cognitive attitudes. *Psychology & Health*, *26*(2), 133–149. https://doi.org/10.1080/08870446.2011.531570

Cornelius, T., Gettens, K., & Gorin, A. A. (2016). Dyadic dynamics in a randomized weight loss intervention. *Annals of Behavioral Medicine*, *50*(4), 506–515. https://doi.org/10.1007/s12160-016-9778-8

Craig, C. L., Marshall, A. L., Sjöström, M., Bauman, A. E., Booth, M. L., Ainsworth, B. E., Pratt, M., Ekelund, U., Yngve, A., Sallis, J. F., & Oja, P. (2003). International physical activity questionnaire: 12-country reliability and validity. *Medicine and Science in Sports and Exercise*, *35*(8), 1381–1395. https://doi.org/10.1249/01.MSS.0000078924.61453.FB

Croes, E., & Bartels, J. (2021). Young adults' motivations for following social influencers and their relationship to identification and buying behavior. *Computers in Human Behavior*, *124*, Article 106910. https://doi.org/10.1016/j.chb.2021.106910

Cullen, K. W., Baranowski, T., Rittenberry, L., Cosart, C., Hebert, D., & de Moor, C. (2001). Child-reported family and peer influences on fruit, juice and vegetable consumption:

Reliability and validity of measures. *Health Education Research*, *16*(2), 187–200. https://doi.org/10.1093/her/16.2.187

Curtis, B. L., Lookatch, S. J., Ramo, D. E., McKay, J. R., Feinn, R. S., & Kranzler, H. R. (2018). Meta-analysis of the association of alcohol-related social media use with alcohol consumption and alcohol-related problems in adolescents and young adults. *Alcoholism: Clinical and Experimental Research*, *42*(6), 978–986. https://doi.org/10.1111/acer.13642

Dahl, A. A., Hales, S. B., & Turner-McGrievy, G. M. (2016). Integrating social media into weight loss interventions. *Current Opinion in Psychology*, *9*, 11–15. https://doi.org/10.1016/j.copsyc.2015.09.018

Davis, R., Campbell, R., Hildon, Z., Hobbs, L., & Michie, S. (2015). Theories of behaviour and behaviour change across the social and behavioural sciences: A scoping review. *Health Psychology Review*, *9*(3), 323–344. https://doi.org/10.1080/17437199.2014.941722

de la Peña, A., & Quintanilla, C. (2015). Share, like and achieve: The power of Facebook to reach health-related goals. *International Journal of Consumer Studies*, *39*(5), 495–505. https://doi.org/10.1111/ijcs.12224

de Ridder, D., Kroese, F., Evers, C., Adriaanse, M., & Gillebaart, M. (2017). Healthy diet: Health impact, prevalence, correlates, and interventions. *Psychology & Health*, *32*(8), 907–941. https://doi.org/10.1080/08870446.2017.1316849

Deci, E. L., & Ryan, R. M. (2000). The “what” and “why” of goal pursuits: Human needs and the self-determination of behavior. *Psychological Inquiry*, *11*(4), 227–268. https://doi.org/10.1207/S15327965PLI1104_01

Del Vicario, M., Vivaldo, G., Bessi, A., Zollo, F., Scala, A., Caldarelli, G., & Quattrociocchi, W. (2016). Echo chambers: Emotional contagion and group polarization on Facebook. *Scientific Reports*, *6*(1), Article 37825. https://doi.org/10.1038/srep37825

Di Noia, J., & Cullen, K. W. (2015). Fruit and vegetable attitudes, norms, and intake in low-income youth. *Health Education & Behavior*, *42*(6), 775–782. https://doi.org/10.1177/1090198115578752

Djafarova, E., & Rushworth, C. (2017). Exploring the credibility of online celebrities’ Instagram profiles in influencing the purchase decisions of young female users. *Computers in Human Behavior*, *68*, 1–7. https://doi.org/10.1016/j.chb.2016.11.009

Dunton, G. F., Rothman, A. J., Leventhal, A. M., & Intille, S. S. (2021). How intensive longitudinal data can stimulate advances in health behavior maintenance theories and interventions. *Translational Behavioral Medicine*, *11*(1), 281–286.

https://doi.org/10.1093/tbm/ibz165

Edelmann, N. (2016). What is lurking? A literature review of research on lurking. In G. Riva, B. K. Wiederhold, & P. Cipresso (Eds.), *The Psychology of Social Networking: Personal Experience in Online Communities* (pp. 159–174). De Gruyter Open Ltd.

Ellison, N. B., & Boyd, D. M. (2013). Sociality Through Social Network Sites. In W. H. Dutton (Ed.), *The Oxford Handbook of Internet Studies* (pp. 151–172). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199589074.013.0008

Enders, C. K., & Tofighi, D. (2007). Centering predictor variables in cross-sectional multilevel models: A new look at an old issue. *Psychological Methods*, *12*(2), 121–138. https://doi.org/10.1037/1082-989X.12.2.121

Epton, T., Currie, S., & Armitage, C. J. (2017). Unique effects of setting goals on behavior change: Systematic review and meta-analysis. *Journal of Consulting and Clinical Psychology, 85*(12), 1182–1198. https://doi.org/10.1037/ccp0000260

Erinosho, T. O., Pinard, C. A., Nebeling, L. C., Moser, R. P., Shaikh, A. R., Resnicow, K., Oh, A. Y., & Yaroch, A. L. (2015). Development and implementation of the National Cancer Institute's Food Attitudes and Behaviors Survey to assess correlates of fruit and vegetable intake in adults. *PLoS ONE*, *10*(2), Article e0115017. https://doi.org/10.1371/journal.pone.0115017

Eurostat. (2021, February 16). *International Standard Classification of Education (ISCED)*. https://ec.europa.eu/eurostat/statistics-explained/index.php/International_Standard_Classification_of_Education_(ISCED)#Implementation_of_ISCED_2011_.28levels_of_education.29

Eysenbach, G. (2005). The law of attrition. *Journal of Medical Internet Research*, *7*(1), Article e11. https://doi.org/10.2196/jmir.7.1.e11

Fishbein, M., & Ajzen, I. (2011). *Predicting and changing behavior: The reasoned action approach*. Psychology Press, Taylor & Francis Group.

Fitzsimons, G. M., & Finkel, E. J. (2010). Interpersonal influences on self-regulation. *Current Directions in Psychological Science*, *19*(2), 101–105. https://doi.org/10.1177/0963721410364499

Fitzsimons, G. M., Finkel, E. J., & vanDellen, M. R. (2015). Transactive goal dynamics. *Psychological Review*, *122*(4), 648–673. https://doi.org/10.1037/a0039654

Folkvord, F., & de Bruijne, M. (2020). The effect of the promotion of vegetables by a social influencer on adolescents' subsequent vegetable intake: A pilot study. *International Journal of Environmental Research and Public Health*, *17*(7), Article 2243.

https://doi.org/10.3390/ijerph17072243

Freelon, D. (2013). ReCal OIR: ordinal, interval, and ratio intercoder reliability as a web service. *International Journal of Internet Science*, *8*(1), 10–16.

GBD 2017 Diet Collaborators. (2019). Health effects of dietary risks in 195 countries, 1990–2017: A systematic analysis for the Global Burden of Disease Study 2017. *The Lancet*, *393*(10184), 1958–1972. https://doi.org/10.1016/S0140-6736(19)30041-8

GBD 2019 Risk Factors Collaborators. (2020). Global burden of 87 risk factors in 204 countries and territories, 1990–2019: A systematic analysis for the Global Burden of Disease Study 2019. *The Lancet*, *396*(10258), 1223–1249. https://doi.org/10.1016/S0140-6736(20)30752-2

Gelman, A., & Hill, J. (2006). *Data analysis using regression and multilevel/hierarchical models*. Cambridge University Press.

German Federal Centre for Nutrition. (2020, February 2). *Ernährungspyramide: Wie groß ist eine Portion? Die Hand als Maß für die richtige Portionsgröße*. https://www.bzfe.de/ernaehrung/die-ernaehrungspyramide/die-ernaehrungspyramide-eine-fuer-alle/ernaehrungspyramide-wie-gross-ist-eine-portion/

Geusens, F., & Beullens, K. (2019). A longitudinal examination of the moderating influence of peer and parental socialization on alcohol-related social media self-effects among late adolescents. *Media Psychology*, *22*(2), 273–297. https://doi.org/10.1080/15213269.2018.1476159

Geusens, F., & Beullens, K. (2021). I see, therefore I am: Exposure to alcohol references on social media, but not on traditional media, is related to alcohol consumption via drinking and non-drinking identity. *Health Communication*. https://doi.org/10.1080/10410236.2021.1954301

Geusens, F., Bigman-Galimore, C. A., & Beullens, K. (2020). A cross-cultural comparison of the processes underlying the associations between sharing of and exposure to alcohol references and drinking intentions. *New Media & Society*, *22*(1), 49–69. https://doi.org/10.1177/1461444819860057

Giese, H., Taut, D., Ollila, H., Baban, A., Absetz, P., Schupp, H., & Renner, B. (2015). Children's and adolescents' snacking: Interplay between the individual and the school class. *Frontiers in Psychology*, *6*, Article 1308. https://doi.org/10.3389/fpsyg.2015.01308

Gillison, F. B., Rouse, P., Standage, M., Sebire, S. J., & Ryan, R. M. (2019). A meta-analysis of techniques to promote motivation for health behaviour change from a self-determination theory perspective. *Health Psychology Review*, *13*(1), 110–130.

https://doi.org/10.1080/17437199.2018.1534071

Godino, J. G., Merchant, G., Norman, G. J., Donohue, M. C., Marshall, S. J., Fowler, J. H., Calfas, K. J., Huang, J. S., Rock, C. L., Griswold, W. G., Gupta, A., Raab, F., Fogg, B. J., Robinson, T. N., & Patrick, K. (2016). Using social and mobile tools for weight loss in overweight and obese young adults (Project SMART): A 2 year, parallel-group, randomised, controlled trial. *The Lancet Diabetes & Endocrinology*, *4*(9), 747–755. https://doi.org/10.1016/S2213-8587(16)30105-X

Granheim, S. I., Løvhaug, A. L., Terragni, L., Torheim, L. E., & Thurston, M. (2022). Mapping the digital food environment: A systematic scoping review. *Obesity Reviews*, *23*(1), Article e13356. https://doi.org/10.1111/obr.13356

Haftenberger, M., Heuer, T., Heidemann, C., Kube, F., Krems, C., & Mensink, G. B. (2010). Relative validation of a food frequency questionnaire for national health and nutrition monitoring. *Nutrition Journal, 9,* Article 36. https://doi.org/10.1186/1475-2891-9-36

Hagger, M. S. (2015). Retired or not, the theory of planned behaviour will always be with us. *Health Psychology Review*, *9*(2), 125–130. https://doi.org/10.1080/17437199.2015.1034470

Hagger, M. S., Cameron, L. D., Hamilton, K., Hankonen, N., & Lintunen, T. (Eds.). (2020). *The handbook of behavior change*. Cambridge University Press. https://doi.org/10.1017/9781108677318

Hagger, M. S., & Chatzisarantis, N. L. D. (2009). Integrating the theory of planned behaviour and self-determination theory in health behaviour: A meta-analysis. *British Journal of Health Psychology*, *14*(2), 275–302. https://doi.org/10.1348/135910708X373959

Hagger, M. S., & Chatzisarantis, N. L. D. (2012). Transferring motivation from educational to extramural contexts: A review of the trans-contextual model. *European Journal of Psychology of Education*, *27*(2), 195–212. https://doi.org/10.1007/s10212-011-0082-5

Hagger, M. S., Moyers, S., McAnally, K., & McKinley, L. E. (2020). Known knowns and known unknowns on behavior change interventions and mechanisms of action. *Health Psychology Review*, *14*(1), 199–212. https://doi.org/10.1080/17437199.2020.1719184

Hampton, K. N., Goulet, L. S., Marlow, C., & Rainie, L. (2012). *Why most Facebook users get more than they give*. Pew Research Center. https://www.pewresearch.org/internet/2012/02/03/why-most-facebook-users-get-more-than-they-give/

Hankonen, N. (2021). Participants' enactment of behavior change techniques: A call for increased focus on what people do to manage their motivation and behavior. *Health*

Psychology Review, *15*(2), 185–194. https://doi.org/10.1080/17437199.2020.1814836

Harkin, B., Webb, T. L., Chang, B. P. I., Prestwich, A., Conner, M., Kellar, I., Benn, Y., & Sheeran, P. (2016). Does monitoring goal progress promote goal attainment? A meta-analysis of the experimental evidence. *Psychological Bulletin*, *142*(2), 198–229. https://doi.org/10.1037/bul0000025

Hawkins, L., Farrow, C., & Thomas, J. M. (2020). Do perceived norms of social media users' eating habits and preferences predict our own food consumption and BMI? *Appetite*, *149*, Article 104611. https://doi.org/10.1016/j.appet.2020.104611

Hawkins, L., Farrow, C., & Thomas, J. M. (2021). Does exposure to socially endorsed food images on social media influence food intake? *Appetite*, *165*, Article 105424. https://doi.org/10.1016/j.appet.2021.105424

Hawks, J. R., Madanat, H., Walsh-Buhi, E. R., Hartman, S., Nara, A., Strong, D., & Anderson, C. (2020). Narrative review of social media as a research tool for diet and weight loss. *Computers in Human Behavior*, *111*, Article 106426. https://doi.org/10.1016/j.chb.2020.106426

Helmerhorst, H. H. J., Brage, S., Warren, J., Besson, H., & Ekelund, U. (2012). A systematic review of reliability and objective criterion-related validity of physical activity questionnaires. *International Journal of Behavioral Nutrition and Physical Activity*, *9*(1), 103. https://doi.org/10.1186/1479-5868-9-103

Hendriks, H., Nooy, W. de, Gebhardt, W. A., & Putte, B. van den. (2021). Causal effects of alcohol-related Facebook posts on drinking behavior: Longitudinal experimental study. *Journal of Medical Internet Research*, *23*(11), Article e28237. https://doi.org/10.2196/28237

Higgs, S., & Thomas, J. (2016). Social influences on eating. *Current Opinion in Behavioral Sciences*, *9*, 1–6. https://doi.org/10.1016/j.cobeha.2015.10.005

Holmberg, C., E. Chaplin, J., Hillman, T., & Berg, C. (2016). Adolescents' presentation of food in social media: An explorative study. *Appetite*, *99*, 121–129. https://doi.org/10.1016/j.appet.2016.01.009

Hou, S.-I., Charlery, S.-A. R., & Roberson, K. (2014). Systematic literature review of Internet interventions across health behaviors. *Health Psychology and Behavioral Medicine*, *2*(1), 455–481. https://doi.org/10.1080/21642850.2014.895368

Howard, J. L., Gagné, M., & Bureau, J. S. (2017). Testing a continuum structure of self-determined motivation: A meta-analysis. *Psychological Bulletin*, *143*(12), 1346–1377. https://doi.org/10.1037/bul0000125

Hu, Y., Manikonda, L., & Kambhampati, S. (2014). What we Instagram: A first analysis of Instagram photo content and user types. In *Proceedings of the Eighth International AAAI Conference on Weblogs and Social Media* (pp. 595–598). Association for the Advancement of Artificial Intelligence. https://www.aaai.org/ocs/index.php/ICWSM/ICWSM14/paper/view/8118

Inauen, J., Bolger, N., Shrout, P. E., Stadler, G., Amrein, M., Rackow, P., & Scholz, U. (2017). Using smartphone-based support groups to promote healthy eating in daily life: A randomised trial. *Applied Psychology: Health and Well-Being*, *9*(3), 303–323. https://doi.org/10.1111/aphw.12093

Inauen, J., Shrout, P. E., Bolger, N., Stadler, G., & Scholz, U. (2016). Mind the gap? An intensive longitudinal study of between-person and within-person intention-behavior relations. *Annals of Behavioral Medicine*, *50*(4), 516–522. https://doi.org/10.1007/s12160-016-9776-x

International Labour Office. (2012). *International Standard Classification of Occupations. ISCO-08. Structure, group definitions and correspondence tables*. https://www.ilo.org/public/english/bureau/stat/isco/docs/publication08.pdf

International Telecommunication Union. (2020). *Key ICT indicators for developed and developing countries, the world and special regions (totals and penetration rates)*. https://www.itu.int/en/ITU-D/Statistics/Documents/facts/ITU_regional_global_Key_ICT_indicator_aggregates_Nov_2020.xlsx

Jane, M., Hagger, M., Foster, J., Ho, S., Kane, R., & Pal, S. (2017). Effects of a weight management program delivered by social media on weight and metabolic syndrome risk factors in overweight and obese adults: A randomised controlled trial. *PLoS ONE*, *12*(6), Article e0178326. https://doi.org/10.1371/journal.pone.0178326

Jin, S. V., Muqaddam, A., & Ryu, E. (2019). Instafamous and social media influencer marketing. *Marketing Intelligence & Planning*, *37*(5), 567–579. https://doi.org/10.1108/MIP-09-2018-0375

Joglekar, S., Sastry, N., Coulson, N. S., Taylor, S. J., Patel, A., Duschinsky, R., Anand, A., Evans, M. J., Griffiths, C. J., Sheikh, A., Panzarasa, P., & Simoni, A. D. (2018). How online communities of people with long-term conditions function and evolve: Network analysis of the structure and dynamics of the Asthma UK and British Lung Foundation online communities. *Journal of Medical Internet Research*, *20*(7), e238. https://doi.org/10.2196/jmir.9952

Johansson, V., Islind, A. S., Lindroth, T., Angenete, E., & Gellerstedt, M. (2021). Online communities as a driver for patient empowerment: Systematic review. *Journal of Medical Internet Research, 23*(2), Article e19910. https://doi.org/10.2196/19910

Johnston, M., Carey, R. N., Connell Bohlen, L. E., Johnston, D. W., Rothman, A. J., de Bruin, M., Kelly, M. P., Groarke, H., & Michie, S. (2021). Development of an online tool for linking behavior change techniques and mechanisms of action based on triangulation of findings from literature synthesis and expert consensus. *Translational Behavioral Medicine, 11*(5), 1049–1065. https://doi.org/10.1093/tbm/ibaa050

Kalajas-Tilga, H., Hein, V., Koka, A., Tilga, H., Raudsepp, L., & Hagger, M. S. (2022). Application of the trans-contextual model to predict change in leisure time physical activity. *Psychology & Health*, *37*(1), 62–86. https://doi.org/10.1080/08870446.2020.1869741

Kelders, S. M., Kok, R. N., Ossebaard, H. C., & Gemert-Pijnen, J. E. V. (2012). Persuasive system design does matter: A systematic review of adherence to web-based interventions. *Journal of Medical Internet Research*, *14*(6), e152. https://doi.org/10.2196/jmir.2104

Kent de Grey, R. G., Uchino, B. N., Trettevik, R., Cronan, S., & Hogan, J. N. (2018). Social support and sleep: A meta-analysis. *Health Psychology, 37*(8), 787–798. https://doi.org/10.1037/hea0000628

Kilb, M., Giese, H., & Mata, J. (2022). *How social media affects healthy eating in senders and receivers of eating-related online postings: Two field experiments with intensive longitudinal data* [Manuscript in preparation].

Kilb, M., & Mata, J. (2022). *How social media influences offline health behaviors: A behavioral science perspective* [Manuscript in preparation].

Kim, B. R., & Mackert, M. (2022). Social media use and binge eating: An integrative review. *Public Health Nursing*. https://doi.org/10.1111/phn.13069

Kim, H.-M. (2022). Social comparison of fitness social media postings by fitness app users. *Computers in Human Behavior,* 107204. https://doi.org/10.1016/j.chb.2022.107204

Kim, S. C., & Hawkins, K. H. (2020). The psychology of social media communication in influencing prevention intentions during the 2019 U.S. measles outbreak. *Computers in Human Behavior*, *111*, 106428. https://doi.org/10.1016/j.chb.2020.106428

Kim, Y., Park, I., & Kang, M. (2013). Convergent validity of the International Physical Activity Questionnaire (IPAQ): Meta-analysis. *Public Health Nutrition*, *16*(3), 440–452. https://doi.org/10.1017/S1368980012002996

Klassen, K. M., Douglass, C. H., Brennan, L., Truby, H., & Lim, M. S. C. (2018). Social media use for nutrition outcomes in young adults: A mixed-methods systematic review. *International Journal of Behavioral Nutrition and Physical Activity*, *15*(1), Article 70. https://doi.org/10.1186/s12966-018-0696-y

Klein, H. J., & Cooper, J. T. (2013). Goal commitment. In E. A. Locke & G. P. Latham (Eds.), *New developments in goal setting and task performance* (pp. 65–89). Routledge/Taylor & Francis Group.

Klein, H. J., Lount Jr., R. B., Park, H. M., & Linford, B. J. (2020). When goals are known: The effects of audience relative status on goal commitment and performance. *Journal of Applied Psychology*, *105*(4), 372–389. https://doi.org/10.1037/apl0000441

Klein, H. J., Molloy, J. C., & Brinsfield, C. T. (2012). Reconceptualizing workplace commitment to redress a stretched construct: Revisiting assumptions and removing confounds. *Academy of Management Review*, *37*(1), 130–151. https://doi.org/10.5465/amr.2010.0018

Klein, H. J., Wesson, M. J., Hollenbeck, J. R., & Alge, B. J. (1999). Goal commitment and the goal-setting process: Conceptual clarification and empirical synthesis. *Journal of Applied Psychology*, *84*(6), 885–896. https://doi.org/10.1037/0021-9010.84.6.885

Klein, H. J., Wesson, M. J., Hollenbeck, J. R., Wright, P. M., & DeShon, R. P. (2001). The assessment of goal commitment: A measurement model meta-analysis. *Organizational Behavior and Human Decision Processes*, *85*(1), 32–55. https://doi.org/10.1006/obhd.2000.2931

Knittle, K., Heino, M., Marques, M. M., Stenius, M., Beattie, M., Ehbrecht, F., Hagger, M. S., Hardeman, W., & Hankonen, N. (2020). The compendium of self-enactable techniques to change and self-manage motivation and behaviour v.1.0. *Nature Human Behaviour*, *4*(2), 215–223. https://doi.org/10.1038/s41562-019-0798-9

Knobl, V., Dallacker, M., Hertwig, R., & Mata, J. (2022). Happy and healthy: How family mealtime routines relate to child nutritional health. *Appetite*, *171*, Article 105939. https://doi.org/10.1016/j.appet.2022.105939

König, L. M., Giese, H., Stok, F. M., & Renner, B. (2017). The social image of food: Associations between popularity and eating behavior. *Appetite*, *114*, 248–258. https://doi.org/10.1016/j.appet.2017.03.039

König, L. M., Van Emmenis, M., Nurmi, J., Kassavou, A., & Sutton, S. (2021). Characteristics of smartphone-based dietary assessment tools: A systematic review. *Health Psychology Review*. https://doi.org/10.1080/17437199.2021.2016066

Kozyreva, A., Lewandowsky, S., & Hertwig, R. (2020). Citizens versus the internet:

Confronting digital challenges with cognitive tools. *Psychological Science in the Public Interest, 21*(3), 103–156. https://doi.org/10.1177/1529100620946707

Kurten, S., Vanherle, R., Beullens, K., Gebhardt, W. A., van den Putte, B., & Hendriks, H. (2022). Like to drink: Dynamics of liking alcohol posts and effects on alcohol use. *Computers in Human Behavior*, *129*, Article 107145. https://doi.org/10.1016/j.chb.2021.107145

Kwasnicka, D., Dombrowski, S. U., White, M., & Sniehotta, F. (2016). Theoretical explanations for maintenance of behaviour change: A systematic review of behaviour theories. *Health Psychology Review*, *10*(3), 277–296. https://doi.org/10.1080/17437199.2016.1151372

Kwasnicka, D., Ntoumanis, N., & Sniehotta, F. F. (2021). Setting performance and learning goals is useful for active and inactive individuals, if goals are personalized and flexible: Commentary on Swann et al. (2020). *Health Psychology Review*, *15*(1), 51–55. https://doi.org/10.1080/17437199.2020.1762107

Lakens, D., & Evers, E. R. K. (2014). Sailing from the seas of chaos into the corridor of stability: Practical recommendations to increase the informational value of studies. *Perspectives on Psychological Science*, *9*(3), 278–292. https://doi.org/10.1177/1745691614528520

Laranjo, L., Arguel, A., Neves, A. L., Gallagher, A. M., Kaplan, R., Mortimer, N., Mendes, G. A., & Lau, A. Y. S. (2015). The influence of social networking sites on health behavior change: A systematic review and meta-analysis. *Journal of the American Medical Informatics Association*, *22*(1), 243–256. https://doi.org/10.1136/amiajnl-2014-002841

Lawton, R., Conner, M., & McEachan, R. (2009). Desire or reason: Predicting health behaviors from affective and cognitive attitudes. *Health Psychology*, *28*(1), 56–65. https://doi.org/10.1037/a0013424

Lee, E., Karimi, F., Wagner, C., Jo, H.-H., Strohmaier, M., & Galesic, M. (2019). Homophily and minority-group size explain perception biases in social networks. *Nature Human Behaviour*, *3*(10), 1078–1087. https://doi.org/10.1038/s41562-019-0677-4

Lee, I.-M., & Shiroma, E. J. (2014). Using accelerometers to measure physical activity in large-scale epidemiological studies: Issues and challenges. *British Journal of Sports Medicine*, *48*(3), 197–201. https://doi.org/10.1136/bjsports-2013-093154

Lee, I.-M., Shiroma, E. J., Lobelo, F., Puska, P., Blair, S. N., & Katzmarzyk, P. T. (2012). Effect of physical inactivity on major non-communicable diseases worldwide: An analysis of burden of disease and life expectancy. *The Lancet*, *380*(9838), 219–229. https://doi.org/10.1016/S0140-6736(12)61031-9

Lefebvre, R. C., & Bornkessel, A. S. (2013). Digital social networks and health. *Circulation, 127*(17), 1829–1836. https://doi.org/10.1161/CIRCULATIONAHA.112.000897

Lerman, K., & Ghosh, R. (2010). Information contagion: An empirical study of the spread of news on Digg and Twitter social networks. *Proceedings of the International AAAI Conference on Weblogs and Social Media, 4(1)*, 90–97. https://www.aaai.org/ocs/index.php/ICWSM/ICWSM10/paper/view/1509

Lerman, K., Yan, X., & Wu, X.-Z. (2016). The "majority illusion" in social networks. *PLoS ONE, 11*(2), Article e0147617. https://doi.org/10.1371/journal.pone.0147617

Lewis, K., Gonzalez, M., & Kaufman, J. (2012). Social selection and peer influence in an online social network. *Proceedings of the National Academy of Sciences of the United States of America*, *109*(1), 68–72. https://doi.org/10.1073/pnas.1109739109

Leys, C., Delacre, M., Mora, Y. L., Lakens, D., & Ley, C. (2019). How to classify, detect, and manage univariate and multivariate outliers, with emphasis on pre-registration. *International Review of Social Psychology*, *32*(1), 1–10. https://doi.org/10.5334/irsp.289

Leys, C., Ley, C., Klein, O., Bernard, P., & Licata, L. (2013). Detecting outliers: Do not use standard deviation around the mean, use absolute deviation around the median. *Journal of Experimental Social Psychology*, *49*(4), 764–766. https://doi.org/10.1016/j.jesp.2013.03.013

Liu, D., Ainsworth, S. E., & Baumeister, R. F. (2016). A meta-analysis of social networking online and social capital. *Review of General Psychology*, *20*(4), 369–391. https://doi.org/10.1037/gpr0000091

Liu, D., Wright, K. B., & Hu, B. (2018). A meta-analysis of social network site use and social support. *Computers & Education*, *127*, 201–213. https://doi.org/10.1016/j.compedu.2018.08.024

Liu, Y., & Kashian, N. (2021). Sharing workout experiences on social networking sites: Its moderating factors and well-being outcomes. *Health Communication*, *36*(11), 1309–1319. https://doi.org/10.1080/10410236.2020.1750774

Liu, Y., & Yin, Z. (2020). Understanding weight loss via online discussions: Content analysis of Reddit posts using topic modeling and word clustering techniques. *Journal of Medical Internet Research*, *22*(6), Article e13745. https://doi.org/10.2196/13745

Lonsdale, C., Hodge, K., & Rose, E. A. (2008). The Behavioral Regulation in Sport Questionnaire (BRSQ): Instrument development and initial validity evidence. *Journal of*

Sport and Exercise Psychology, *30*(3), 323–355. https://doi.org/10.1123/jsep.30.3.323

Lu, W., & Hampton, K. N. (2017). Beyond the power of networks: Differentiating network structure from social media affordances for perceived social support. *New Media & Society*, *19*(6), 861–879. https://doi.org/10.1177/1461444815621514

Lüscher, J., Berli, C., Schwaninger, P., & Scholz, U. (2019). Smoking cessation with smartphone applications (SWAPP): Study protocol for a randomized controlled trial. *BMC Public Health*, *19*(1), 1400. https://doi.org/10.1186/s12889-019-7723-z

Maher, C., Ryan, J., Kernot, J., Podsiadly, J., & Keenihan, S. (2016). Social media and applications to health behavior. *Current Opinion in Psychology*, *9*, 50–55. https://doi.org/10.1016/j.copsyc.2015.10.021

Marsh, E. J., & Rajaram, S. (2019). The digital expansion of the mind: Implications of internet usage for memory and cognition. *Journal of Applied Research in Memory and Cognition*, *8*(1), 1–14. https://doi.org/10.1016/j.jarmac.2018.11.001

Martela, F., Hankonen, N., Ryan, R. M., & Vansteenkiste, M. (2021). Motivating voluntary compliance to behavioural restrictions: Self-determination theory–based checklist of principles for COVID-19 and other emergency communications. *European Review of Social Psychology*, *32*(2), 305–347. https://doi.org/10.1080/10463283.2020.1857082

Mata, J., & Baumann, E. (2017). The dose makes the poison: Theoretical considerations and challenges of health-related POPC. In P. Vorderer, D. Hefner, L. Reinecke, & C. Klimmt (Eds.), *Permanently online, permanently connected—Living and communicating in a POPC World* (pp. 254–263). Routledge.

Mata, J., Dallacker, M., Vogel, T., & Hertwig, R. (2018). The role of attitudes in diet, eating, and body weight. In D. Albarracin, B. T. Johnson, & M. P. Zanna (Eds.), *The handbook of attitudes* (2nd ed.). Routledge.

Mata, J., Silva, M. N., Vieira, P. N., Carraça, E. V., Andrade, A. M., Coutinho, S. R., Sardinha, L. B., & Teixeira, P. J. (2009). Motivational “spill-over” during weight control: Increased self-determination and exercise intrinsic motivation predict eating self-regulation. *Health Psychology*, *28*(6), 709–716. https://doi.org/10.1037/a0016764

Mc Carthy, C. M., de Vries, R., & Mackenbach, J. D. (2022). The influence of unhealthy food and beverage marketing through social media and advergaming on diet-related outcomes in children—A systematic review. *Obesity Reviews*, *23*(6), Article e13441. https://doi.org/10.1111/obr.13441

McAllister, P., Zheng, H., Bond, R., & Moorhead, A. (2018). Combining deep residual neural network features with supervised machine learning algorithms to classify diverse food image datasets. *Computers in Biology and Medicine*, *95*, 217–233. https://doi.org/10.1016/j.compbiomed.2018.02.008

McClung, H. L., Ptomey, L. T., Shook, R. P., Aggarwal, A., Gorczyca, A. M., Sazonov, E. S., Becofsky, K., Weiss, R., & Das, S. K. (2018). Dietary intake and physical activity assessment: Current tools, techniques, and technologies for use in adult populations. *American Journal of Preventive Medicine*, *55*(4), e93–e104. https://doi.org/10.1016/j.amepre.2018.06.011

McEachan, R. R. C., Conner, M., Taylor, N. J., & Lawton, R. J. (2011). Prospective prediction of health-related behaviours with the theory of planned behaviour: A meta-analysis. *Health Psychology Review*, *5*(2), 97–144. https://doi.org/10.1080/17437199.2010.521684

McEachan, R. R. C., Taylor, N., Harrison, R., Lawton, R., Gardner, P., & Conner, M. (2016). Meta-analysis of the reasoned action approach (RAA) to understanding health behaviors. *Annals of Behavioral Medicine*, *50*(4), 592–612. https://doi.org/10.1007/s12160-016-9798-4

McFarland, L. A., & Ployhart, R. E. (2015). Social media: A contextual framework to guide research and practice. *Journal of Applied Psychology*, *100*(6), 1653–1677. https://doi.org/10.1037/a0039244

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual Review of Sociology*, *27*(1), 415–444. https://doi.org/10.1146/annurev.soc.27.1.415

Meier, A., & Reinecke, L. (2021). Computer-mediated communication, social media, and mental health: A conceptual and empirical meta-review. *Communication Research*, *48*(8), 1182–1209. https://doi.org/10.1177/0093650220958224

Mejova, Y., Haddadi, H., Noulas, A., & Weber, I. (2015). #FoodPorn: Obesity patterns in culinary interactions. In *Proceedings of the 5th International Conference on Digital Health 2015* (pp. 51–58). Association for Computing Machinery. https://doi.org/10.1145/2750511.2750524

Meng, J., Peng, W., Shin, S. Y., & Chung, M. (2017). Online self-tracking groups to increase fruit and vegetable intake: A small-scale study on mechanisms of group effect on behavior change. *Journal of Medical Internet Research*, *19*(3), Article e63. https://doi.org/10.2196/jmir.6537

Menon, V., & Demaray, M. K. (2013). Child and Adolescent Social Support Scale for Healthy Behaviors: Scale development and assessment of the relation between targeted social support and body size dissatisfaction. *Children's Health Care*, *42*(1), 45–66. https://doi.org/10.1080/02739615.2013.753800

Mensink, G. B. M., Truthmann, J., Rabenberg, M., Heidemann, C., Haftenberger, M., Schienkiewitz, A., & Richter, A. (2013). Obst- und Gemüsekonsum in Deutschland. *Bundesgesundheitsblatt - Gesundheitsforschung - Gesundheitsschutz*, *56*(5), 779–785. https://doi.org/10.1007/s00103-012-1651-8

Mi, R. Z., Kornfield, R., Shah, D. V., Maus, A., & Gustafson, D. H. (2022). Intraindividual, dyadic, and network communication in a digital health intervention: Distinguishing message exposure from message production. *Health Communication*, *37*(4), 397–408. https://doi.org/10.1080/10410236.2020.1846273

Michie, S., Abraham, C., Whittington, C., McAteer, J., & Gupta, S. (2009). Effective techniques in healthy eating and physical activity interventions: A meta-regression. *Health Psychology*, *28*(6), 690–701. https://doi.org/10.1037/a0016136

Michie, S., Richardson, M., Johnston, M., Abraham, C., Francis, J., Hardeman, W., Eccles, M. P., Cane, J., & Wood, C. E. (2013). The behavior change technique taxonomy (v1) of 93 hierarchically clustered techniques: Building an international consensus for the reporting of behavior change interventions. *Annals of Behavioral Medicine*, *46*(1), 81–95. https://doi.org/10.1007/s12160-013-9486-6

Michie, S., Thomas, J., Johnston, M., Aonghusa, P. M., Shawe-Taylor, J., Kelly, M. P., Deleris, L. A., Finnerty, A. N., Marques, M. M., Norris, E., O'Mara-Eves, A., & West, R. (2017). The human behaviour-change project: Harnessing the power of artificial intelligence and machine learning for evidence synthesis and interpretation. *Implementation Science*, *12*(1), Article 121. https://doi.org/10.1186/s13012-017-0641-5

Michie, S., West, R., Campbell, R., Brown, J., & Gainforth, H. (2014). *ABC of behaviour change theories book—An essential resource for researchers, policy makers and practitioners*. Silverback Publishing.

Miller, S., Ainsworth, B., Yardley, L., Milton, A., Weal, M., Smith, P., & Morrison, L. (2019). A Framework for analyzing and measuring usage and engagement data (AMUsED) in digital interventions: Viewpoint. *Journal of Medical Internet Research*, *21*(2), e10966. https://doi.org/10.2196/10966

Moorhead, S. A., Hazlett, D. E., Harrison, L., Carroll, J. K., Irwin, A., & Hoving, C. (2013). A new dimension of health care: Systematic review of the uses, benefits, and limitations of social media for health communication. *Journal of Medical Internet Research*, *15*(4), Article e1933. https://doi.org/10.2196/jmir.1933

Mosleh, M., Pennycook, G., & Rand, D. G. (2021). Field experiments on social media. *Current Directions in Psychological Science*, Article 09637214211054761. https://doi.org/10.1177/09637214211054761

Murray, C. J. L., Aravkin, A. Y., Zheng, P., Abbafati, C., Abbas, K. M., Abbasi-Kangevari, M., Abd-Allah, F., Abdelalim, A., Abdollahi, M., Abdollahpour, I., Abegaz, K. H., Abolhassani, H., Aboyans, V., Abreu, L. G., Abrigo, M. R. M., Abualhasan, A., Abu-Raddad, L. J., Abushouk, A. I., Adabi, M., … Lim, S. S. (2020). Global burden of 87 risk factors in 204 countries and territories, 1990–2019: A systematic analysis for the Global Burden of Disease Study 2019. *The Lancet*, *396*(10258), 1223–1249. https://doi.org/10.1016/S0140-6736(20)30752-2

Murthy, B. P., LeBlanc, T. T., Vagi, S. J., & Avchen, R. N. (2021). Going viral: The 3 Rs of social media messaging during public health emergencies. *Health Security*, *19*(1), 75–81. https://doi.org/10.1089/hs.2020.0157

Musca, S., Kamiejski, R., Nugier, A., Méot, A., Er-rafiy, A., & Brauer, M. (2011). Data with hierarchical structure: Impact of intraclass correlation and sample size on type-I error. *Frontiers in Psychology, 2,* 74. https://doi.org/10.3389/fpsyg.2011.00074

Myneni, S., Cobb, N., & Cohen, T. (2016). In pursuit of theoretical ground in behavior change support systems: Analysis of peer-to-peer communication in a health-related online community. *Journal of Medical Internet Research*, *18*(2), Article e4671. https://doi.org/10.2196/jmir.4671

Nabi, R. L., Huskey, R., Nicholls, S. B., Keblusek, L., & Reed, M. (2019). When audiences become advocates: Self-induced behavior change through health message posting in social media. *Computers in Human Behavior*, *99*, 260–267. https://doi.org/10.1016/j.chb.2019.05.030

Napolitano, M. A., Hayes, S., Bennett, G. G., Ives, A. K., & Foster, G. D. (2013). Using Facebook and text messaging to deliver a weight loss program to college students. *Obesity*, *21*(1), 25–31. https://doi.org/10.1002/oby.20232

Naska, A., Lagiou, A., & Lagiou, P. (2017). Dietary assessment methods in epidemiological research: Current state of the art and future prospects. *F1000Research*, *6*, 926. https://doi.org/10.12688/f1000research.10703.1

Nezlek, J. B. (2017). A practical guide to understanding reliability in studies of within-person variability. *Journal of Research in Personality*, *69*, 149–155. https://doi.org/10.1016/j.jrp.2016.06.020

Ng, J. Y. Y., Ntoumanis, N., Thøgersen-Ntoumani, C., Deci, E. L., Ryan, R. M., Duda, J. L.,

& Williams, G. C. (2012). Self-determination theory applied to health contexts: A meta-analysis. *Perspectives on Psychological Science*, *7*(4), 325–340. https://doi.org/10.1177/1745691612447309

Ngqangashe, Y., & Backer, C. J. S. D. (2021). The differential effects of viewing short-form online culinary videos of fruits and vegetables versus sweet snacks on adolescents' appetites. *Appetite*, *166*, Article 105436. https://doi.org/10.1016/j.appet.2021.105436

Nielsen, L., Riddle, M., King, J. W., Aklin, W. M., Chen, W., Clark, D., Collier, E., Czajkowski, S., Esposito, L., Ferrer, R., Green, P., Hunter, C., Kehl, K., King, R., Onken, L., Simmons, J. M., Stoeckel, L., Stoney, C., Tully, L., & Weber, W. (2018). The NIH science of behavior change program: Transforming the science through a focus on mechanisms of change. *Behaviour Research and Therapy, 101*, 3–11. https://doi.org/10.1016/j.brat.2017.07.002

Ntoumanis, N., Ng, J. Y. Y., Prestwich, A., Quested, E., Hancox, J. E., Thøgersen-Ntoumani, C., Deci, E. L., Ryan, R. M., Lonsdale, C., & Williams, G. C. (2021). A meta-analysis of self-determination theory-informed intervention studies in the health domain: Effects on motivation, health behavior, physical, and psychological health. *Health Psychology Review*, *15*(2), 214–244. https://doi.org/10.1080/17437199.2020.1718529

Ntoumanis, N., Quested, E., Reeve, J., & Cheon, S. H. (2017). Need-supportive communication: Implications for motivation in sport, exercise, and physical activity. In B. Jackson, J. A. Dimmock, & J. Compton (Eds.), *Persuasion and Communication in Sport, Exercise, and Physical Activity* (pp. 155–169). Routledge.

Ofcom. (2022). *Children and parents: Media use and attitudes report 2022*. https://www.ofcom.org.uk/__data/assets/pdf_file/0024/234609/childrens-media-use-and-attitudes-report-2022.pdf

Ohly, S., Sonnentag, S., Niessen, C., & Zapf, D. (2010). Diary studies in organizational research. *Journal of Personnel Psychology*, *9*(2), 79–93. https://doi.org/10.1027/1866-5888/a000009

Ohme, J., Araujo, T., de Vreese, C. H., & Piotrowski, J. T. (2021). Mobile data donations: Assessing self-report accuracy and sample biases with the iOS screen time function. *Mobile Media & Communication*, *9*(2), 293–313. https://doi.org/10.1177/2050157920959106

Olander, E. K., Fletcher, H., Williams, S., Atkinson, L., Turner, A., & French, D. P. (2013). What are the most effective techniques in changing obese individuals' physical activity self-efficacy and behaviour: A systematic review and meta-analysis. *International*

Journal of Behavioral Nutrition and Physical Activity, *10*(1), Article 29. https://doi.org/10.1186/1479-5868-10-29

Pagoto, S., & Nebeker, C. (2019). How scientists can take the lead in establishing ethical practices for social media research. *Journal of the American Medical Informatics Association*, *26*(4), 311–313. https://doi.org/10.1093/jamia/ocy174

Pagoto, S., Waring, M. E., May, C. N., Ding, E. Y., Kunz, W. H., Hayes, R., & Oleski, J. L. (2016). Adapting behavioral interventions for social media delivery. *Journal of Medical Internet Research*, *18*(1), Article e24. https://doi.org/10.2196/jmir.5086

Pagoto, S., Waring, M., Jake-Schoffman, D., Goetz, J., Michaels, Z., Oleski, J., & DiVito, J. (2018). What type of engagement predicts success in a Facebook weight loss group? *Proceedings of the 51st Hawaii International Conference on System Sciences*, 3304–3312. https://doi.org/10.24251/HICSS.2018.419

Pagoto, S., Waring, M., Olendzki, E., Oleski, J., May, C., & Evans, M. (2017, January 4). The feasibility of incentivizing participation in an online social network weight loss program. *Proceedings of the 50th Hawaii International Conference on System Sciences*. https://doi.org/10.24251/HICSS.2017.457

Pappa, G. L., Cunha, T. O., Bicalho, P. V., Ribeiro, A., Silva, A. P. C., Jr, W. M., & Beleigoli, A. M. R. (2017). Factors associated with weight change in online weight management communities: A case study in the LoseIt Reddit community. *Journal of Medical Internet Research*, *19*(1), Article e5816. https://doi.org/10.2196/jmir.5816

Parry, D. A., Davidson, B. I., Sewall, C. J. R., Fisher, J. T., Mieczkowski, H., & Quintana, D. S. (2021). A systematic review and meta-analysis of discrepancies between logged and self-reported digital media use. *Nature Human Behaviour*, *5*(11), 1535–1547. https://doi.org/10.1038/s41562-021-01117-5

Parry, D. A., Fisher, J. T., Mieczkowski, H., Sewall, C. J. R., & Davidson, B. I. (2022). Social media and well-being: A methodological perspective. *Current Opinion in Psychology*, *45*, Article 101285. https://doi.org/10.1016/j.copsyc.2021.11.005

Peng, C.-T., Wu, T.-Y., Chen, Y., & Atkin, D. J. (2019). Comparing and modeling via social media: The social influences of fitspiration on male instagram users' work out intention. *Computers in Human Behavior*, *99*, 156–167. https://doi.org/10.1016/j.chb.2019.05.011

Perski, O., Blandford, A., West, R., & Michie, S. (2017). Conceptualising engagement with digital behaviour change interventions: A systematic review using principles from critical interpretive synthesis. *Translational Behavioral Medicine*, *7*(2), 254–267. https://doi.org/10.1007/s13142-016-0453-1

Petkovic, J., Duench, S., Trawin, J., Dewidar, O., Pardo, J. P., Simeon, R., DesMeules, M., Gagnon, D., Roberts, J. H., Hossain, A., Pottie, K., Rader, T., Tugwell, P., Yoganathan, M., Presseau, J., & Welch, V. (2021). Behavioural interventions delivered through interactive social media for health behaviour change, health outcomes, and health equity in the adult population. *Cochrane Database of Systematic Reviews*, *5*, Article CD012932. https://doi.org/10.1002/14651858.CD012932.pub2

Pew Research Center. (2018). *Teens, Social Media and Technology 2018*. https://www.pewresearch.org/internet/wp-content/uploads/sites/9/2018/05/PI_2018.05.31_TeensTech_FINAL.pdf

Pew Research Center. (2021). *Social media use in 2021*. https://www.pewresearch.org/internet/wp-content/uploads/sites/9/2021/04/PI_2021.04.07_Social-Media-Use_FINAL.pdf

Pilař, L., Stanislavská, L. K., Kvasnička, R., Hartman, R., & Tichá, I. (2021). Healthy food on Instagram social network: Vegan, homemade and clean eating. *Nutrients*, *13*(6), Article 1991. https://doi.org/10.3390/nu13061991

Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of Method Bias in Social Science Research and Recommendations on How to Control It. *Annual Review of Psychology*, *63*(1), 539–569. https://doi.org/10.1146/annurev-psych-120710-100452

Prestwich, A., Kellar, I., Parker, R., MacRae, S., Learmonth, M., Sykes, B., Taylor, N., & Castle, H. (2014). How can self-efficacy be increased? Meta-analysis of dietary interventions. *Health Psychology Review*, *8*(3), 270–285. https://doi.org/10.1080/17437199.2013.813729

Prince, S. A., Adamo, K. B., Hamel, M. E., Hardt, J., Gorber, S. C., & Tremblay, M. (2008). A comparison of direct versus self-report measures for assessing physical activity in adults: A systematic review. *International Journal of Behavioral Nutrition and Physical Activity*, *5*(1), 56. https://doi.org/10.1186/1479-5868-5-56

Qutteina, Y., Hallez, L., Mennes, N., De Backer, C., & Smits, T. (2019). What do adolescents see on social media? A diary study of food marketing images on social media. *Frontiers in Psychology*, *10*, Article 2637. https://doi.org/10.3389/fpsyg.2019.02637

Qutteina, Y., Hallez, L., Raedschelders, M., Backer, C. D., & Smits, T. (2022). Food for teens: How social media is associated with adolescent eating outcomes. *Public Health Nutrition*, *25*(2), 290–302. https://doi.org/10.1017/S1368980021003116

Rheu, M., Peng, W., & Haung, K.-T. (2021). Leveraging upward social comparison in social media to promote healthy parenting. *Health Communication*.

https://doi.org/10.1080/10410236.2021.1943891

Rimal, R. N., & Lapinski, M. K. (2015). A re-explication of social norms, ten years later. *Communication Theory*, *25*(4), 393–409. https://doi.org/10.1111/comt.12080

Robinson, E., Fleming, A., & Higgs, S. (2014). Prompting healthier eating: Testing the use of health and social norm based messages. *Health Psychology*, *33*(9), 1057–1064. https://doi.org/10.1037/a0034213

Robinson, E., Thomas, J., Aveyard, P., & Higgs, S. (2014). What everyone else is eating: A systematic review and meta-analysis of the effect of informational eating norms on eating behavior. *Journal of the Academy of Nutrition and Dietetics*, *114*(3), 414–429. https://doi.org/10.1016/j.jand.2013.11.009

Roser, M., Ritchie, H., & Ortiz-Ospina, E. (2015, July 14). *Internet*. Our World in Data. https://ourworldindata.org/internet

Rounsefell, K., Gibson, S., McLean, S., Blair, M., Molenaar, A., Brennan, L., Truby, H., & McCaffrey, T. A. (2020). Social media, body image and food choices in healthy young adults: A mixed methods systematic review. *Nutrition & Dietetics*, *77*(1), 19–40. https://doi.org/10.1111/1747-0080.12581

Rui, J. R., & Liu, S. (2021). How Do Social Network Sites Influence Workout Intentions: A Social Norm Approach. *Frontiers in Psychology*, *12*, Article 753189.

Ryan, R. M., & Deci, E. L. (2017). *Self-Determination Theory: Basic Psychological Needs in Motivation, Development, and Wellness*. The Guilford Press.

Ryan, R. M., Patrick, H., Deci, E. L., & Williams, G. C. (2008). Facilitating health behaviour change and its maintenance: Interventions based on self-determination theory. *European Health Psychologist*, *10*(1), 2–5. https://www.ehps.net/ehp/index.php/contents/article/view/ehp.v10.i1.p2

Sallis, J. F., Cervero, R. B., Ascher, W., Henderson, K. A., Kraft, M. K., & Kerr, J. (2006). An ecological approach to creating active living communities. *Annual Review of Public Health*, *27*(1), 297–322. https://doi.org/10.1146/annurev.publhealth.27.021405.102100

Scholz, U. (2019). It's time to think about time in health psychology. *Applied Psychology: Health and Well-Being*, *11*(2), 173–186. https://doi.org/10.1111/aphw.12156

Scholz, U., Berli, C., Lüscher, J., & Knoll, N. (2020). Dyadic behavior change interventions. In K. Hamilton, L. D. Cameron, M. S. Hagger, N. Hankonen, & T. Lintunen (Eds.), *The handbook of behavior change* (pp. 632–648). Cambridge University Press. https://doi.org/10.1017/9781108677318.043

Scholz, U., Ochsner, S., Hornung, R., & Knoll, N. (2013). Does social support really help to eat a low-fat diet? Main effects and gender differences of received social support within the health action process approach. *Applied Psychology: Health and Well-Being*, *5*(2), 270–290. https://doi.org/10.1111/aphw.12010

Schouten, A. P., Janssen, L., & Verspaget, M. (2020). Celebrity vs. influencer endorsements in advertising: The role of identification, credibility, and product-endorser fit. *International Journal of Advertising*, *39*(2), 258–281. https://doi.org/10.1080/02650487.2019.1634898

Schulze, M. B., Martínez-González, M. A., Fung, T. T., Lichtenstein, A. H., & Forouhi, N. G. (2018). Food based dietary patterns and chronic disease prevention. *BMJ*, *361*, Article k2396. https://doi.org/10.1136/bmj.k2396

Schwarzer, R. (2007). *Health action process approach (HAPA) assessment tools*. http://userpage.fu-berlin.de/~health/hapa_assessment.pdf

Schwarzer, R. (2008). Modeling health behavior change: How to predict and modify the adoption and maintenance of health behaviors. *Applied Psychology*, *57*(1), 1–29. https://doi.org/10.1111/j.1464-0597.2007.00325.x

Shaikh, A. R., Yaroch, A. L., Nebeling, L., Yeh, M.-C., & Resnicow, K. (2008). Psychosocial predictors of fruit and vegetable consumption in adults: A review of the literature. *American Journal of Preventive Medicine*, *34*(6), 535–543. https://doi.org/10.1016/j.amepre.2007.12.028

Sheeran, P. (2002). Intention—behavior relations: A conceptual and empirical review. *European Review of Social Psychology*, *12*(1), 1–36. https://doi.org/10.1080/14792772143000003

Sheeran, P., Klein, W. M. P., & Rothman, A. J. (2017). Health behavior change: Moving from observation to intervention. *Annual Review of Psychology*, *68*(1), 573–600. https://doi.org/10.1146/annurev-psych-010416-044007

Sheeran, P., Maki, A., Montanaro, E., Avishai-Yitshak, A., Bryan, A., Klein, W. M. P., Miles, E., & Rothman, A. J. (2016). The impact of changing attitudes, norms, and self-efficacy on health-related intentions and behavior: A meta-analysis. *Health Psychology*, *35*(11), 1178–1188. https://doi.org/10.1037/hea0000387

Sheeran, P., & Webb, T. L. (2016). The intention–behavior gap. *Social and Personality Psychology Compass*, *10*(9), 503–518. https://doi.org/10.1111/spc3.12265

Shiffman, S., Stone, A. A., & Hufford, M. R. (2008). Ecological momentary assessment. *Annual Review of Clinical Psychology*, *4*(1), 1–32. https://doi.org/10.1146/annurev.clinpsy.3.022806.091415

Short, C. E., DeSmet, A., Woods, C., Williams, S. L., Maher, C., Middelweerd, A., Müller, A. M., Wark, P. A., Vandelanotte, C., Poppe, L., Hingle, M. D., & Crutzen, R. (2018). Measuring engagement in eHealth and mHealth behavior change interventions: Viewpoint of methodologies. *Journal of Medical Internet Research*, *20*(11), Article e9397. https://doi.org/10.2196/jmir.9397

Shrout, P. E., & Rodgers, J. L. (2018). Psychology, Science, and Knowledge Construction: Broadening Perspectives from the Replication Crisis. *Annual Review of Psychology*, *69*(1), 487–510. https://doi.org/10.1146/annurev-psych-122216-011845

Silva, M. N., Markland, D., Carraça, E. V., Vieira, P. N., Coutinho, S. R., Minderico, C. S., Matos, M. G., Sardinha, L. B., & Teixeira, P. J. (2011). Exercise autonomous motivation predicts 3-yr weight loss in women. *Medicine and Science in Sports and Exercise*, *43*(4), 728–737. https://doi.org/10.1249/MSS.0b013e3181f3818f

Silva, M. N., Markland, D., Minderico, C. S., Vieira, P. N., Castro, M. M., Coutinho, S. R., Santos, T. C., Matos, M. G., Sardinha, L. B., & Teixeira, P. J. (2008). A randomized controlled trial to evaluate self-determination theory for exercise adherence and weight control: Rationale and intervention description. *BMC Public Health*, *8*(1), 234. https://doi.org/10.1186/1471-2458-8-234

Silva, M. N., Marques, M. M., & Teixeira, P. J. (2014). Testing theory in practice: The example of self-determination theory-based interventions. *European Health Psychologist*, *16*(5), 171–180. https://ehps.net/ehp/index.php/contents/article/view/ehp.v16.i5.p171

Silva, M. N., Vieira, P. N., Coutinho, S. R., Minderico, C. S., Matos, M. G., Sardinha, L. B., & Teixeira, P. J. (2010). Using self-determination theory to promote physical activity and weight control: A randomized controlled trial in women. *Journal of Behavioral Medicine*, *33*(2), 110–122. https://doi.org/10.1007/s10865-009-9239-y

Simeon, R., Dewidar, O., Trawin, J., Duench, S., Manson, H., Pardo, J. P., Petkovic, J., Roberts, J. H., Tugwell, P., Yoganathan, M., Presseau, J., & Welch, V. (2020). Behavior change techniques included in reports of social media interventions for promoting health behaviors in adults: Content analysis within a systematic review. *Journal of Medical Internet Research*, *22*(6), Article e16002. https://doi.org/10.2196/16002

Simunaniemi, A.-M., Sandberg, H., Andersson, A., & Nydahl, M. (2011). Laypeople blog about fruit and vegetables for self-expression and dietary influence. *Health Communication*, *26*(7), 621–630. https://doi.org/10.1080/10410236.2011.561520

Sina, E., Boakye, D., Christianson, L., Ahrens, W., & Hebestreit, A. (2022). Social media and children’s and adolescents’ diets—A systematic review of the underlying social and physiological mechanisms. *Advances in Nutrition*, Article nmac018. https://doi.org/10.1093/advances/nmac018

Skender, S., Ose, J., Chang-Claude, J., Paskow, M., Brühmann, B., Siegel, E. M., Steindorf, K., & Ulrich, C. M. (2016). Accelerometry and physical activity questionnaires—A systematic review. *BMC Public Health*, *16*(1), Article 515. https://doi.org/10.1186/s12889-016-3172-0

Smit, E. S., Dima, A. L., Immerzeel, S. A. M., Putte, B. van den, & Williams, G. C. (2017). The Virtual Care Climate Questionnaire: Development and validation of a questionnaire measuring perceived support for autonomy in a virtual care setting. *Journal of Medical Internet Research*, *19*(5), Article e155. https://doi.org/10.2196/jmir.6714

Smock, A. D., Ellison, N. B., Lampe, C., & Wohn, D. Y. (2011). Facebook as a toolkit: A uses and gratification approach to unbundling feature use. *Computers in Human Behavior*, *27*(6), 2322–2329. https://doi.org/10.1016/j.chb.2011.07.011

Sniehotta, F. F., Presseau, J., & Araújo-Soares, V. (2014). Time to retire the theory of planned behaviour. *Health Psychology Review*, *8*(1), 1–7. https://doi.org/10.1080/17437199.2013.869710

Sniehotta, F. F., Scholz, U., & Schwarzer, R. (2005). Bridging the intention–behaviour gap: Planning, self-efficacy, and action control in the adoption and maintenance of physical exercise. *Psychology & Health*, *20*(2), 143–160. https://doi.org/10.1080/08870440512331317670

Spence, C., Okajima, K., Cheok, A. D., Petit, O., & Michel, C. (2016). Eating with our eyes: From visual hunger to digital satiation. *Brain and Cognition*, *110*, 53–63. https://doi.org/10.1016/j.bandc.2015.08.006

Steinmetz, H., Knappstein, M., Ajzen, I., Schmidt, P., & Kabst, R. (2016). How effective are behavior change interventions based on the theory of planned behavior? *Zeitschrift Für Psychologie*, *224*(3), 216–233. https://doi.org/10.1027/2151-2604/a000255

Stok, F. M., de Ridder, D. T. D., de Vet, E., & de Wit, J. B. F. (2014). Don’t tell me what I should do, but what others do: The influence of descriptive and injunctive peer norms on fruit consumption in adolescents. *British Journal of Health Psychology*, *19*(1), 52–64. https://doi.org/10.1111/bjhp.12030

Stok, F. M., de Vet, E., de Ridder, D. T. D., & de Wit, J. B. F. (2016). The potential of peer social norms to shape food intake in adolescents and young adults: A systematic review of effects and moderators. *Health Psychology Review*, *10*(3), 326–340. https://doi.org/10.1080/17437199.2016.1155161

Stok, F. M., Verkooijen, K. T., de Ridder, D. T. D., de Wit, J. B. F., & de Vet, E. (2014). How norms work: Self-identification, attitude, and self-efficacy mediate the relation between descriptive social norms and vegetable intake. *Applied Psychology: Health and Well-Being*, *6*(2), 230–250. https://doi.org/10.1111/aphw.12026

Strowger, M., & Braitman, A. L. (2022). Using social network methodology to examine the effects of exposure to alcohol-related social media content on alcohol use: A critical review. *Experimental and Clinical Psychopharmacology*. https://doi.org/10.1037/pha0000561

Su, Y.-L., & Reeve, J. (2011). A meta-analysis of the effectiveness of intervention programs designed to support autonomy. *Educational Psychology Review*, *23*(1), 159–188. https://doi.org/10.1007/s10648-010-9142-7

Tajfel, H., & Turner, J. C. (1979). An integrative theory of intergroup conflict. In W. G. Austin & S. Worchel (Eds.), *The social psychology of intergroup relations* (pp. 33–37). Brooks/Cole.

TechCrunch. (2018). *How Instagram's algorithm works*. TechCrunch. https://social.techcrunch.com/2018/06/01/how-instagram-feed-works/

Teixeira, P. J., Carraça, E. V., Markland, D., Silva, M. N., & Ryan, R. M. (2012). Exercise, physical activity, and self-determination theory: A systematic review. *International Journal of Behavioral Nutrition and Physical Activity*, *9*(1), Article 78. https://doi.org/10.1186/1479-5868-9-78

Teixeira, P. J., Marques, M. M., Silva, M. N., Brunet, J., Duda, J. L., Haerens, L., La Guardia, J., Lindwall, M., Lonsdale, C., Markland, D., Michie, S., Moller, A. C., Ntoumanis, N., Patrick, H., Reeve, J., Ryan, R. M., Sebire, S. J., Standage, M., Vansteenkiste, M., … Hagger, M. S. (2020). A classification of motivation and behavior change techniques used in self-determination theory-based interventions in health contexts. *Motivation Science*, *6*(4), 438–455. https://doi.org/10.1037/mot0000172

Teixeira, P. J., Patrick, H., & Mata, J. (2011). Why we eat what we eat: The role of autonomous motivation in eating behaviour regulation. *Nutrition Bulletin*, *36*(1), 102–107. https://doi.org/10.1111/j.1467-3010.2010.01876.x

Terry, D. J., Hogg, M. A., & McKimmie, B. M. (2000). Attitude-behaviour relations: The role of in-group norms and mode of behavioural decision-making. *British Journal of Social Psychology*, *39*(3), 337–361. https://doi.org/10.1348/014466600164534

Thomas, F., Shehata, A., Otto, L. P., Möller, J., & Prestele, E. (2021). How to capture reciprocal communication dynamics: Comparing longitudinal statistical approaches in order to analyze within- and between-person effects. *Journal of Communication*, *71*(2), 187–219. https://doi.org/10.1093/joc/jqab003

Trifiro, B. M., & Gerson, J. (2019). Social media usage patterns: Research note regarding the lack of universal validated measures for active and passive Use. *Social Media + Society, 5*(2), Article 2056305119848743. https://doi.org/10.1177/2056305119848743

Tromble, R. (2021). Where have all the data gone? A critical reflection on academic digital research in the post-API age. *Social Media + Society*, *7*(1), Article 2056305121988929. https://doi.org/10.1177/2056305121988929

Trull, T. J., & Ebner-Priemer, U. (2014). The role of ambulatory assessment in psychological science. *Current Directions in Psychological Science, 23*(6), 466–470. https://doi.org/10.1177/0963721414550706

Turner-McGrievy, G. M., & Tate, D. F. (2013). Weight loss social support in 140 characters or less: Use of an online social network in a remotely delivered weight loss intervention. *Translational Behavioral Medicine*, *3*(3), 287–294. https://doi.org/10.1007/s13142-012-0183-y

Valkenburg, P. M. (2017). Understanding self-effects in social media. *Human Communication Research*, *43*(4), 477–490. https://doi.org/10.1111/hcre.12113

Valkenburg, P. M., Beyens, I., Pouwels, J. L., van Driel, I. I., & Keijsers, L. (2022). Social media browsing and adolescent well-being: Challenging the "passive social media use hypothesis." *Journal of Computer-Mediated Communication*, *27*(1), Article zmab015. https://doi.org/10.1093/jcmc/zmab015

Valkenburg, P. M., Peter, J., & Walther, J. B. (2016). Media effects: Theory and research. *Annual Review of Psychology*, *67*(1), 315–338. https://doi.org/10.1146/annurev-psych-122414-033608

Valkenburg, P. M., van Driel, I. I., & Beyens, I. (2021). The associations of active and passive social media use with well-being: A critical scoping review. *New Media & Society*, *24*(2), Article 14614448211065425. https://doi.org/10.1177/14614448211065425

van 't Veer, A. E., & Giner-Sorolla, R. (2016). Pre-registration in social psychology—A discussion and suggested template. *Journal of Experimental Social Psychology, 67,* 2–12. https://doi.org/10.1016/j.jesp.2016.03.004

Vaterlaus, J. M., Patten, E. V., Roche, C., & Young, J. A. (2015). #Gettinghealthy: The perceived influence of social media on young adult health behaviors. *Computers in Human Behavior*, *45*, 151–157. https://doi.org/10.1016/j.chb.2014.12.013

Verduyn, P., Lee, D. S., Park, J., Shablack, H., Orvell, A., Bayer, J., Ybarra, O., Jonides, J., & Kross, E. (2015). Passive Facebook usage undermines affective well-being: Experimental and longitudinal evidence. *Journal of Experimental Psychology: General*, *144*(2), 480–488. https://doi.org/10.1037/xge0000057

Verduyn, P., Ybarra, O., Résibois, M., Jonides, J., & Kross, E. (2017). Do social network sites enhance or undermine subjective well-being? A critical review. *Social Issues and Policy Review*, *11*(1), 274–302. https://doi.org/10.1111/sipr.12033

Wang, X., Lan, Y., & Xiao, J. (2019). Anomalous structure and dynamics in news diffusion among heterogeneous individuals. *Nature Human Behaviour*, *3*(7), 709–718. https://doi.org/10.1038/s41562-019-0605-7

Waring, M. E., Jake-Schoffman, D. E., Holovatska, M. M., Mejia, C., Williams, J. C., & Pagoto, S. L. (2018). Social media and obesity in adults: A review of recent research and future directions. *Current Diabetes Reports*, *18*(6), Article 34. https://doi.org/10.1007/s11892-018-1001-9

Wickham, R. E., & Knee, C. R. (2013). Examining temporal processes in diary studies. *Personality and Social Psychology Bulletin*, *39*(9), 1184–1198. https://doi.org/10.1177/0146167213490962

Williams, G., Hamm, M. P., Shulhan, J., Vandermeer, B., & Hartling, L. (2014). Social media interventions for diet and exercise behaviours: A systematic review and meta-analysis of randomised controlled trials. *BMJ Open*, *4*(2), Article e003926. https://doi.org/10.1136/bmjopen-2013-003926

Xu, R., & Cavallo, D. (2021). Social network analysis of the effects of a social media–based weight loss intervention targeting adults of low socioeconomic status: Single-arm intervention trial. *Journal of Medical Internet Research*, *23*(4), Article e24690. https://doi.org/10.2196/24690

Yang, Q. (2017). Are social networking sites making health behavior change interventions more effective? A meta-analytic review. *Journal of Health Communication*, *22*(3), 223–233. https://doi.org/10.1080/10810730.2016.1271065

Yang, Q. (2020). Understanding computer-mediated support groups: A revisit using a meta-analytic approach. *Health Communication*, *35*(2), 209–221. https://doi.org/10.1080/10410236.2018.1551751

Yoo, W., Yang, J., & Cho, E. (2016). How social media influence college students' smoking attitudes and intentions. *Computers in Human Behavior*, *64*, 173–182. https://doi.org/10.1016/j.chb.2016.06.061

Zhang, J., Brackbill, D., Yang, S., Becker, J., Herbert, N., & Centola, D. (2016). Support or competition? How online social networks increase physical activity: A randomized controlled trial. *Preventive Medicine Reports, 4,* 453–458. https://doi.org/10.1016/j.pmedr.2016.08.008

Zhang, J., & Centola, D. (2019). Social networks and health: New developments in diffusion, online and offline. *Annual Review of Sociology*, *45*(1), 91–109. https://doi.org/10.1146/annurev-soc-073117-041421

Zhang, W., Zhao, D., Gong, W., Li, Z., Lu, Q., & Yang, S. (2015). Food image recognition with convolutional neural networks. *2015 IEEE 12th Intl Conf on Ubiquitous Intelligence and Computing and 2015 IEEE 12th Intl Conf on Autonomic and Trusted Computing and 2015 IEEE 15th Intl Conf on Scalable Computing and Communications and Its Associated Workshops (UIC-ATC-ScalCom),* 690–693. https://doi.org/10.1109/UIC-ATC-ScalCom-CBDCom-IoP.2015.139

Zhou, G., Gan, Y., Hamilton, K., & Schwarzer, R. (2017). The role of social support and self-efficacy for planning fruit and vegetable intake. *Journal of Nutrition Education and Behavior, 49*(2), 100–106. https://doi.org/10.1016/j.jneb.2016.09.005

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"The best and most beautiful things in the world cannot be seen or even touched — they must be felt with the heart."
Helen Keller

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Michael Kilb

Mannheim, June 2022

Statement of Originality

Eidesstattliche Versicherung gemäß § 9 Absatz 1 Buchstabe e) der Promotionsordnung der Universität Mannheim zur Erlangung des Doktorgrades der Sozialwissenschaften:

1. Bei der eingereichten Dissertation mit dem Titel „How social media use influences health behaviors – a social-cognitive perspective“ handelt es sich um mein eigenständig erstelltes eigenes Werk.
2. Ich habe nur die angegebenen Quellen und Hilfsmittel benutzt und mich keiner unzulässigen Hilfe Dritter bedient. Insbesondere habe ich wörtliche Zitate aus anderen Werken als solche kenntlich gemacht.
3. Die Arbeit oder Teile davon habe ich bisher nicht an einer Hochschule des In- oder Auslands als Bestandteil einer Prüfungs- oder Qualifikationsleistung vorgelegt.
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Mannheim, 01.06.2022

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Michael Kilb

Co-Author Statements

Co-author: Oliver Dickhäuser

I confirm that the following manuscript included in the dissertation *How social media use influences health behaviors – a social-cognitive perspective* was primarily conceived and written by Michael Kilb, doctoral candidate at the School of Social Sciences at the University of Mannheim:

Kilb, M., Dickhäuser, O., & Mata, J. (2022). A theory-based video intervention to enhance communication and engagement in online health communities: Two experiments. *Health Psychology and Behavioral Medicine*, *10*(1), 199–228. https://doi.org/10.1080/21642850.2022.2032074

I sign this statement to the effect that Michael Kilb is credited as the primary source of the ideas and the main author of the manuscript as he derived the theoretical and methodological background, collected the data, implemented the statistical analyses, wrote the first draft, and contributed to improving and revising the manuscript. I contributed to refining the theoretical background and improving the developed video intervention, suggested ideas for the interpretation of the results, and provided recommendations for refining and improving the manuscript.

Prof. Dr. Oliver Dickhäuser

Mannheim, May 2022

Co-author: Helge Giese

I confirm that the following manuscript included in the dissertation *How social media use influences health behaviors – a social-cognitive perspective* was primarily conceived and written by Michael Kilb, doctoral candidate at the School of Social Sciences at the University of Mannheim:

Kilb, M., Giese, H., & Mata, J. (2022). *How social media affects healthy eating in senders and receivers of eating-related online postings: Two field experiments with intensive longitudinal data* [Manuscript submitted for publication].

I sign this statement to the effect that Michael Kilb is credited as the primary source of the ideas and the main author of the manuscript as he derived the theoretical and methodological background, collected the data, implemented the statistical analyses, wrote the first draft, and contributed to improving and revising the manuscript. I contributed to refining the theoretical background, provided recommendations for improving the study design of both included studies, contributed to data collection, suggested ideas for the statistical analyses and their interpretations, and provided recommendations for refining and improving the manuscript.

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Kilb, M., Dickhäuser, O., & Mata, J. (2022). A theory-based video intervention to enhance communication and engagement in online health communities: Two experiments. *Health Psychology and Behavioral Medicine*, *10*(1), 199–228. https://doi.org/10.1080/21642850.2022.2032074

I sign this statement to the effect that Michael Kilb is credited as the primary source of the ideas and the main author of the manuscripts as he derived the theoretical and methodological background, collected the data, implemented the statistical analyses, wrote the first drafts, and contributed to improving and revising the manuscripts. I developed the basic idea for the third manuscript, contributed to refining the theoretical backgrounds, provided recommendations for improving the study designs of the empirical studies, suggested ideas for the statistical analyses and their interpretations, and provided recommendations for structuring and improving the manuscripts.

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