Title
Social Support Across Contexts: In times of crisis and in interventions

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Publication Date
2022

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA

Los Angeles

Social Support Across Contexts:

In times of crisis and in interventions

A dissertation submitted in partial satisfaction of the

requirements for the degree Doctor of Philosophy

in Psychology

by

Peter Nooteboom

2022

ABSTRACT OF THE DISSERTATION

Social Support Across Contexts:

In times of crisis and in interventions

by

Peter Nooteboom

Doctor of Philosophy in Psychology

University of California, Los Angeles, 2022

Professor Theodore F. Robles, Chair

Study 1. As an active ingredient in lifestyle interventions, social support is shown to be effective for promoting positive health outcomes. However, many interventions do not directly assess social support, leaving its impact in these contexts ambiguous. The Diabetes Prevention Program is one of the most well supported lifestyle interventions, and specifically targets decreased weight and increased physical activity. The DPP intervention has many opportunities for the exchange of social resources, but these social aspects remain unassessed. The present study assesses the relationship between perceived social support and the Diabetes Prevention Program outcomes of weight and physical activity. Results demonstrate a significant negative relationship between intraindividual change in social support and intraindividual changes in weight across the trajectory of the intervention. Additionally, this relationship was significantly mediated by intraindividual changes in self-efficacy. However, these relationships were not supported for physical activity. This study contributes to the literature investigating the role of social support in lifestyle interventions, and is the first to do so within the Diabetes Prevention Program.

Study 2. The COVID-19 pandemic resulted in drastic restrictions limiting in-person social connection, but also drove adoption and progression in digital communication. Social support can act as a buffer for stress during such times of crisis. However, when social distancing was required, many adapted much of their social interaction into a digital context. There is minimal work understanding how digital social support differs from in-person social support, particularly during a time when in-person social support is already displaced. The present study investigates the relationship between strictness of distancing and perceived digital social support, perceived general social support, and higher perceived loneliness. In a randomized controlled trial (RCT), the present study also assessed the effectiveness of a brief video-based social support intervention for increasing perceived digital social support, increasing perceived general social support, and decreasing perceived stress. Higher strictness of distancing was related to lower perceived digital social support, perceived general social support, and perceived loneliness. Additionally, the intervention group had significantly greater increases in perceived digital social support than controls, but no significant difference in change for general social support or perceived stress. The present study demonstrates the unique context that COVID-19 created for social interaction, and provides initial evidence in support of a brief and low-resource intervention for increasing perceptions of digital social support.

The dissertation of Peter Nooteboom is approved.

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2022

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Robles, T. F., Mercado, E., **Nooteboom, P.**, Price, J.E., & Romney, C.E. (2018). Biological processes of health. In T. A. Revenson & R. A. R. Gurung (Eds.), *Handbook of health psychology 3rd ed*. New York, NY: Taylor & Francis/Routledge.

Cummings, J. R., Ray, L. A., **Nooteboom, P**., & Tomiyama, A. J. (2019). Acute effect of eating sweets on alcohol cravings in a sample with at-risk drinking. *Annals of Behavioral Medicine, 54(2),* 132–138. https://doi.org/10.1093/abm/kaz031

RESEARCH PRESENTATIONS

Nooteboom, P., & Robles, T. (2018, July). *Development of the Digital Social Support Scale for Chronic Illness (DS3-CI)*. Poster presented at 2018 meeting for the International Association of Relationship Research in Fort Collins, CO.

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Social Support Across Contexts: In times of crisis and in interventions

Humans are inherently social in nature, and the absence of social resources can have devastating effects. Extensive research demonstrates that social relationships, and specifically lack of social support, can have an equal or greater impact on mortality as smoking fifteen cigarettes a day (Holt-Lunstad & Smith, 2012). However, in contrast to this, there are certain contexts in which people may benefit particularly well from access to social support. On one hand, social support as a construct has been studied extensively in a variety of contexts. However, across the context of many lifestyle interventions, social support is often not specifically addressed as an active ingredient or measured as an outcome. Rather, social support is frequently assumed to act as a non-specific intervention component, which subsequently results in its lack of measurement and assessment as an active ingredient.

Furthermore, the rapid development of technology has facilitated increasingly remote forms of communication (Guerriero et al., 2013; van der Eijk et al., 2013). These technological developments also allow for the exchange of support within a novel and understudied context (Hampton, 2016). While initial research has begun to explore digital-based social support, the field is still nascent. To compound that, the COVID-19 pandemic has not only increased the relevance of such investigations, but it also created an unprecedented stressful scenario in which many people explored novel remote communication methods. Despite the tragedies that the pandemic unleashed, it also presented a unique opportunity to investigate social support during a time of heightened stress and increased digital social interaction. Investigating the role of social support within this specific context will not only inform the use of digital social support in general, but will also inform responses to the current situation and similar future events. Overall, further investigation of social support in the context of lifestyle health interventions, as well as in digital interactions during crises such as the COVID-19 pandemic crisis, will help push social support research forward as a whole.

Broadly, social support refers to the perception or actual presence of others to provide resources in times of hardship or need (Cohen & Syme, 1985). Structural support refers to the extent to which an individual is integrated in a network of others that can provide such resources. Functional support refers to the specific kinds of resources that members of a network can provide. Within these two paradigms the resource of social support can come in a variety of forms such as emotional support, informational support, self-esteem support, belonging support, appraisal support, or tangible support (Bloom, 1990). Additionally, support can be provided from a variety of sources such as friends, family, acquaintances, and strangers. Finally, it can also be exchanged through a variety of avenues such as in-person, via telephone, or even digitally through video.

Social support focused research also distinguishes between received social support and perceived social support. Received social support refers to support that is objectively exchanged between individuals or within groups. It is frequently measured through direct observation or by asking individuals to report the quantity of recently received support. Received support can also be provided to participants in research studies and interventions through facilitated social interaction. Conversely, perceived social support refers to the quantity of support that someone believes to be available to them if they were to want or need it, regardless of the objective amount actually received. Perceived social support is generally assessed with self-report measures. In both cases, existing research on social support's relationship with health outcomes is mixed. On one hand, multiple studies have shown correlational relationships between higher social support and health outcomes such as lower morbidity and mortality with comparable effect sizes to many other common health determinants (Holt-Lunstad et al., 2017; Uchino, 2006). However, the causal role of social support has yet to be strongly established (Holt-Lunstad et al., 2017; Larocco et al., 1980; The ENRICHD Investigators, 2003).

Specifically, the correlational role of social support for health has been explored with a variety of outcomes. Such research has investigated the link between higher perceived social support and similar outcomes such as lower disease morbidity and mortality, lower all-cause mortality, and more beneficial health-behaviors (Greenwood et al., 1996; Holt-Lunstad et al., 2017; Kaplan, B. H., Cassel, J. C., and Gore, 1977; Uchino, 2006). For example, Holt-Lunstad et al. (2017) demonstrated that higher social support was significantly related to lower mortality with an odds ratio of 1.35 for perceived support, an odds ratio of 1.22 for received support, with larger effect sizes corresponding to greater odds of survival over the duration of the study. Additionally, Greenwood et al. (1996) conducted a review assessing the relationship between social support and coronary heart disease, and showed that higher support was associated with both lower initial incidence of mortality and lower disease specific mortality. While much research has supported the associations between social support and such outcomes, there has also been some inconsistent findings across some studies (Cohen & Syme, 1985; Kaplan, B. H., Cassel, J. C., and Gore, 1977; Uchino, 2006).

Further study of social support within the context of interventions has revealed evident heterogeneity across treatment protocols, support intents, delivery methods, and outcomes in these studies (Hogan et al., 2002). Hogan et al. (2002) reviewed 100 interventions that included aspects of received social support. This research addressed the relationship between received social support and positive outcomes in illnesses (e.g., cancer, diabetes), and health behaviors (e.g., weight loss, physical activity, substance use) (Hogan et al., 2002). Further supporting this heterogeneity in approaches and outcomes, Smith et al. (2021) conducted a meta-analysis of psychosocial behavioral support interventions and demonstrated inconsistent outcomes across different intervention types (Smith et al., 2021). Overall, participants in interventions compared to controls were more likely to be alive at study conclusion and had increased likelihood of longer survival, but these results varied highly across studies (Smith et al., 2021). For example, findings were most apparent when the intervention included a component promoting health behaviors, and were notably absent in higher severity patients, or compared to group education controls (Smith et al., 2021). Across interventions, some utilize a participant's natural network of family and close friends as a supportive source while others focus on interactions with peers. Despite the heterogeneity across studies, effects are present in both group and individual studies.

In a review of eight group-based studies that utilized family and friends as the source of support, positive outcomes were demonstrated in all of them (Hogan et al., 2002). However, in many of these studies, support was only included as a supplement to existing treatments such as other behavioral or educational components (Hogan et al., 2002). Additionally, social support was rarely measured as an outcome, and in many of these cases any positive effects did not sustain over time (Hogan et al., 2002). Similar to group interventions, individual interventions can also take advantage of support from family and close friends. While three of the four individual family/friend support interventions produced similar meaningful outcomes to those described in group interventions, there was again a lack of measurement of perceived social support, and a large amount of heterogeneity across intervention methods (Hogan et al., 2002). This lack of measurement of social support across interventions prevents conclusions about whether the intervention targets were engaged. Specifically, it is difficult discern whether social support was a key contributing factor in the observed outcomes. Taken together, both individual and group interventions that utilize friends and family as a source of support offer tentative evidence of a positive effect of increased support on outcomes.

Similarly, interventions that utilize group-based peer social support are also promising. In one particular instance, five of six reviewed studies showed positive outcomes for either general well-being or symptomatology for disorders such as bulimia and substance abuse (Hogan et al., 2002). It is also suggested that social support may be an active ingredient in these forms of peer support interventions, with social connection and social support being primary factors driving attendance in self-help groups (Humphreys et al., 1999; Nealon-Woods et al., 1995; Snow et al., 1994). Hogan et al. (2002) also discussed the outcomes from peer-based social support interventions that occur on an individual level. For individual interventions that provided support via peer interactions, nine out of the fourteen studies showed positive outcomes (Hogan et al., 2002).

Four of the reviewed interventions also combined group and individual social support interactions, which contributed to positive outcomes such as lower depression and better social support from caregivers (Hogan et al., 2002). Overall, the intervention research has provided initial support for the effectiveness of received social support in producing positive health outcomes (Hogan et al., 2002). However, several of the reviewed studies also failed to find any meaningful results showing its effectiveness. These inconsistencies may be due to the heterogeneity of the treatment protocols, support intents, delivery methods, and outcomes studied (Hogan et al., 2002). Overall, despite some shortcomings in several of the reviewed studies, and although a lack of measurement makes it is difficult to know if the intervention targets were actually engaged, to some extent it appears that social support is able to make a meaningful impact on health outcomes within lifestyle interventions.

There are several mechanisms by which social support may ultimately impact health outcomes. One of the prominent theories suggests that social support impacts health and health behavior outcomes through stress buffering (Cohen & Wills, 1985). This theory proposes that social support may not always have a direct impact on health and health-behavior outcomes, but rather that it may impact them by alleviating the negative health effects that stress can apply (Cohen & Wills, 1985). Cohen et al. (1985) suggest that social support interrupts the impact of stress on health by positively impacting stress appraisals, and by allowing for reappraisals or counter responses to stress. Stress, particularly that which is unpredictable and uncontrollable, can have many negative effects on health such as increased risk of illness, disease progression, and other markers of morbidity and mortality (Schneiderman et al., 2005; Thoits, 2010). Additionally, social support has also been independently linked to stress appraisals, perceptions of stress, and other psychological outcomes (Dunkel-Schetter et al., 1987). However, despite existing theory, as well as these independent links between social support and psychological outcomes, Uchino et al. (2012) argue that existing evidence does not strongly support a psychological pathway between social support and health outcomes. Specifically, it is argued that there is no strong evidence for social cognitive and affective psychological mechanisms such as perceived stress, self-esteem, social competence, self-efficacy, and depression (Uchino et al., 2012). However, Uchino et al. (2012) discussed shortcomings in statistical analyses and study design, underutilized conceptual considerations, and incorrect study models as potential explanations for the lack of findings in the literature. Further high-quality research may allow for the demonstration of these effects, or may help confirm the lack of effect. Ultimately, the lack of strong evidence in support of this pathway has not stopped researchers from continuing to investigate the psychological pathways between support and health outcomes (Uchino et al., 2012).

Despite the arguments presented by Uchino et al. (2012), self-efficacy remains commonly assessed as another potential psychological mechanism of action in the positive relationship between social support and health outcomes. Specifically, researchers hypothesize that higher levels of social support may lead to better health outcomes by increasing perceptions of self-efficacy. Self-efficacy refers to an internal perception of one's own capabilities for facing challenges (French, 2015). Both general and specific forms of self-efficacy are associated with health and health-related outcomes such as autonomic responses, medication adherence, health decision making, and a variety of other health behaviors (Schönfeld et al., 2017; Son et al., 2014; Strecher et al., 1986). Bandura proposed that self-efficacy plays a mediational role in the relationship between social support and health promoting behaviors (Bandura, 1986). Specifically, Bandura's proposals support the idea that that those who experience a high level of social support could see an increase in their self-efficacy, which could subsequently lead to better health behavior outcomes such as increased exercise. Existing research has demonstrated the relationship between social support and self-efficacy in a health-related context. For example, in a pilot RCT for recovering radical prostatectomy patients, participants in the intervention social support group showed significantly larger increases in self-efficacy for domain-specific problems compared to controls (Weber et al., 2007). Even more, several studies have demonstrated a mediating effect of self-efficacy in the relationship between social support and health outcomes. Using both cross-sectional and longitudinal analyses, Duncan et al. (1993) showed a mediating effect of exercise self-efficacy on the relationship between perceived social support and exercise behavior, such that higher support led to more exercise via increased exercise self-efficacy (Duncan & Stoolmiller, 1993). Additionally, general self-efficacy has shown to be a significant mediator in the relationship between social support and self-care health behaviors in patients with heart failure, such that higher perceived support related to better self-care through increased general self-efficacy (Mansouriyeh et al., 2018). Given these findings and the strong theoretical framework connecting support to health through self-efficacy, there is a need for further exploration of this pathway.

In a review of mechanisms of action for behavior change techniques, Carey et al. (2018) attempted to categorize potential psychological and behavioral mechanisms of action such as stress buffering and self-efficacy, but also other mechanisms such as modeling and self-regulation, into broad categories (Carey et al., 2018). The behavior change techniques of social support, social influences, social/professional roles and identity, and environmental context and resources were all identified as potential mechanisms of action (Carey et al., 2018). Beyond the basic exchange of social support, these additional mechanisms increase in relevance when moving into group intervention settings where they are likely to be most prevalent. Social influences refer to interpersonal processes that lead to changes in someone's thoughts, feelings, and behaviors, and was found to be a mechanism of action in 38 of the reviewed studies (Carey et al., 2018). Social/professional roles and identity refer to behaviors and qualities of an individual in a social or work environment, and was found to be a mechanism of action in five of the reviewed studies (Carey et al., 2018). Finally, environmental context and resources refer to characteristics of someone's environment or surroundings that encourage or discourage a given behavior, and was found to be a mechanism of action in four of the reviewed studies (Carey et al., 2018). Along with the previously discussed pathways, these categories of mechanisms provide a framework for how social support may influence health outcomes and health behavior change, and provides direction for research further seeking the examination of social support across contexts.

The present dissertation seeks to address the gaps in the literature through the investigation of social support within novel contexts across a set of two studies. The first study investigates the role of social support in the lifestyle health intervention Diabetes Prevention Program. The Diabetes Prevention Program is a year-long education-based lifestyle program targeted at reducing risk of diabetes primarily through weight loss, physical activity, and nutrition (The Diabetes Prevention Program Research Group, 2002). The main aim of study 1 is to assess the longitudinal relationship between changes in perceived social support and changes in weight and physical activity across the trajectory of the program, as well as assess the potential role of change in self-efficacy as a mediator of those relationships.

The second study evaluates the role of digital social support and physical distancing in perceptions of support, loneliness, and stress during the COVID-19 pandemic. Specifically, the study aims to assess the relationship between strictness of physical distancing, and three outcomes: perceptions of general social support, perceptions of digital social support, and perceived loneliness. Additionally, it aims to assess the impact of a brief video-based intervention for receiving digital social support on perceptions of support (general and digital) and perceived stress during the COVID-19 pandemic.

Study 1: The role of social support in the Diabetes Prevention Program

Even when not included in an intervention as a primary focus or active ingredient, many existing lifestyle health interventions facilitate the opportunity for the exchange of social support, such as social interaction within group-based interventions (Verheijden et al., 2005). Some interventions include support as a primary active ingredient of the intervention, while others offer it more indirectly as non-specific intervention components. Initial support for the positive impact of social support in lifestyle interventions has been demonstrated. That said, while social support is shown to have a positive effect on outcomes in such interventions, there is a clear need for more robust research investigating the impact that social support broadly has in lifestyle interventions, but also within specific implementations of particular lifestyle interventions such as the Diabetes Prevention Program.

Social Support in Lifestyle Interventions

There are multiple aspects of lifestyle interventions that may be social or socially supportive in nature. Additionally, these various components offer differing forms of social support, both functional and structural (Verheijden et al., 2005). Many lifestyle interventions are group-based and allow peers, friends, coworkers, family, or professionals to interact and socially engage with one another (Hartmann-Boyce et al., 2014). These interactions can also occur on an individual basis, or even in a combination of both (Hartmann-Boyce et al., 2014). For example, an intervention may be primarily group-based, but also assign individual intervention partners who can support each other outside of group sessions. These group and individual social interactions can happen in an in-person setting, a remote digital setting, or both (Hartmann-Boyce et al., 2014). Additionally, the frequency of these interactions may differ across intervention implementations (Hartmann-Boyce et al., 2014).

Nevertheless, these group and individual interactions allow for social comparison, social reward, learning of social skills, restructuring of the social environment, and also direct exchange of social support (Carey et al., 2018; Michie et al., 2013). In a lifestyle intervention setting, participants are often given the opportunity to share stories, barriers, successes, and struggles that they are facing in their health journey. While these are often non-specific intervention components, they still offer structure for the exchange of social support. This form of interaction may result in social comparisons (implicit and explicit) that contribute to feelings of esteem support, provision of professional or personal insights that may result in feelings of informational support, encouragement or sympathy that may result in feelings of emotional support, or even an offering of direct assistance that may result in feelings of tangible support. Participation in lifestyle interventions can also help garner similar forms of support from individuals outside of the intervention (Carey et al., 2018). Many lifestyle interventions also actively teach skills targeted at restructuring or improving social relationships and social support. These skills improve the ability of individuals to access social support, and therefore may impact their overall perceived availability of social support. Several mechanisms of action for how these supportive ingredients may function were discussed previously. Several of these mechanisms include stress buffering, self-efficacy, modeling, self-regulation, social influences, social/professional roles and identity, and environmental context and resources (Carey et al., 2018; Cohen & Wills, 1985; Mcauley & Courneya, 1993).

Across multiple reviews, the role of social support as a behavior change technique in lifestyle interventions has been examined. Verheijden et al. (2005) reviewed 10 randomized lifestyle weight management interventions, and described partial support showing that interventions that include social support can be effective in promoting positive outcomes in dietary change and weight loss (Verheijden et al., 2005). Due to heterogeneity in intervention methods of the studies, no analyses of effectiveness were able to be made (Verheijden et al., 2005). That said, individually most of the studies showed a statistically significant impact of the intervention on weight loss compared to controls (Verheijden et al., 2005). However, many of these studies had very low sample sizes (8-120), had high rates of attrition, and failed to measure social support as an intervention outcome (Verheijden et al., 2005).

Hartmann-Boyce et al. (2014) conducted a meta-regression examining the effectiveness of behavioral change techniques for weight management in 37 RCT interventions, and showed that social support did not significantly contribute to weight loss. For the purposes of this meta-regression, the intervention components of communication skills training, motivational interviewing, and planning for social support were coded as social support (Hartmann-Boyce et al., 2014). Finally, Greaves et al. (2011) conducted a systematic review of reviews assessing the effectiveness of intervention components in impacting diet and physical activity outcomes for those at risk of type 2 diabetes. In this review, evidence was found that interventions that included a social support module (often from family) had an additional weight loss of up to 3.0 kg at 1-year (Greaves et al., 2011). Overall, while a positive impact of social support in lifestyle interventions is shown in outcomes such as weight loss, physical activity, adherence, and diet, results are still partially mixed.

To date, one of the most successful lifestyle interventions is the Diabetes Prevention Program, which is targeted as reducing risk for diabetes. As of 2010, diabetes mellitus was estimated to affect nearly 14% of Americans, with projections of reaching 25% to 28% by 2050 (Boyle et al., 2010). Furthermore, as of 2018, it was estimated that about 88 million Americans 18 years or older have prediabetes, and as of 2022 it was estimated at 96 million

(38% of the US population) (Center for Disease Control and Prevention, 2020, 2022). Common risk factors for developing type-2 diabetes include obesity, physical inactivity, and smoking, as well as elevated blood glucose, blood pressure, and cholesterol (Center for Disease Control and Prevention, 2020). Common treatments include statin and metformin treatments, as well as changes to lifestyle factors such as weight management, physical activity, and nutrition. These lifestyle health behavior changes are prominently featured in the Diabetes Prevention Program.

Diabetes Prevention Program

In 2002, the landmark study on the Diabetes Prevention Program was published demonstrating its effectiveness in reducing the incidence of the type-2 diabetes compared to metformin and controls (Knowler et al., 2002). At an average of 2.8-year follow-up, incidence of type-2 diabetes per 100 individuals was 11 for controls, 7.8 for metformin, and 4.8 for participants in the Diabetes Prevention Program (Avenell et al., 2004). At the end of the program, about 75% of the participants met the physical activity goal, and the weight loss goal was reached by about 49% of participants (The Diabetes Prevention Program Research Group, 2004). Additionally, the Diabetes Prevention Program continued to outperform metformin in both 10-year and 15-year follow-ups (Diabetes Prevention Program Research Group, 2009; Nathan et al., 2016). Further investigation from the trial showed that weight-loss was the primary factor driving reductions in diabetes risk, such that each kilogram of weight loss corresponded to 16% reduction in risk (Hamman et al., 2006). Additionally, a review of 66 lifestyle health interventions for prevention of type-2 diabetes, many of which were specifically implementations of the Diabetes Prevention Program, showed decreases in type-2 diabetes incidence, body weight, and fasting glucose levels, as well as improved cardiometabolic risk factors (Balk et al., 2015).

Researchers have also investigated the impact of the Diabetes Prevention Program in producing outcomes for a variety of specific populations. For example, Aroda et al. (2015) investigated its effectiveness in women with a history of gestational diabetes. These women showed a 35% decreased risk of diabetes over a 10-year period (Aroda et al., 2015). Additionally, Ali et al. (2012) reviewed the effectiveness of 28 real-world lifestyle interventions modeled after the Diabetes Prevention Program. An average weight loss of 4% of body weight was seen, and each additional program session attended by a participant related to an additional 0.26% weight loss (Ali et al., 2012). The Diabetes Prevention Program has also conferred tertiary benefits for outcomes such as lowered CRP levels, and cardiovascular disease risk factors with less medication use than controls (The Diabetes Prevention Program Research Group, 2004, 2013). Overall, the Diabetes Prevention Program is an extensively studied lifestyle health intervention that has had its effectiveness in decreasing risk for diabetes strongly demonstrated.

Specifically, the Diabetes Prevention Program is targeted at reducing risk for diabetes primarily through weight loss, physical activity, and nutrition (The Diabetes Prevention Program Research Group, 2002). The program lasts 12 months, and is comprised of about 20-25 sessions depending on the particular implementation. In the standard program, during the first 3 months, the sessions are weekly. During the second 3 months, the sessions take place every other week. Finally, during the last 6 months, the sessions take place monthly. Each session is group-based and is led by a trained lifestyle coach. Each of the sessions focuses on a specific topic such as healthy eating, problem solving, getting support, and exercise planning. The full list of session topics for the specific implementation of the Diabetes Prevention Program addressed in the present study is presented in Table 1. Participants in the program are given the opportunity to learn new information, but also interact with other participants to exchange stories, socially support each other, and provide positive feedback.

As the Diabetes Prevention Program became increasingly prolific, the Center for Disease Control and Prevention (CDC) founded a nationwide Diabetes Prevention Program initiative bringing together public and private organizations to offer the program on a larger scale. Along with this effort, the CDC issued a set of standards to help guide the program's implementation (Center for Disease Control and Prevention, 2018). Under these guidelines, participants are eligible for the program if they are over the age of 18, have a body mass index of ≥25 kg/m2 (≥23 kg/m2, if Asian American), have had a recent positive screening for prediabetes or blood test with elevated glucose levels, and have no previous diagnosis of type-1 or type-2 diabetes (Center for Disease Control and Prevention, 2018). The guidelines also provide a preset selection of curriculum topics, as well as outcome targets required for CDC approval. The primary weight guideline targets an average loss of 5% of starting body weight, and a target physical activity goal of 150-minutes per week. These CDC guidelines have helped proliferate the structured deployment of the Diabetes Prevention Program widely, and also facilitated further research.

Social Support and Diabetes

Research linking social support to the disease of diabetes itself has also accumulated (Strom & Egede, 2012). In the illness of diabetes, a particularly important variable related to disease progression is self-management (Strom & Egede, 2012). Strom et al. (2012) reviewed 21 observational studies assessing the impact of social support on diabetes outcomes. The studies had a range of sample sizes from 12 to 3,535, and majority of these studies were cross-sectional (18 studies) (Strom & Egede, 2012). As an example, in a study of 1,788 diabetic adults over 60, more social support was positively related to higher adherence to treatment and health-promoting activities (Nicklett & Liang, 2010). Additionally, in a study of 1,097 diabetic adults over 50, higher diabetes-related social support was significantly related to lower odds of having high HbA1c levels (Okura et al., 2009). Across all of the reviewed observational studies, greater social support was related to better clinical outcomes (HbA1c, BP, lipids), as well as health behaviors (exercise, diet, treatment adherence) (Strom & Egede, 2012). Additionally, these relationships were present across multiple sources of support (peers, friends, and family) (Strom & Egede, 2012). However, this review also discusses several studies that failed to find significant associations between social support and diabetes outcomes. Additionally, many of the studies had small sample sizes or had other flaws such as high attrition (Strom & Egede, 2012).

While minimal, some existing literature has utilized controlled intervention studies to assess the impact of social support on various factors that may explain the relationship between social support and diabetes patient self-care and disease outcomes (van Dam et al., 2005). Van Dam et al. (2005) reviewed six controlled intervention trials that together targeted a variety of outcomes such as physical activity, self-care, metabolic control, perceived social support, goal setting, coping, diabetes knowledge, and psychosocial functioning. Sample sizes of these interventions ranged from 32 to 200 (712 total), and targeted a diverse set of populations (van Dam et al., 2005). The social support exchanged within these interventions also varied, with some taking place in-person, and others taking place in internet-based support groups (van Dam et al., 2005). In aggregate, the reviewed social support interventions demonstrated better outcomes compared to controls on physical activity, perceptions and use of social support, weight loss in women, and HbA1c levels (van Dam et al., 2005). Additionally, the studies that did show significant effects were generally rated to be of higher quality (van Dam et al., 2005).

That said, the reviewed studies were heterogenous in nature making it difficult to identify any single feature or form of support that was most responsible for outcomes.

Social Variables in the Diabetes Prevention Program

Despite this link between social support and diabetes, there has been minimal research exploring social variables specifically in the Diabetes Prevention Program. Bishop et al. (2013) explored the effect of perceived control over the health behaviors of socially close others. The researchers found that participants expressed perceptions that they socially impacted others through lifestyle changes, knowledge dissemination, and motivation changes (Bishop et al., 2013). That said, this study did not specifically measure or assess the role of social support received within the intervention (Bishop et al., 2013). Additionally, researchers who were focused on adapting the Diabetes Prevention Program for delivery in the community, cited the role that social support can play in weight loss management through accountability for regular participation and goal-directed efforts (Ackermann & Marrero, 2007; Jakicic et al., 2001). As a result, they explicitly emphasized social support in their adapted program by addressing social challenges involved in facilitating healthy lifestyle behaviors (Ackermann & Marrero, 2007). However, they did not track social support as an outcome (Ackermann & Marrero, 2007).

As previously discussed, within lifestyle interventions there are many opportunities for the presence or exchange of social support, and the Diabetes Prevention Program is no exception to this. In the initial development of the Diabetes Prevention Program, social support was considered as an important factor (The Diabetes Prevention Program Research Group, 1999). One of the more explicit opportunities for the presence of social support in the Diabetes Prevention Program is the addition of social skills in the curriculum. Class curriculum options recommended by the CDC include information focused on getting support, as well as information for managing social cues (Center for Disease Control and Prevention, 2018). The educational information provided about these skills are designed to help facilitate perceptions of and access to social support for intervention participants. However, other sessions also include social intervention aspects such as social comparison, social reward, restructuring of the social environment, and also direct exchange of social support (Carey et al., 2018; Michie et al., 2013) A complete list of social aspects of the Diabetes Prevention Program, and examples of when they are expressed within the program is presented in Table 2. Many of the sessions focus on education about specific topics such as physical activity, eating, and cooking. In these sessions, the group-based nature of the program allows participants to interact and provide each other with esteem, informational, emotional, tangible, and appraisal support focused on a given topic. Additionally, similar support can be garnered from the trained program coach, as well as other outside individuals such as friends, family, and peers. While the Diabetes Prevention Program does not treat social support as a primary active ingredient or outcome, as a construct it is very present in the intervention.

The present study seeks to address the lack of assessment of social support within the context of the Diabetes Prevention Program, and within lifestyle interventions as a whole. Specifically, this study's aims were to (1) assess the impact of change in social support across the Diabetes Prevention Program on changes in its primary outcomes (weight and physical activity), (2) to assess the mediating role of self-efficacy in the relationship between changes in social support and changes in outcomes across the program. Specifically, I hypothesized that intraindividual increases in perceived social support would be significantly correlated with interindividual decreases in weight and increases in physical activity. Additionally, I hypothesized that those relationships would be significantly mediated by intraindividual changes in self-efficacy.

Method

Participants

The present study is a single-arm longitudinal study that follows participants (N=79) across a single in-person cohort of the Diabetes Prevention Program. This particular implementation of the Diabetes Prevention Program consisted of 25 sessions spread across a 49-week period. The entirety of the program took place prior to the COVID-19 pandemic. Participants were recruited from the UCLA Housing and Hospitality Services (HHS) in cooperation with the HHS administrative team. At the time of the program, HHS offered free Diabetes Prevention Program enrollment to their employees. This program was offered on the UCLA campus, and occurred during paid employee time. Participants were recruited during the cohort's kickoff meeting at the beginning of the Diabetes Prevention Program. To be eligible for the study, participants must have been enrolled in the Diabetes Prevention Program and agreed to attend the in-person group sessions. Participants were given an overview of the study and were informed about what their involvement would entail. They were then asked if they would like to participate. If they wished to participate and were eligible, they were consented and enrolled in the study. Participants were compensated with a total of $10 for enrolling in the study, and completion of 90% or more of the surveys throughout the study resulted in an additional compensation of $30.

The sample was comprised of 39 males (49.3%) and 40 females (50.6%) with a mean age of 44.6 (SD=11.01), and mean income of $54,253.85 (SD=$25,360.96). The sample was predominantly Hispanic (35), followed by Caucasian/White (18), African American/Black (8), Asian (6), and undisclosed (12). The majority of the sample was married (37), followed by single (12), divorced (6), living with a partner (4). In terms of highest education level reached, the majority of participants completed some college (22), followed by completed high school (17), completed college (14), completed middle school (2), and completed graduate school (2).

Procedure

Five waves of participant survey data were collected using paper surveys distributed to participants during the last 5-10 minutes of several of the program sessions. In-person paper surveys were used to help increase adherence, and due to a lack of access to technology from many of the HHS staff. Since this method also did not require participants to allocate extra time to study activities beyond what had already been committed to as part of the larger Diabetes Prevention Program, deploying surveys during sessions also increased adherence. In several rare instances of a participant having to leave a session early, or in the cases of prearranged absences, makeup surveys were sent via email to the participant. Study survey were collected directly by the study team and individual responses were never shared with the DPP staff, or with the participants' employer. Overall, this methodology limited the ability to collect a complete wave of surveys in a single session. Therefore, each of the five waves of this study were comprised of a set of multiple surveys collected across a subseries of consecutive sessions during a 5-week period. Table 1 describes the specific sessions and weeks in which each measure was collected. Figure 1 illustrates the progression of the Diabetes Prevention Program, and shows at which sessions each of the survey measures was collected. Figure 1 also illustrates which wave each of the collected measures is attributed to, and the corresponding sample sizes for each measure in each wave. As part of the Diabetes Prevention Program, at every session the weight of each participant is measured using a scale, and weekly physical activity minutes are self-reported. In this particular implementation of the Diabetes Prevention Program sessions took place weekly during the first 4 months, every 2 to 3 weeks for months 5 and 6, and every 4 to 5 weeks for the remainder of the program. In order maximize sample size at each wave and to parallel the structure of the survey variables in my statistical models, for each participant their first instance of weight and physical activity in each of the first four waves was utilized, and their final instance of weight and physical activity was utilized for the final wave.

Measures

Demographics. Age, sex, race, education, income, and relationship status were assessed. Participants had the ability to identify as multiple races. Education was assessed as highest level of schooling completed. Income was assessed as self-reported annual individual income. This set of measures was only collected in wave 1 of the study.

Perceived Social Support. The 12-item Interpersonal Support Evaluation List (ISEL) short-form questionnaire was administered as a self-report measure of perceived availability of social support (Cohen & Hoberman, 1983). This version of the ISEL has three subscales: tangible support, belonging support, and appraisal support. Sample items include “There is someone I can turn to for advice about handling problems with my family.” and “If I wanted to have lunch with someone, I could easily find someone to join me.”. For this measure, participants are asked to respond to each item with the following anchors: definitely false, probably false, probably true, definitely true. This measure was collected across all five waves of the study. Across all waves, the overall ISEL had an average Cronbach’s alpha of 0.83. Table 3 provides a full list of Cronbach alphas for each wave and subscale.

Generalized Self-Efficacy. The 10-item General Self-Efficacy Scale (GSE) was administered as a self-report measure of perceived general self-efficacy (Schwarzer & Jerusalem, 1995). Sample items include “I can always manage to solve difficult problems if I try hard enough.”, “I can usually handle whatever comes my way.”, and “Thanks to my resourcefulness, I know how to handle unforeseen situations.”. For this measure, participants are asked to respond to each item with the following anchors: not at all true, hardly true, moderately true, exactly true. This measure was collected during the first four waves of the study in the session immediately following the session in which each social support measure was collected. Across all waves, the overall GSE had an average Cronbach’s alpha of 0.86. Table 3 provides a full list of Cronbach alphas for each wave.

Body Weight. At the beginning of every Diabetes Prevention Program session, participants were asked to weigh themselves. These weights were then recorded by the Diabetes Prevention Program coach. Participants used the same scale at every session and were asked to step on the scale wearing holding similar items each time to minimize measurement error (e.g. no shoes, empty pockets). To maximize the sample size of weight measurements in each wave, and to match them close in time to when social support was collected, only a single instance of weight was selected for each participant at each wave. For wave one through four a participant’s first instance of weight was utilized, and in wave five their final weight measurement was utilized. This method allows for the analysis of weight trajectory from the baseline of the study to its completion, as well as alignment with the 5-wave structure of the collected survey variables.

Physical Activity. At the beginning of every Diabetes Prevention Program session, participants self-reported to the coach their number of physical activity minutes they completed in the last week. For the purposes of the program, participants were only asked to report activity that was considered moderate-to-vigorous. To maximize the sample size of physical activity measurements at each time point, and to match them close in time to when social support was collected, only a single instance of physical activity was selected for each participant at each wave. For wave one through four a participant's first instance of physical activity was utilized, and in wave five their final physical activity measurement was utilized. This method allows for the analysis of weight trajectory from the baseline of the study to its completion, as well as alignment with the 5-wave structure of the collected survey variables.

Data Analysis

Study 1 Aim 1

The present study aimed to assess the impact of change in social support across the Diabetes Prevention Program on change in the program's primary outcomes (i.e. weight and physical activity). Specifically, I hypothesized that intraindividual increases in perceived social support would significantly relate to interindividual decreases in weight and increases in physical activity across the year-long program. To address these hypotheses, a set of two conditional parallel process latent growth curve models with a maximum likelihood estimator were completed within a SEM framework. Figure 6 illustrates the conceptual path diagram for the completed analytical model with weight as an outcome. Latent intercepts and slopes were specified to correlate. Additionally, to allow for non-linear change, baseline wave 1 scores were given a factor loading of 0, wave 2 to 4 loadings were freely estimated, and wave 5 scores were given a loading of 1. Additionally, intercepts were centered at the wave 1 time point, and mean slope values acted as an indication of change across the study. Due to lack of association between demographics and the other variables at wave 1, as well as with change in those variables, no additional covariates were included. Model fit was evaluated using the chi-square goodness of fit test, root mean square error of approximation (RMSEA), the comparative fit index (CFI), and the standardized root-mean-square residual (SRMR). Strong model fit is denoted by RMSEA values between.05-.08, CFI values greater than .95, and SRMR values between.05-.08 (Hu & Bentler, 1999). Descriptive analyses for all aims were completed using Python 3.9, and growth curve modeling was completed using Mplus 8.7.

While other longitudinal methods such as cross-lagged models allow for investigation of interindividual standing over time, the parallel process latent growth curve model approach allows for investigation of idiographic change to assess whether within-person change in social support relates to within-person change in weight and physical activity (Cole & Maxwell, 2003; Selig & Preacher, 2009). The proposed models operate best with sample sizes approaching at least 100, which is slightly higher than in the present study (Curran et al., 2010). However, growth curve models have also been successfully fitted to samples as small as 22 (Curran et al., 2010). Additionally, this analytic approach is also capable of accommodating partially missing data and unequally spaced time points.

Study 1 Aim 2

Additionally, the present study aimed to assess the mediating effect of intraindividual change in self-efficacy within the relationship between change in social support across the program and change in the primary program outcomes (weight and physical activity). Specifically, I hypothesized that the relationship between intraindividual changes in perceived social support and interindividual changes in weight and physical activity would be significantly mediated by intraindividual changes in general self-efficacy. To address these hypotheses, another set of two conditional parallel process latent growth curve models with a maximum likelihood estimator were completed within a SEM framework. This allows for the observation of change in all three variables as distinct processes. The mediational process was then modeled with the growth in social support relating to growth in the outcome variable (weight or physical activity) through growth in self-efficacy. Intercepts were centered at wave 1, and mean slope values acted as an indication of the change across the study. Due to lack of association between demographics and our other variables at wave 1, as well as with change in those variables, no additional covariates were included. Model fit was again evaluated using the chi-square goodness of fit test, root mean square error of approximation (RMSEA), the comparative fit index (CFI), and the standardized root-mean-square residual (SRMR). Figure 7 illustrates the conceptual path diagram for the completed analytical model with weight as an outcome. Mediation is successfully shown if the trajectory in social support relates to the trajectory of self-efficacy, which subsequently relates to the trajectory of the weight or physical activity (Cheong et al., 2003).

Results

Longitudinal Changes

Table 4 contains means and standard deviations of all collected variables across the study. Average perceived social support consistently increased through the study from baseline (wave 1) (M = 25.17, SD = 5.77) through wave 5 (M = 28.34, SD = 5.84). That is, aggregated across the present sample, an average absolute increase in support of 3.17 was demonstrated at wave 5 compared to wave 1. Independent of wave, average support change from each participant's first and last rating of social support increased across waves (M = 2.75, SD = 5.63). Figure 2 depicts social support ratings across the five study waves categorized by a tertile-split of overall support change. The top third of participants had overall changes in support ratings from 5 to 17. The middle third of participants had overall changes in support ratings from 0 to 5. The lower third of participants had overall changes in support ratings from -13 to 0.

Average weight consistently decreased through the study from baseline (*M* = 201.19, *SD* = 38.82) through wave 3 (*M* = 196.62, *SD* = 37.74). However, by wave 5 (*M* = 199.63, *SD* = 35.04), average weight again increased. That is, aggregated across the present sample, an average absolute reduction of 4.57 pounds (2.27%) was seen at wave 3 compared to wave 1, and an average absolute reduction of 1.6 pounds (0.7%) at wave 5 compared to wave 1. Independent of wave, average absolute weight reduction from each participant's first and last rating of weight across the study waves was 4.61 pounds (*M* = 2.25%, *SD* = 3.63%). Figure 3 depicts weight across the five study waves categorized by a tertile-split of overall weight change. The top third of participants had overall changes in weight from -29 to -7 pounds. The middle third of participants had overall changes in weight from -7 to -1. The lower third of participants had overall changes in weight from -1 to +12.

Average physical activity minutes consistently increased through the study from baseline (*M* = 124.71, *SD* = 110.29) through wave 5 (*M* = 276.60, *SD* = 315.03). That is, aggregated across the present sample, an average absolute increase of 151.89 physical activity minutes was demonstrated at wave 5 compared to wave 1. Independent of wave, average physical activity change from each participant's first and last rating of physical activity increased across the study waves (*M* = 83.34, *SD* = 270.59). Figure 4 depicts physical activity minutes across the five study waves categorized by a tertile-split of physical activity minutes change. The top third of participants had overall changes in physical activity minutes from +49 to +1340 pounds. The middle third of participants had overall changes in physical activity minutes from 0 to +49. The lower third of participants had overall changes in physical activity minutes from -480 to 0.

Average self-efficacy consistently increased through the study from baseline (*M* = 19.85, *SD* = 3.58) through wave 4 (*M* = 23.58, *SD* = 3.89). That is, aggregated across the present sample, an average absolute increase in self-efficacy of 3.73 was demonstrated at wave 4 compared to wave 1. Independent of wave, average self-efficacy change from each participant's first and last rating of self-efficacy increased across the study waves (M = 2.61, SD = 3.35). Figure 5 depicts self-efficacy ratings across the five study waves categorized by a tertile-split of overall self-efficacy change. The top third of participants had overall changes in self-efficacy from +4 to +11 pounds. The middle third of participants had overall changes in self-efficacy from 0 to +4. The lower third of participants had overall changes in self-efficacy from -5 to 0.

Table 5 shows means and standard deviations of wave 1 to wave 2 changes in social support, self-efficacy, weight, and physical activity for individuals who dropped out of the study by wave 3, and for those who adhered to the program past wave 3. Comparing those who dropped out of the program by wave 3 to those who adhered to the program past wave 3, there were no significant differences in wave 1 to wave 2 changes in social support (t = 0.26, p = .80), self-efficacy (t = -0.08, p = .94), weight (t = 0.65, p = .52), and physical activity (t = 0.27, p = .79).

Baseline and Change Correlations

Table 6 contains Pearson correlations between all variables in the study collected at baseline, as well as change scores for those variables calculated from a participant's first instance of a measure to their last. Across the outcomes of interest, higher baseline values were consistently related to lower change. Additionally, change in social support was significantly positively related to change in self-efficacy (r = .38, p = .002), such that larger increases in support were related to larger increases in self-efficacy. Conversely, change in social support was significantly negatively related to change in weight (r = -.40, p < .001), such that larger increases in support were related to larger decreases in weight. Change in self-efficacy was also significantly negatively associated with change in weight (r = -.59, p < .001), such that larger increases in self-efficacy were related to larger decreases in weight. Baseline weight was significantly negatively related to sex (r = -.29, p = .01) such that females had significantly lower average baseline weight than males. Baseline age was significantly positively related to income (r = .39, p = .004), such that individuals older ages were related to higher individual incomes.

Parallel Process Latent Growth Curve Models

Addressing aim 1, the relationship between intraindividual change in perceived social support and intraindividual change in weight when examined in a parallel process latent growth curve model showed adequate fit ($\chi 2(37) = 99.62$, p < .001; RMSEA = .13, 90% CI: 0.12-0.19; CFI = 0.94; SRMR = .13). Growth factor loadings, means and slopes estimates, and slope-to-slope and intercept-to-intercept coefficients for the present model are displayed in Table 7. The latent factor intercept for perceived social support was significantly negatively related to the latent growth factor slope for social support (β = -0.46, p = .01), such that higher baseline support was related to smaller intraindividual increases in social support. Furthermore, the latent growth factor slope for perceived social support was significantly negatively related to the latent growth factor slope for weight (β = -25.47, p < .001), such that intraindividual increases in perceived social support were associated with intraindividual decreases in weight (i.e. weight loss) across the trajectory of the Diabetes Prevention Program. A visualized representation of the model results is depicted in Figure 6.

Further addressing aim 1, the relationship between intraindividual change in perceived social support and intraindividual change in physical activity when examined in a parallel process latent growth curve model also showed adequate fit ($\chi 2(35) = 51.23$, p < .04; RMSEA =

.08, 90% CI: 0.02-0.12; CFI = 0.96; SRMR = .12). The latent growth factor slope for perceived social support was not significantly related to the latent growth factor slope for physical activity (β = -1.39, p = .68).[1] Growth factor loadings, means and slopes estimates, and slope-to-slope and intercept-to-intercept coefficients for the present model are displayed in Table 8. No latent factor slopes or intercepts were significantly related to each other.

Addressing aim 2, the mediating role of intraindividual change in self-efficacy in the relationship between intraindividual change in perceived social support and intraindividual change in weight when examined in a parallel process latent growth curve model showed adequate fit ($\chi 2(70) = 145.48$, $p < .001$; RMSEA = .12, 90% CI: 0.09-0.14; CFI = 0.94; SRMR = 0.11). Growth factor loadings, means and slopes estimates, and slope-to-slope and intercept-to-intercept coefficients for the present model are displayed in Table 9. The latent factor intercept for perceived social support was significantly negatively related to the latent growth factor slope for social support (β = -0.37, p = .04), such that higher baseline support was related to smaller intraindividual increases in social support. Additionally, the latent factor intercept for self-efficacy was significantly negatively related to the latent growth factor slope for self-efficacy (β = -0.53, p < 0.001), such that higher baseline self-efficacy was related to smaller intraindividual increases in self-efficacy. The latent factor intercept for perceived social support was significantly positively related to the latent factor intercept for self-efficacy (β = 6.03, p = .04), such that higher baseline support was related to higher baseline self-efficacy. Furthermore, the latent growth factor slope for perceived social support was significantly negatively related to the latent growth factor slope for weight (β = -21.18, p = .003), such that intraindividual increases in

[1] In an attempt to account for fluctuations in activity, this analysis was also completed with physical activity values at each wave being calculated by averaging across all activity ratings for each participant at a given wave. With this approach, there was still no significant relationship (β = -1.21, p = .55).

perceived social support were associated with intraindividual decreases in weight (i.e. weight loss). The latent growth factor slope for perceived social support was significantly positively related to the latent growth factor slope for self-efficacy (β = 5.05, p = .0048), such that intraindividual increases in perceived social support were associated with intraindividual increases of self-efficacy. Finally, the latent growth factor slope for self-efficacy was significantly negatively related to the latent growth factor slope for weight (β = -17.10, p < 0.001), such that intraindividual increases in self-efficacy were associated with intraindividual decreases in weight (i.e. weight loss).

Further addressing aim 2, the mediating role of intraindividual change in self-efficacy in the relationship between intraindividual change in perceived social support and intraindividual change in physical activity when examined in a parallel process latent growth curve model showed adequate fit ($\chi2(70) = 92.05$, p < .04; RMSEA = .06, 90% CI: 0.02-0.10; CFI = 0.96; SRMR = 0.12). Growth factor loadings, means and slopes estimates, and slope-to-slope and intercept-to-intercept coefficients for the present model are displayed in Table 10. Only the latent factor intercept for perceived social support was significantly positively related to the latent growth factor slope for physical activity (β = 0.22, p = .03), such that higher baseline support was related to larger intraindividual increases in physical activity.

Discussion

The present study aimed to assess the relationship between intraindividual changes in perceived social support and intraindividual changes in weight and physical activity across the trajectory of the 12-month Diabetes Prevention Program. Firstly, I hypothesized that intraindividual increases in perceived social support would be significantly negatively related to intraindividual decreases in weight. In a conditional parallel process latent growth curve model, this hypothesis was supported such that across the trajectory of the Diabetes Prevention Program, as intraindividual increases in social support were seen, intraindividual decreases in weight (i.e. more weight loss) were seen. Additionally, I hypothesized that intraindividual increases in social support would be significantly negatively related to intraindividual increases in physical activity. In a conditional parallel process latent growth curve model, this hypothesis was not supported, such that there was no significant relationship between changes social support and changes in weekly physical activity minutes across trajectory of the Diabetes Prevention Program.

Exploring these relationships further, the present study also aimed to assess the mediating role of intraindividual changes in self-efficacy within the relationship between intraindividual changes in perceived social support and intraindividual changes in weight and physical activity. I specifically hypothesized that increases in perceived social support would be significantly related to increases in self-efficacy, which would subsequently be significantly related to decreases in weight. In a conditional parallel process latent growth curve model, this hypothesis was supported such that across the trajectory of the Diabetes Prevention Program, larger intraindividual increases in social support were significantly related to larger intraindividual increases in self-efficacy, which were significantly related to larger intraindividual decreases in weight (i.e. more weight loss). Furthermore, I hypothesized that the relationship between intraindividual changes in perceived social support and intraindividual changes in physical activity would be significantly mediated by intraindividual changes in self-efficacy. In a conditional parallel process latent growth curve model, this hypothesis was not supported, such that there were no significant relationships amongst intraindividual changes in social support, intraindividual changes in self-efficacy, and intraindividual changes in weekly physical activity minutes across trajectory of the Diabetes Prevention Program.

Overall, the present implementation of the Diabetes Prevention Program resulted in an overall increase in perceived social support, self-efficacy, and physical activity minutes, as well as decreases in weight across the waves of the study. An overall reduction in weight of 1.6 pounds (0.7%) was present at wave 5 compared to wave 1. Independent of wave, average absolute weight reduction from a participant's first and last rating of weight across the study waves was 4.61 pounds (2.25%). Assessed either way, this weight reduction is slightly lower than comparative implementations of the Diabetes Prevention Program. For example, the initial trial showed a reduction of around 15 pounds at 1-year, and other trials showed similar findings beyond 7% reduction (Baker et al., 2011; Brown et al., 2018; Knowler et al., 2002). That said, weight and physical activity of the enrolled sample in the present study may systematically differ from the larger overall results of this particular DPP implementation as agreement to participate was not based on randomization. Additionally, the present results include all initially enrolled participants regardless of attrition. Furthermore, the segmentation of results into waves may also account for differences from the overall results of this particular DPP implementation, as well as from others. Crucially, it is also important to acknowledge that the present analytical approach assesses the relationship between social support and weight on the intraindividual level and is therefore able to assess the present aims independent of aggregated changes in outcomes.

Beyond the present study, other studies have assessed the role of social support in interventions. As discussed previously, positive health outcomes are seen in many of the lifestyle weight interventions that include some aspect of social support (Verheijden et al., 2005). Additionally, using similar latent growth curve modeling methods, some studies have even examined longitudinal changes in social support across interventions and demonstrated its association with intervention outcomes. In a trauma therapy intervention, increases in social support were significantly related to decreases in post-traumatic stress symptoms across the trajectory of the intervention using similar modeling methods (Birkeland et al., 2020). Even more similar to the present study, in a health promotion intervention, the growth trajectory of social support was significantly related to the growth trajectory of physical activity (Roesch et al., 2009). However, the present study is the first to assess the longitudinal role of social support specifically in the Diabetes Prevention Program. That said, in addition to previously discussed literature these further findings connect weight and physical activity with social support, and add valuable context to the present results.

The present study's findings regarding the relationship between weight and social support are mostly consistent with existing literature. Within behavioral and lifestyle interventions, similar relationships are seen between social support and weight. In a study comparing a standard behavioral treatment alone to a standard behavioral treatment combined with support strategies included, those who received social support had a 95% completion rate versus 76% in the comparison group, and a 66% weight loss maintenance rate versus 24% in the comparison group (Wing & Jeffery, 1999). In a review of strategies for weight loss in African American women, social support was discussed as a useful tool for both weight loss and maintenance (Wolfe, 2004). Lastly, in a behavioral weight loss program, individuals who had experienced friend and family support were more likely to lose weight (71.6%) than those without support from family (45.7%) (Kiernan et al., 2012). Beyond weight loss interventions broadly, the relationship between social support and weight is also present within other diabetes specific programs. For example, in an intervention for Latino individuals with type 2 diabetes similar to the Diabetes Prevention Program, having support from family and friends was associated with more weight loss at the end of the program (Marquez et al., 2016). Given these findings within lifestyle interventions, the present finding linking increases in social support to decreases in weight within the Diabetes Prevention Program are compatible within the larger literature context.

The present study also identified a mediating role of changes in self-efficacy in the relationship between changes in social support and changes in weight. In the present study, this finding is consistent with the significant Pearson correlation between overall change in social support and self-efficacy. Existing literature also provides a consistent context for the present findings. In cross-sectional analyses of baseline weight and self-efficacy in the Diabetes Prevention Program, both self-efficacy for not overeating and exercise self-efficacy were significantly related to BMI. While the present study assesses self-efficacy in a general way, we were still able to build on this finding to show the effect self-efficacy can have on weight when assessed longitudinally. Furthermore, specifically in a lifestyle weight loss program designed to incorporate self-efficacy, as self-efficacy improved weight loss was greater (Roach et al., 2003).

Conversely, to the findings for weight, the present study's findings regarding the relationship between physical activity and social support are mostly inconsistent with the literature. In multiple cross-sectional findings across youth, middle-aged, and older individuals, social support is linked with higher physical activity. In a set of two studies in young adults, social support positively correlated with more physical activity, and similar findings were supported in a systematic review of adolescents (Mendonça et al., 2014; Treiber et al., 1991). In a study of middle- to older-aged women, individuals who received more physical activity specific social support were significantly less likely to be sedentary compared to individuals who received less (Eyler et al., 1999). Finally, within a systematic review of exclusively older adults, a positive association between social support for physical activity and engagement in physical activity was demonstrated (Lindsay et al., 2017). Example survey questions addressing social support for physical activity include “I have a friend or acquaintance who encouraged me to exercise” and “I have a friend or acquaintance who changed their schedule so we could exercise together” (Sallis et al., 1987). However, no clear relationship between general social support and physical activity was demonstrated (Lindsay et al., 2017).

Beyond cross-sectional studies, lifestyle and behavioral interventions demonstrate a similar positive relationship between social support and physical activity. In a social support intervention RCT, support from family and friends was positively related to increases in aerobic physical activity (Keller et al., 2014). Furthermore, in a 12-week online social network intervention, social support demonstrated a small significant impact on physical activity (Cavallo et al., 2014). While these intervention findings are not specific to diabetes, they show that social support in a lifestyle intervention context can play an important role in physical activity outcomes.

Building on these findings, longitudinal change in social support have also been specifically linked to longitudinal change in physical activity beyond the literature already discussed. In a systematic review of physical activity behavior in adolescent girls, across the studies social support from friends and families was consistently related to change in physical activity with follow-ups ranging from 1 to 5 years (Laird et al., 2016). This pattern of findings also persisted when looking at baseline social support and its positive relationship with physical activity (Laird et al., 2016). Marques et. al. (2016) demonstrated a positive relationship between physical activity specific social support and physical activity adherence (Marquez et al., 2016). Moreover, they demonstrated that physical activity adherence mediated the relationship between social support and weight loss at a 1-year follow-up (Marquez et al., 2016). That said, this study differs in several ways from the present study. The study focused only on Latino participants aged 45 to 76 with type 2 diabetes, and assessed physical activity as a single cumulative measure. The present study had a sample with a wider range in race and age, and focused on pre-diabetes. Additionally, rather than a single measure of physical activity, the present study tracked physical activity repeatedly. Together, these factors may partially account for differences in outcomes compared to the present study.

Not only did the present study fail to find a significant relationship between changes in perceived social support and changes in physical activity, it also failed to show self-efficacy as a significant mediator of that relationship. However, within existing literature self-efficacy seems to play an important role in affecting physical activity. In a study of women with a history of gestational diabetes mellitus, both physical activity specific social support and self-efficacy were significantly positively related to engagement in physical activity (Kim et al., 2008). In a study of physical activity in middle- and older-aged adults, self-efficacy was directly and indirectly related to physical activity through several social cognitive constructs (Ayotte et al., 2010). Furthermore, self-efficacy was shown to moderate the relationship between declines in perceived social support and physical activity, such that those who had strong social support saw less decline in physical activity if they also had high self-efficacy (Dishman et al., 2009). Even more, in an 8-week longitudinal exercise intervention, received social support was indirectly related to physical activity through the mediator of self-efficacy (Rackow et al., 2015). That said, the study focused on received support, compared to perceived support in the present study.

Together, these findings are mostly in contrast to the findings of the present study. There are several potential factors that may account for differences in findings. The most consistent difference in existing literature compared to the present study was in the type of social support being assessed. Many of the studies that found a significant association between social support and physical activity, did so assessing social support and self-efficacy that was specific to physical exercise. Neither the self-efficacy measure nor the social support measure in the present study assessed constructs specific to physical activity. The broadness of the measures may have failed to capture changes in support and self-efficacy constructs most relevant to physical activity. Furthermore, the utilized measures in the present study focused on perceptions of support, rather than actual received support. While the literature demonstrating the benefit of received support is mixed, several studies have demonstrated significant associations with physical activity.

One further explanation for the inconsistent findings between weight and physical activity may be due to the differing nature of how these two outcomes can fluctuate over time. Across time, weight is a cumulative variable in which each successive value is directly dependent on the previous measure. To see a change in weight from one time point to the next, the participant must shift directly from the previous weight level. However, measuring change in a participant's weekly physical activity minutes does not follow this same pattern. Given that a participant's number of minutes for each week starts at zero, their final total for that week is only determined by effort exerted in that particular week. Compared to weight, each weekly physical activity measurement is partially independent from previous weeks and is far less cumulative in nature. Given this difference, physical activity fluctuations were much larger in the present sample than fluctuations in weight. It is possible that this lack of cumulative change is not suited well for tracking intraindividual changes over time in relation to other variables. In much of the comparative literature, physical activity was either viewed cumulatively, or was assessed at a single point in time. That said, in an effort to assess the role that activity fluctuations played in the findings, the present analyses were also conducted with each wave's physical activity values being calculated as an average of all weekly activity values across the 5-week period of each wave, instead of a single week's value. Unfortunately, when calculated using this method, there were still no significant findings. As shown in table 4 and in figure 4, variance in physical activity increased across the trajectory of the study, possibly accounting for a lack of a significant relationship with support. Overall, there are a number of factors that may have led to findings that are incongruent with the larger literature.

Despite the mixed results of the study, the present findings have meaningful implications for future implementations of the Diabetes Prevention Program, as well as lifestyle interventions more broadly. Firstly, the implications following the lack of findings in regards to physical activity are lessened due to previous studies showing the that risk for diabetes was primarily mediated through weight loss, rather than physical activity, with physical activity showing minimal independent risk reduction effects (Knowler et al., 2002). That said, the present findings for weight outcomes broadly suggest the importance of social support as a factor to monitor in the Diabetes Prevention Program, and lifestyle interventions more broadly. Future implementations of the program may benefit from further incorporation of social support topics spaced across the curriculum to encourage growth in social support over time. Additionally, tracking social support as an outcome of the program could allow coaches to provide targeted intervention for individuals or groups who are perceiving less support. Furthermore, emphasizing the importance of healthy and productive group interactions may also facilitate greater feelings of support, and therefore may lead to better weight outcomes.

The present implementation of the Diabetes Prevention Program took place prior to the COVID-19 pandemic, and allowed for uninhibited in-person group interaction. It is likely that much of the support from other members of the program benefitted from this format. However, as a result of pandemic restrictions, as well as workplace norms, it is likely that many future implementations of the Diabetes Prevention Program will take place online and remotely. Even prior to the pandemic, digital Diabetes Prevention Program implementations existed and were demonstrated to be of equal effectiveness to in-person versions (Moin et al., 2018; Sepah et al., 2014). That said, translating social support to digital settings can be difficult. Those aiming to implement digital program versions will need to take extra care to emphasize the social aspects of the program to potentially garner similar benefits to those seen in the present study.

However, these implications should be viewed within the context of the strengths and limitations of the present study. There are several limitations of the study. First, the method in which surveys were collected at the end of classes forced inconsistent spacing in measurements and waves. While the particular statistical methods used partially account for these issues, having more defined time points would allow for cleaner analysis. A further downside of the statistical approach is that it lacks the ability to make causal claims between changes in support and changes in outcomes, which is further exacerbated by the lack of strict temporal precedence within each wave of the mediation models. Similarly, with the current design, we are unable to causally attribute changes in support to the intervention. While the models presented showed adequate fit, a larger sample size may have led to stronger fit, and potentially different results. As mentioned previously, the present study also focused on general social support rather than outcome-specific measures of support that may have also led to different findings.

There were also several strengths and unique aspects to the present study. For example, the use of parallel process latent growth curve models allows for the comparison of intraindividual change across the trajectory of the study. Many other similar studies and approaches are only able to assess intraindividual standing or group level differences. Given that the models examine relationships on the intraindividual level, each person's values are compared to their own over time, and therefore there is less need to assess change in outcomes such as percentage weight change, or other standardized measures such as BMI. Additionally, the piecewise approach helps account for the role that initially high baseline values could play in reducing changes in each outcome. The study is the first of its kind to assess the role of longitudinal changes in social support within the Diabetes Prevention Program on outcomes, and provides a strong platform for further explorations.

Moving forward, future research should more deeply explore the role that changes in social support can lead to. Specifically, a deeper comparison of the types of social support, as well as source of that support would help disentangle what aspects of the support are most beneficial. Similarly, future work should explore what aspects of the group interactions lead to the largest increases in perceptions of support. Additionally, translating the questions posed in the present study to an RCT setting would allow for more causal analyses. Finally, as the opportunity and prevalence of digital Diabetes Prevention Program implementations expand, a deeper examination of how social support can be implemented effectively in this setting would also be beneficial.

Overall, the present study examined the relationships between intraindividual changes in social support and intraindividual changes in weight and physical activity. Furthermore, the mediating role of intraindividual change in self-efficacy in these relationships was also assessed. Evidence supporting the inverse relationship between increases in social support and decrease in weight were found, as well as evidence that this relationship was mediated by increases in self-efficacy. The same findings were not supported for physical activity. Together, these findings provide several implications for future implementations of the Diabetes Prevention Program, as well as future research exploring social support's role in the program.

Study 2: Digital social support during crisis

In study 1, I addressed the role of social support within the novel context of the Diabetes Prevention Program, a lifestyle health intervention for decreasing risk of diabetes. In-person social support is a very prominent aspect within the Diabetes Prevention Program. In study 2, I further built upon the social support literature by investigating the ability of a brief video-based peer social support intervention to positively impact perceived general social support, perceived digital social support, and perceived stress, within the context of digital social interaction during the COVID-19 pandemic. Current communication technology has allowed for extensive interaction both digitally and remotely, especially following the increased rates of social/physical distancing experienced during the COVID-19 pandemic. Therefore, study 2 also aims to assess the association between strictness of social/physical distancing and perceived general social support, perceived digital social support, and perceived loneliness.

Psychological research in the context of COVID-19

As a result of the COVID-19 pandemic, the world has experienced unprecedented circumstances across many aspects of life. Many policies were put into place that prioritized and required social/physical distancing. Additionally, many norms were changed regarding in-person interaction. Not only did the pandemic, and its subsequent impact on social norms likely have a meaningful impact in the short term, it will likely also have a long-lasting impact on many aspects of daily life. The hypotheses and design of the present study were drastically impacted by the current situation and required extended contemplation and adaptation for this context. Psychological research and interventions must take into consideration the current and future global context created by COVID-19. Additionally, while COVID-19 created a specific context of circumstances, there is a high likelihood that the future will be fraught with similar crises that require the application of concepts generated from carefully considered research during such times.

In general, the overall use of digital communication-based technologies has been steadily increasing in recent years. However, the COVID-19 pandemic accelerated the adoption of online communication technologies beyond levels that would have likely been seen without such an event (Al-Maroof et al., 2020; Clipper, 2020; Pierri & Timmer, 2020). As a result, many individuals are engaging in more long-distance global communication, remote working, and general reliance on technology for communication. This growing digital-reliance paired with the current relevance following the COVID-19 pandemic presents unaddressed questions about the impact that digital-based social support may have on psychological outcomes moving forward.

Given the impact of COVID-19, researchers rapidly began to explore the ways in which COVID-19 may affect psychological outcomes. However, previous research following past events of similar magnitude can also shed light on what was to be expected during COVID-19. For example, large societal transitions such as those created from natural disasters or global events also drastically impact the global context (Mikal et al., 2013). Mikal et al. (2013) describe the presence of elevated stress during major societal transitions. Additionally, they propose that in many major transitions, online social support may emerge as more beneficial than in-person methods because it allows people to create, access, and maintain strong and weak social ties in a low-risk manner (Mikal et al., 2013). Other research following the 9/11 terrorist attacks further substantiates the likely emergence of stress and long-lasting stress-related disorders resulting from such events (Neria et al., 2008; Silver, 2011). Looking further to similar events that also require forms of physical distancing, we see that HIV-positive individuals are shown to have high levels of social isolation, loneliness, and lack of social satisfaction while practicing distancing (Elmer et al., 2020; Marziali et al., 2020). In the context of COVID-19, policies and norms around distancing expanded far beyond certain populations or locations, likely having an impact on a large portion of society.

Research has also described the initial impact that the pandemic had on psychological outcomes. During the time of elevated stress during the initial onset of COVID-19, common stressors for students shifted from concerns about social life to concerns about their health, family, friends, and future (Elmer et al., 2020). Furthermore, early in the pandemic, Banerjee et al. (2020) described the impact that the pandemic would likely have on loneliness. Loneliness refers to the emotional response that emerges from perceptions of social isolation (Cacioppo et al., 2013). Isolation and social/physical distancing created by COVID-19 were expected to lead to higher perceptions of loneliness in both the short term and the long term (Banerjee & Rai, 2020). Additionally, it was expected that the impact would likely be exaggerated for older individuals who have limited access to technology (Armitage & Nellums, 2020). Furthermore, a study that tracked individuals over the initial months of the pandemic showed that following the onset of the COVID-19 pandemic, both introverts and extraverts experienced modest declines in social connection (Folk et al., 2020). Additionally, participants in the Love in the Time of COVID survey on average reported feeling less connected and more frequent feelings of depression in the early months of the pandemic (Balzarini et al., 2020). Data also showed that distress and loneliness were significantly associated with perceptions of perceived health impact of the COVID-19 outbreak, such that those with higher distress and loneliness perceived a higher impact of COVID-19 on their health (Cerami et al., 2020). As COVID-19 progressed, and as people’s behavior adapted to the different phases of the pandemic, its impact on psychological outcomes likely also shifted, requiring further research. For example, a meta-analysis of studies assessing loneliness at various times throughout the pandemic found heterogenous effects (Ernst et al., 2022).

As a result of the outbreak of the COVID-19 pandemic, policies emerged around social/physical distancing, placing restrictions on face-to-face interactions for many. As a result, usage of video conferencing software drastically increased, and phone carriers reported large increases in text-messaging. For example, the video conferencing service Zoom Video Communications, Inc. reported that in the month following the spread of COVID-19, the average number of daily video calls increased by 100 million (Yuan, 2020). Additionally, T-Mobile reported a 26% increase in SMS text messaging following COVID-19 (Ray, 2020). Drastic increases in remote work were also seen, with industries embracing remote work seeing less economic contraction (Espitia et al., 2022). These abrupt increases in usage of remote/digital methods for interaction show the importance that digital-forms of social communication have played in filling the absence of face-to-face interaction resulting from the COVID-19 pandemic.

Beyond the impact of social/physical distancing on remote interaction, the extent to which someone engages in strict physical distancing may also impact various psychological outcomes such as perceived social support. Initial research showed that during the COVID-19 pandemic, social activities were negatively related to being at home (Fried et al., 2020). Practicing strict distancing at home limits the access to and availability of other individuals whom one may regularly perceive as an available social support resource. This may therefore decrease someone's general perceptions of social support availability. However, in contrast perceived online social support may be higher during such a time. As discussed previously, the displacement hypothesis of online social interactions suggests that social internet use may negatively impact outcomes such as perceived support and loneliness through the replacement of in-person social relationships (Valkenburg & Peter, 2007). However, in the current context of the COVID-19 pandemic, many of these in-person social relationships were already disrupted. Additionally, research shows that preference for online social interaction is significantly higher for those who are currently dissatisfied with the support available to them in-person (Chung, 2013). Individuals who practiced strict social/physical distancing in response to the COVID-19 pandemic may have been likely to experience more dissatisfaction with in-person support relationships, and therefore view digital-based support and interaction more favorably. A preference for digital social support, as well as pre-disrupted in-person relationships may therefore lead to increases in perceived digital social support availability.

The context of COVID-19 also calls into question the relevance of certain theoretical frameworks within which perceived social support operates. Uchino (2009) proposed a life-span perspective for explaining the theoretical underpinnings for how perceived social support is formulated. He proposed that aspects of early family environments such as parental affection, support, and familial conflict inform perceived social support, whereas received support is informed by the context of current stressors (Uchino, 2006). This framework suggests that perceived social support has developmental antecedents such that an individual's level of perceived support is partially determined by events of the past, rather than present context (Uchino, 2006). However, the specific transitionary period presented by COVID-19 may lead to more weight being placed on recent events in the determination of perceived social support. During this turbulent time, individuals may need to rely on reactions to current events more so than usual, and these antecedents may become less relevant. Compared to many other global events, COVID-19 had the unique symptom of limiting in-person social interaction, which may have precluded reliance on attachment and familial antecedents. Under such circumstances, there may be more opportunity to see an impact of acute events on ratings of perceived social support than would be normally expected. Overall, the COVID-19 pandemic led to unprecedented changes in society that provide a unique context for the study of digital social support.

Digital social interactions

The recent rapid development in communication technologies has allowed for a wide range of social interactions online, many of which can be supportive in nature (McKenna & Bargh, 1999). Descriptive content analyses of support interactions show that statements made in online support conversations are similar to those that are made in in-person support groups (Coulson et al., 2007; Mo & Coulson, 2008; Salem et al., 1997). That is, they offer many of the same types of social support that are seen in-person, such as informational support, esteem support, tangible support, and emotional support. With many of these online interaction methods, similar forms of support can be exchanged, but within a different context. For example, someone could provide a friend with informational support by sending a text-message with pointers on how to maintain a workout routine. Alternatively, someone could monetarily give tangible support, but instead of exchanging money in-person, they might donate to someone's online crowdfunding campaign for their illness. In this online context, informational and emotional support are the most frequently exchanged, followed by other forms such as esteem and tangible support (Coulson et al., 2007; Mo & Coulson, 2008). In my previous research creating and assessing the validity of a measure of perceived online social support, a unique form of support was identified and referred to as response support. Response support refers to the feeling of support drawn from small discrete response-based actions performed online such as a "like" on a social media post. Together, these findings show that interactions online are in many ways similar to those of in-person interactions such that they offer similar forms of support.

Simultaneously, interactions in this unique context are also a very different experience compared to in-person interactions.

The present study focuses on one of the most common digital communication forms, video-based interaction. This form of digital interaction is not only one of the most frequently utilized, but also allows for a high throughput of information. Video-interaction allows for the synchronous exchange of complex verbal and nonverbal communication. However, such interactions still differ from in-person interactions due to their partial lack of some nonverbal cues such as touch or off-screen gestures which may otherwise help regulate a conversation (Kraut et al., 1982). That said, in some cases online interactions have demonstrated benefits even when the opportunity for face-to-face interaction is unavailable. Coyle et al. (2019) showed that mirrored use of emojis in text-messaging interactions was related to higher perceptions of responsiveness, and to higher positive perceptions of the other individual (Coyle & Carmichael, 2019). While text messaging interactions are usually devoid of nonverbal communication, the ability to use features such as emojis can bolster online interactions in a way that differs from in-person interactions. With this in mind, it is likely that video-based interactions, while digital, can still closely resemble the interactions exchanged in-person and be viewed as socially supportive.

Received digital support and perceived support

Not only are social interactions online capable of facilitating the exchange of various types of support, they also can positively impact perceived social support. That said, research investigating the relationship between received digital social support and perceived social support is nascent. Much of the research linking received digital social support to perceived social support has been conducted with close others such as friends and family. For example, in a single arm survey study, increased text-messaging between relationship partners was significantly and positively related to perceived social support (Morey et al., 2013). However, the impact of peer-based social support on perceived support is mixed. In general, peer support and the various forms of support that it offers (i.e. informational, emotional, tangible, etc.) is often viewed as beneficial by participants because of the exchanges of resources it can offer, as well as the feelings of normalization that interacting with similar others can facilitate (Gidugu et al., 2015). However, in the context of digital interactions, received support's impact has only been minimally investigated. In a single arm study, Shaw et al. (2002) investigated the impact of five chat sessions between strangers across 4 to 8 weeks on perceived social support. Significant increases in perceived social support were shown from pre to post intervention (Shaw & Gant, 2002). However, due to a lack of control group, attribution of the increase cannot be isolated to the intervention (Shaw & Gant, 2002). Barrera et al. (2002) examined the role of a digital peer support forum for diabetes patients in a RCT. After 3 months, participants who received the social support intervention had significantly larger increases in perceived support compared to controls (Barrera et al., 2002). However, there have also been failures to detect positive social outcomes (isolation, loneliness, support) for several received support studies conducted both digitally, and not (Barrera & Prelow, 2000; Heller et al., 1991; Houston et al., 2002). Additionally, many of these studies focus on large-scale support communities that contain hundreds of members, rather than smaller scale interactions (Gustafson et al., 2001). They also often only include received support as part of a larger multicomponent intervention, or fail to measure perceived social support as an outcome (Gustafson et al., 2001).

One contributing factor to the nascence of this research is the lack of an established measure for specifically assessing perceived digital social support. Many existing measures of perceived social support do not differentiate the source of the support, and contain many items that only pertain to in-person support interactions. For example, one of the most well-established measures of perceived social support, the Interpersonal Support Evaluation List (ISEL), contains several items that are in-person focused such as, "If I needed a ride to the airport very early in the morning, I would have a hard time finding someone to take me." (Cohen & Hoberman, 1983). As mentioned, the nuances of digital communication differ drastically from in-person interactions. Despite the forms of support being similar, the specific actions and behaviors used to exchange each type of support differs. Any non-significant results assessing the impact of received digital support on perceived social support may not be due to a lack of effect, but rather a lack of appropriate measurement. While digital social support interventions are shown to increase perceived social support generally, larger relationships may be detected between received and perceived support when compared within congruent contexts.

Received digital support and perceived stress

As mentioned previously, one of the primary proposed mechanisms of action for how social support can impact health is the stress buffering hypothesis (Cohen & Hoberman, 1983). Cohen's view is that higher levels of available support may improve someone's perceived coping ability to demands being placed upon them thereby altering their appraisals of the stressor (Cohen, 2004). Since the stress buffering hypothesis was proposed, social support has been linked to stress appraisals, perceptions of stress, and other psychological outcomes (Dunkel-Schetter et al., 1987). As discussed previously, Uchino et al. (2012) outline the lack of strong evidence supporting a mediational effect of psychological outcomes in the relationship between social support on health outcomes. The majority of existing studies addressing this question underutilized conceptual considerations, were flawed in statistical analyses and study design, or used incorrect study models (Uchino et al., 2012). Despite these findings, researchers continue to assume that psychological mechanisms such as stress appraisals may explain the link between social support and health. Transitioning into the context on digital social support, this assumption has persisted. However, at the same time, similar shortcomings in digital support studies are also present. Further investigation using longitudinal randomize control trial studies to test the link between digital social support and psychological mechanisms will help elucidate whether these misguided assumptions should also be discarded in the digital context. The present study can help address this question in an experimentally controlled study that specifically focuses on received support.

In general, received digital social support's relationship with perceptions of stress is nascent. That said, there are several studies which have demonstrated this relationship. In a 6-month single arm longitudinal intervention study, Dunham et al. (1998) assessed the impact of a digital peer-support network for 42 single mothers on perceived parenting stress. While average perceived stress did not significantly differ from pre- to post-intervention, higher interaction in the online peer-support community was significantly related to lower post-intervention parenting stress ($X^2 = 6.05$, $p < .04$) (Dunham et al., 1998). In a cluster RCT for caregivers, Gleeson et al. (2017) assessed the impact of a digital social therapy program that included peer-support on perceptions of stress. At follow-up, there was a significant reduction in perceived stress for the intervention group, and more use of the program was significantly related to a greater degree of improvement in perceived stress ($r = 0.548$, $p = 0.003$). However, peer-support was included alongside other intervention components, such as online therapy, making it difficult to attribute outcomes exclusively to received digital peer-support (Gleeson et al., 2017). Additionally, cross-sectionally in an online cancer support community, received digital emotional support from peers was significantly associated with perceived stress, such that higher support related to lower perceptions of stress (Wright, 2002). However, there are also conflicting results showing no significant relationship between received digital social support and stress. For example, in a cross-sectional study, received social support on Facebook was not shown to be significantly related to perceptions of stress, but rather support giving on Facebook was actually related to higher perceptions of stress (Chen & Bello, 2017). Ultimately, the link between received digital peer-support and perceptions of stress remains unclear and in need of further research.

This RCT seeks to further the understanding of social support, specifically within the contexts of digital communication and the COVID-19 pandemic. Within this unique context, the present study assesses the effects of a brief video-based peer social support intervention on perceived digital social support, perceived general social support, and perceived stress. The brief nature of the intervention allows for the acute assessment of digital social support in a manner that would allow it to be integrated as a component of future interventions. Additionally, if successful this brief intervention could be rapidly and easily deployed to a large number of individuals with few barriers and low cost. Furthermore, the peer-based nature of the intervention allows for large scalability. For example, in an academic setting, there are only a very limited number of trained professionals who can provide support to students. Utilizing peer support would help scale the availability of supportive resources to a large number of individuals who are all simultaneously experiencing the same stressor.

The study aims assess the relationship between strictness of physical distancing and perceived digital social support, perceived general social support, and perceived loneliness during the COVID-19 pandemic. I hypothesized that strictness of distancing will be negatively correlated with perceived general social support, and positively correlated with perceived digital social support and perceived loneliness, such that higher strictness ratings will be related to lower general social support, and higher loneliness and digital social support. The second aim of the study is to assess the effects of a brief longitudinal video-based peer social support intervention on perceived digital social support, perceived general social support, and perceived stress compared to no-support controls. I hypothesized a significant condition by session interaction, such that those in the video-support condition would show significantly greater increases in digital and general social support, and significantly greater decreases in perceived stress compared to no-support controls.

Method

Participants

The present study is a two-arm RCT. As part of a larger program of research, participants were also simultaneously recruited for a third condition that is not discussed in the present study. In the present study, participants were UCLA students (N=142) recruited through the Department of Psychology's subject pool system (SONA). An initial power analysis was used to estimate a required sample size of 60-70 participants for each group. A total of 67 participants were in the social support intervention group, and 75 were in the no-support control group. Participants were eligible for the study if they were English speaking and 18 years of age or older. Figure 9 depicts the CONSORT participant flow and attrition through the stages of the study. Participants who did not complete all support sessions were excluded from data analysis. Participants were compensated three SONA credits for their participation in the study. Upon enrollment, participants were assigned to a condition using simple randomization. If a participant was randomized to the intervention group, they were paired with another participant of the same sex who had signed up for the study within the same 5-day period and also been randomized to the support condition. If multiple other participants had signed up within the same period of time, participants were paired with the participant that enrolled closest in time. If no other participants were enrolled at that time, the participant was rescheduled and then paired. Participant randomization and pairing was completed by the study coordinator. Participants in the control condition were not paired with another individual. All participants were recruited during weeks in which the university system was holding remote classes due to COVID-19 (Summer 2020 – Summer 2021). Additionally, all participants were recruited during times in which COVID-19 was experiencing a surge in new reported cases. Recruitment was terminated upon UCLA's decision to reinitiate in-person classes and housing for the Fall 2021 quarter. Figure 8 illustrates a comparison between when participants were recruited and the total number of newly reported COVID-19 cases in the U.S. during that given period of time.

The sample was comprised of 29 males, 110 females, and 2 who reported their sex as "other", with a mean age of 20.87 (*SD*=3.88), and mean individual income of $12,417.21 (*SD*=$52,226.77). The sample was predominantly Caucasian/White (45), followed by Chinese (25), Mexican (18), Korean (10), Asian Indian (9), Black/African American (9), Vietnamese (7), other Asian (7), other Spanish/Hispanic/Latino (6), Japanese (2), Filipino (2), Pacific Islander (1), Cuban (1). The majority of participants were in their fourth year in college (51), followed by third year (44), second year (25) first year (13), fifth year (5) and sixth year (2). The majority of the sample reported being never married (136), followed by married (4), and divorced (1).

Procedures

Each instance of the intervention took place across a single week, and was comprised of three brief sessions. Each study session took place 3-4 days after the previous one, depending on scheduling availability. Participants in both conditions completed a series of survey measures at each session. Participants in the intervention condition also engaged in a peer social support task via video at each or the three study sessions.

For the video-based peer social support interaction task, matched participants were sent a Zoom video conferencing link, and joined a video call. Participants were then instructed to spend the duration of the interaction discussing any difficulties they had recently experienced, and to interact in a supportive and positive manner with the other individual. Participants were given 15 minutes to talk with each other and receive support. At the first session, this video interaction took place immediately after the surveys. In the second and third study sessions, the video support task took place immediately before the surveys.

In the control group, participants joined the video call for each session and were instructed to complete their assigned set of survey measures. Following the completion of the measures, the session was ended. For both groups, the research assistant facilitating the session only communicated to the participants via the built-in text-based chat system, and never had their camera or audio turned on. Following the completion of the final session, participants were debriefed and reimbursed for their participation.

To maximize participant safety throughout all stages of the study, study protocols were established to handle several possible complications that could potentially arise between participants. Research assistants were extensively trained on these protocols, and were instructed to intervene, mediate, and or provide external resources and referrals when necessary. The participant safety protocols included guidelines for addressing: expression of suicidal ideation, perpetrated discrimination or hate, the occurrence of a heated disagreement or argument, indecent exposure or offensive gestures, nonconsensual advances, and sharing of personal contact information. Upon completion of the study, participants were also asked to cease further communication with the matched partner unless it consensually occurred completely outside the context of the study. Throughout the duration of the study, none of these incidents occurred.

Measures

Demographics. Age, sex, race, education, income, and relationship status were assessed. Participants had the ability to identify as multiple races. Education was assessed as year in college. Income was assessed as self-reported annual individual income. This set of measures was collected at the first session of the study.

Perceived Stress. The 10-item Perceived Stress Scale (PSS) was administered as a self-report measure of perceived stress (Karmakar et al., 2017). The prompts of the measure were adapted from “In last month” to “In the past few days” to more closely measure change over the brief study period. Sample items include “In the past few days, how often have you felt that you were unable to control the important things in your life?”, “In the past few days, how often have you felt nervous and ‘stressed’?”, and “In the past few days, how often have you felt that things were going your way?” Participants were asked to respond to each item with the following anchors: never, almost never, sometimes, fairly often, very often. This measure was assessed at all three study sessions. Across all sessions, the PSS had an average Cronbach’s alpha of 0.90. Table 11 provides a full list of Cronbach alphas across each session.

Loneliness. The 20-item Revised UCLA Loneliness Scale (UCLA) was used to assess loneliness (Russell et al., 1980). Sample items include “I feel left out,” “I am no longer close to anyone,” and “My social relationships are superficial.” Participants were asked to respond to each item with the following anchors indicating how frequently they agree with each statement: never, rarely, sometimes, often. This measure was collected at the first session of the study, and had a Cronbach’s alpha of 0.79.

Perceived General Social Support. The 12-item Interpersonal Support Evaluation List (ISEL) short-form questionnaire was administered as a self-report measure of perceived availability of social support (Cohen & Hoberman, 1983). This version of the ISEL has three subscales: tangible support, belonging support, and appraisal support. Sample items include "There is someone I can turn to for advice about handling problems with my family." and "If I wanted to have lunch with someone, I could easily find someone to join me.". Participants were asked to respond to each item with the following anchors: definitely false, probably false, probably true, definitely true. This measure was assessed at all three study sessions. Across all sessions, the overall ISEL had an average Cronbach's alpha of 0.86. Table 11 provides a full list of Cronbach alphas across each session and subscale.

Perceived Digital Social Support. The self-created 12-item Digital Social Support Scale (DS3) was administered as a self-report measure of perceived availability of digital-based social support. This scale has 4 subscales: tangible support, appraisal support, esteem support, and response support. Sample items include "If I were to post online asking for help, not many people would respond.", "If I were to create an online profile, very few people would join or follow the profile.", and "I know someone online with whom I would feel comfortable discussing problems I might have managing my life struggles." Participants were asked to respond to each item with the following anchors: definitely false, probably false, probably true, definitely true. This measure was be collected at all three study sessions. Across all sessions, the overall DS3 had an average Cronbach's alpha of 0.82. Table 11 provides a full list of Cronbach alphas across each session and subscale.

Distancing Strictness. Strictness of social/physical distancing was assessed using four self-created items. These items include "To what extent have you engaged in social/physical distancing in response to the COVID-19 pandemic?", "To what extent have you followed your city and state's guidelines for social/physical distancing in response to the COVID-19 pandemic?", "To what extent have you confined yourself to your home in response to the COVID-19 pandemic?", and "To what extent have you interacted with others outside the confines of your home following COVID-19?". Participants were asked to respond to each item with the following anchors: not at all, to a small extent, to some extent, to a moderate extent, to a large extent. These four items were combined into a single composite score. This measure was only collected at the first study session, and had a Cronbach's alpha of 0.73.

Data Analysis

Study 2 Aim 1

First, the present study aims to assess the relationship between strictness of physical distancing and perceived digital social support, perceived general social support, and perceived loneliness during COVID-19. I hypothesized that strictness of distancing would be negatively correlated with perceived general social support, such that those with higher strictness would report lower perceived general social support. Additionally, I hypothesized that strictness of distancing would be positively correlated with perceived online social support, such that those with higher strictness would report higher perceived online social support. Finally, I hypothesized that strictness of distancing would be positively correlated with perceived loneliness, such that those with higher strictness would report higher perceived loneliness.

To address these hypotheses, a set of three linear regression models were completed. In the first model, baseline perceived digital social support was regressed on baseline strictness of distancing. In the second model, baseline perceived general social support was regressed on baseline strictness of distancing. In the third model, baseline perceived loneliness was regressed on baseline strictness of distancing. Descriptive analyses and regression analyses were completed using Python 3.9. Regression equations for these three models are provided below.

$$Y_{digital\_support} = \beta_0 + \beta_1 Distancing_{i_i} + e$$

$$Y_{general\_support} = \beta_0 + \beta_1 Distancing_{i_i} + e$$

$$Y_{loneliness} = \beta_0 + \beta_1 Distancing_i + e$$

Study 2 Aim 2

The present study also aimed to assess the effects of a brief longitudinal video-based peer social support intervention on perceived digital social support, perceived general social support, and perceived stress compared to no-support controls. I hypothesized a significant condition by session interaction, such that changes in perceived digital social support, perceived general social support, and perceived stress would significantly depend on intervention condition. Specifically, that those in the video-support condition would evidence significantly greater increases in digital and general social support, and significantly greater decreases in perceived stress compared to no-support controls.

To address this aim, a set of multilevel models were completed to test the effects of the intervention on each of the three outcomes (perceived digital social support, perceived general social support, and perceived stress). In each model, fixed effects included session, condition, the interaction between session and condition, and the baseline score of the particular outcome being tested. Random effects included a participant-specific random intercept accounting for within-participant correlation (repeated study sessions), and a random effect for intervention group dyad (partially nested data). This approach explicitly models the within-group correlation of dyads in the intervention groups, while also allowing the participants in the control group to remain independent (Bauer et al., 2008). Individuals in dyads were modeled with a shared class identifier, while individuals in the control group each had a unique class identifier. Baseline scores were included to account for initial differences between individuals in dyads and non-dyads. An interclass correlation coefficient (ICC) was calculated for each model to estimate the within-dyad correlation. Descriptive analyses and data preparation for these hypotheses were completed using Python 3.9, and the multilevel models were completed in SAS Studio 5.2. An example equation of the described model is provided below.

Level 1:

$$Y_{ij} = \beta_{0j} + \beta_{1j}Condition_{ij} + \beta_{2j}Session_{ij} + \beta_{3j}(Condition * Session)_{ij} + \beta_{4j}Baseline_{ij} + e_{ij}$$

Level 2:

$$\beta_{0j} = \gamma_{00} + u_{0j}$$
$$\beta_{1j} = \gamma_{10} + u_{1j}$$
$$\beta_{2j} = \gamma_{20}$$
$$\beta_{3j} = \gamma_{30}$$
$$\beta_{4j} = \gamma_{40}$$

Results

Baseline differences

Table 12 shows group means and standard deviations for each study variable across each study session. Across all measures (except perceived stress), conditions were balanced at baseline ($p > .3$). However, perceived stress significantly differed across conditions at baseline ($t = -2.09$, $p = .04$), such that individuals in the control condition had significantly higher ratings of stress than those in the intervention condition.

Strictness of Distancing

Results from a multiple linear regression between strictness of distancing and perceived digital social support are displayed in Table 13. Strictness of distancing was significantly negatively related to perceived digital social support ($\beta = -0.07$, $p = 0.037$) with an R^2 of 0.03.

That is, higher ratings of strictness of distancing were significantly related to lower ratings of perceived digital social support, such that for each single unit of increase in strictness of distancing, a -0.07 unit decrease in perceived digital social support is expected.

Results from a multiple linear regression between strictness of distancing and perceived general social support are displayed in Table 14. Strictness of distancing was significantly negatively related to perceived general social support ($\beta = -0.06$, $p = 0.049$) with an R^2 of 0.03. That is, higher ratings of strictness of distancing were significantly related to lower ratings of perceived general social support, such that for each single unit of increase in strictness of distancing, a -0.06 unit decrease in perceived general social support is expected.

Results from a multiple linear regression between strictness of distancing and perceived loneliness are displayed in Table 15. Strictness of distancing was significantly positively related to perceived loneliness ($\beta = 0.03$, $p = 0.048$) with an R^2 of 0.03. That is, higher ratings of strictness of distancing were significantly related to higher ratings of perceived loneliness, such that for each single unit of increase in strictness of distancing, a 0.03 unit increase in perceived loneliness is expected.

Social Support Intervention

Results from the multi-level model assessing the impact of the social support intervention on perceived digital social support are displayed in Table 16. There were no significant effects of condition on perceived digital social support ($\beta = -0.90$, $p = 0.19$), or of session on perceived digital social support ($\beta = 0.26$, $p = 0.2$). However, there was a significant positive condition by session interaction on perceived digital social support ($\beta = 1.01$, $p < .0001$). That is, controlling for baseline perceived digital social support, the effect of session on perceived digital social support is 1.01 units larger in the intervention condition than in the control condition. Individuals in the intervention group experienced significantly greater increases in perceived digital social support than individuals in the control group. Within-dyad correlation was estimated with an ICC of 0.25. Figure 10 illustrates compares changes across sessions in perceived digital social support between conditions.

Results from a multi-level model assessing the impact of the social support intervention on perceived general social support are displayed in Table 16. There were no significant effects of condition on perceived general social support ($\beta = 0.30$, $p = 0.71$). However, there was a significant negative effect of session on perceived general social support ($\beta = -0.59$, $p = 0.02$). That is, controlling for baseline perceived general social support, and independent of condition, for each additional session a decrease of -0.59 units in perceived general social support is expected. Finally, there was no significant condition by session interaction on perceived general social support ($\beta = 0.14$, $p = 0.7$). Within-dyad correlation was estimated with an ICC of 0.14. Figure 10 illustrates compares changes across sessions in perceived general social support between conditions.

Results from a multi-level model assessing the impact of the social support intervention on perceived stress are displayed in Table 16. There were no significant effects of condition on perceived stress ($\beta = -0.91$, $p = 0.43$). However, there was a significant negative effect of session on perceived stress ($\beta = -0.98$, $p = 0.01$). That is, controlling for baseline perceived stress, and independent of condition, for each additional session a decrease of -0.98 units in perceived stress is expected. Finally, there was no significant condition by session interaction on perceived stress ($\beta = 0.32$, $p = 0.53$). Within-dyad correlation was estimated with an ICC of 0.14. Figure 10 illustrates compares changes across sessions in perceived stress between conditions.

Discussion

The present study aimed to assess the relationship between strictness of distancing during COVID-19 and perceptions of perceived general social support, perceived digital social support, and perceived loneliness. Firstly, I hypothesized a significant negative relationship between strictness of distancing and general social support. This hypothesis was supported such that higher strictness of distancing was significantly related to lower perceptions of general social support at baseline. Furthermore, I hypothesized a significant positive relationship with perceptions of digital social support. However, this hypothesis was not supported such that higher strictness of distancing was actually significantly related to lower perceptions of digital social support at baseline. Finally, I hypothesized a significant positive relationship between strictness of distancing and perceptions of loneliness. This hypothesis was supported such that higher strictness of distancing was significantly related to higher perceptions of loneliness at baseline.

The present study also assessed the impact of a brief video-based peer social support intervention on perceptions of digital social support, general social support, perceived stress. Specifically, I hypothesized that the intervention group would have significantly greater increases in perceived digital social support than the control group. Supporting this hypothesis, there was a significant session by condition interaction such that individuals in the intervention group had a significantly greater increase in perceived digital social support than the control group. Furthermore, I also hypothesized that the intervention group would have significantly greater increases in perceived general social support than the control group. This hypothesis was not supported such that no session by condition interaction for perceived general social support was found. Finally, I hypothesized that the intervention group would have significantly greater decreases in perceived stress than the control group. This hypothesis was also not supported such that no session by condition interaction for perceived stress was found.

Overall, the present findings are partially consistent with existing literature. While there is limited research assessing the specific construct of strictness of distancing and its relationship with support and loneliness, similar findings are found for social isolation. Social isolation is defined as a lack of consistent social contact from others and having limited social interactions with others (Cacioppo et al., 2011). Social isolation is a very similar experience to the conditions created by social/physical distancing (Williams et al., 2020). For example, in practice, social isolation is often operationalized as low social interaction and assessed with items such as "Number of times in the past week spent time with someone you are not living with." (Freak-Poli et al., 2021). Similar to the present results, there is an established link between social isolation and perceptions of social support and loneliness. Broadly, research has assessed the overall relationship between social isolation, low social support, and loneliness. For example, Freak-Poli et al. (2021) investigated the overlap and interaction of these three constructs within a sample of older adults (Freak-Poli et al., 2021). The researchers established the three constructs as discrete, yet highly related and frequently overlapping experiences, such that individuals often shared one or more of these constructs (Freak-Poli et al., 2021). On an individual level, social isolation is also directly linked with perceptions of social support. For example, in a review of social support and social isolation in both positive and negative contexts, reported findings showed that individuals who were socially isolated consistently reported lower social support (Gable & Bedrov, 2022). Similarly, social isolation is also strongly related to loneliness. In many cases, social isolation is viewed as an objective measure of lack of social contact, while loneliness is viewed as the subjective manifestation of that isolation (Leigh-Hunt et al., 2017). In a systematic review examining the health effects of social isolation and loneliness, the authors defined social isolation as an objective lack of social contact with others, and loneliness as subjective dissatisfaction with one's relationships (Leigh-Hunt et al., 2017). Across the reviewed studies, social isolation and loneliness were frequently related and shared similar odd-ratios for health outcomes (Leigh-Hunt et al., 2017). The similarity in outcomes suggests a similarity between these subjective and objective measures (Leigh-Hunt et al., 2017).

As mentioned, there is limited research directly examining the specific link between strictness of distancing and perceptions of social support. However, given the previously discussed link between social isolation and social support, many researchers have emerged to advocate for research and policy that emphasize social support during times of distancing. Researchers have consistently agreed that social/physical distancing poses a significant threat to social support. For example, Pantell et al. (2020) made a broad call to action for maintaining social connections in the setting of social distancing (Pantell & Shields-Zeeman, 2020). Ferdous (2021) discussed the impact social distancing can have on older adults, and synthesized action plans for addressing it (Ferdous, 2021). Okoh et al. (2022) called for a need for social support in Law Schools during eras of social distancing (Okoh & Nnoko, 2022). Together these discussions reaffirm the need for the present investigation of strictness of distancing.

While the present findings for perceived social support are consistent with the discussed literature, the significant negative relationship between strictness of distancing and digital social support is inconsistent with initial hypotheses. The initial hypotheses described the expectation that higher strictness of distancing would be related to lower perceptions of general social support and higher perceptions of digital social support. It was thought that with a lack of in-person connections and support, individuals choosing to distance would rely more heavily of digital-based relationships, and that doing so may drive higher perceptions of digital social support. As previously discussed, following the onset of the COVID-19 pandemic, there was a drastic increase in digital communication use (Ray, 2020; Yuan, 2020). However, it does not appear that strictness of distancing operates on perceptions of social support purely through increased usage. Rather, the present findings show that despite increased digital communications usage during these times, higher strictness of distancing was negatively related to both perceptions of general social support and digital social support.

The present finding linking strictness of distancing with loneliness is also consistent with existing research. Within the context of the SARS outbreak in 2003, loneliness was identified as a common experience for those engaging in social distancing, and ultimately was a driver of lowered adherence (Digiovanni et al., 2004). Moreover, preliminary data from the COVID-19 pandemic show that for older individuals during times of increased social distancing, feelings of loneliness were elevated (Fuller & Huseth-Zosel, 2021). Furthermore, Hoffart et al. (2020) showed that for at-risk individuals, loneliness was a key contributing factor for negative psychological outcomes within the context of social distancing (Hoffart et al., 2020). Additionally, researchers have also advocated for the need for special attention to loneliness in a time of social distancing. For example, Cudjoe et al. discussed that prior to COVID-19 older individuals experienced a loneliness rate of 40%, and argued that during social distancing that rate would only increase (Cudjoe & Kotwal, 2020).

Overall, the results from the present study linking strictness of distancing to social support and loneliness are consistent with the existing literature. Researchers argued for policies that focused on physical distancing, and not social distancing, suggesting that social closeness could still be achieved other means such as digital connection (Abel & McQueen, 2020). Despite this assertion, the present findings and existing research suggest that higher strictness of distancing is related to lower perceptions of social support and higher perceptions of loneliness. This finding was consistent for both perceived general social support and perceived digital social support. Given these findings, there is a clear need for interventions targeting perceptions of support within the context of COVID-19 and social/physical distancing.

Beyond strictness of distancing, the present intervention shows mixed consistency with existing literature. As previously discussed, digital-based social support has been significantly related to higher perceptions of social support (Barrera et al., 2002; Morey et al., 2013; Shaw & Gant, 2002). The present results show a similar pattern of findings for perceived digital social support, but not for perceived general social support. Existing intervention research has not assessed both of these constructs simultaneously and compared their outcomes. Moreover, the majority of existing research linking received social support with perceptions of support has focused specifically on in-person/general social support. While the present intervention was shown to be effective for digital social support, the lack of significant findings for general social support is inconsistent with the majority of existing literature assessing larger scale interventions. That said, given the brief nature of the present study, further research is needed to understand the effect video-based support interventions may have on perceptions of general social support.

Similarly, higher digital social support has been partially linked with lower perceptions of stress. As discussed, Dunham et al. showed that higher interaction in a 6-month online peer-support community of 42 women was significantly related to lower post-intervention parenting stress (Dunham et al., 1998). Additionally, in a cross-sectional survey conducted with 103 members of a large online cancer support community, higher received digital emotional support from peers was significantly negatively related to lower perceived stress (Wright, 2002). That said, the inverse of these findings has also been shown. In a cross-sectional survey, received social support on Facebook was not significantly related to perceptions of stress, but more support giving was related to higher perceptions of stress (Chen & Bello, 2017). The present study also did not find a significant intervention impact on stress. Together, the present impact of the intervention is partially consistent with existing findings, but requires further investigation.

There are several potential factors and limitations of the current study that may partially account for the mixed intervention findings. As previously mentioned, one potential limitation of the study is that within the intervention group, the exchange of social support was bidirectional. Therefore, it is not possible within the present study to isolate the effects of the intervention exclusively to changes in received social support. As seen informed by Chen et al. (2017), it is possible that stress-reduction effects from received social support may be blocked by stress increases from support giving. That said, the structure of the intervention is naturalistic to many of the conversational interactions that individuals traditionally receive support from. While the brevity of the intervention is a strong benefit to easy deployment of the intervention in the real world, it also potentially limited the ability to detect effects that may have emerged with a larger dose. A similarly structured intervention with a large dose may result in stronger outcomes. Finally, females were largely overrepresented in the sample, and the study only focused on college students, which narrows the generalizability of the results.

There are also several strengths of the present study and intervention that are important to consider. Firstly, the recruitment of participants exclusively during time where UCLA students were fully remote, and during times when COVID-19 cases were at increased rates allowed for the investigation of social support in a unique context. Additionally, the longitudinal nature of the study design allowed for the measure of change in outcomes across time. This was further strengthened by an appropriate analytic approach that allowed for the direct assessment of this longitudinal effect. The analytic approach also was well suited for accounting for the partial nesting within the intervention group, but not the control group. The intervention itself also specifically has several key strengths. The intervention was brief in nature, low in burden for participants, low in cost, at low risk for harm, and flexible to the remote needs of participants and researchers. Additionally, given the peer-nature of the intervention, it does not require a group of trained staff to facilitate it. These strengths make the intervention ideal for deployment in a variety of situations.

Although the acute impact of the COVID-19 pandemic has lessened, these results have several meaningful short- and long-term implications. The present study demonstrated the role that strict social/physical distancing may have on perceptions of social support and loneliness. While not causal in nature, the findings suggest a plausible relationship such that more strictness of distancing may contribute to lower perceived social support and higher perceived loneliness. In future instances where social/physical distancing is required, it will be important to consider the impact that such policy choices may have on these secondary factors. There are a multitude of factors that contribute to policies about distancing, and more information can help inform both personal and policy decisions in future situations where such adjustments are necessary. Even outside the context of COVID-19, distancing and isolation are still a frequent experience for many individuals. The present results are also informative of the impact that such experiences can have across all contexts.

Given the negative impact that distancing appears to have for psychological outcomes, in the context of COVID-19 and beyond, there is a strong need for feasible and scalable interventions that can effectively address deleterious effects of crises and stress. The present study demonstrates a potential method for driving social engagement across peers in a brief intervention setting. While no effects for general social support and stress were shown, the intervention was able to demonstrate an impact on perceptions of digital social support. Not only does this result continue to identify digital and general social support as separate constructs, it also demonstrates a potential method for specifically targeting digital social support perceptions. The relevance of such an intervention is most applicable to situations such as COVID-19 where a majority of in-person social support is already limited. However, as many previously in-person interactions move to digital settings, the construct of digital social support will continue to be an important intervention target. For example, many individuals have adopted fully remote work, replacing a primary network of in-person interaction with fully digital-based interactions. In such a setting, being able to increase a person's perceptions of digital social support may be a large contributor to a person's workplace happiness and productivity.

Given the present findings there are several areas of future research that may benefit from further exploration. Specifically, an investigation of the cause and motivation for strict distancing may lead to a deeper understanding of its role in psychological outcomes such as social support and loneliness. Some individuals may choose to distance out of preference, while other may engage reluctantly as a result of policy requirements. These differing experiences may have differential effects on psychological outcomes. Furthermore, while strictness of distancing is difficult to manipulate, researchers should also aim to assess its role with more causal-based methods.

Furthermore, to expand upon the present intervention findings, future research should focus on several key areas. To further understand the effects of this brief intervention, further research should be done to assess the impact of similar intervention with varying dosages.

Expanded dosages may demonstrate stronger effects for perceived digital social support, as well as the emergence of significant effects for perceived general support and perceived stress. Additionally, adjustments could be implemented to more specifically target the impact of received support. For example, in future implementations, one peer-partner could be designated as the “supporter”, and the other could be designated as the “supported”. Furthermore, within the present study the interactions were most conducive to informational, emotional, and appraisal support. However, future implementations should also examine the effects of a similar intervention that is optimized for other forms of support such as tangible support. Finally, further research should also explore the impact of the intervention within novel contexts, within new populations, and using other forms of digital communication such as text-based communication.

Together the findings from the present study further elucidate the role of social support within the context of COVID-19. Specifically, they provide support for the role of strictness of distancing in perceived general social support, perceived digital social support, and perceived loneliness. Additionally, the study explored the impact of a brief peer-intervention on digital perceived general social support, perceived digital social support, and perceived stress. This intervention is well suited for future crises similar to COVID-19, as well as for individuals who have a large portion of their social interaction within a digital setting. Additionally, this intervention could be easily deployed in an academic or professional setting to foster feelings of digital social support for students or employees. The present study also provides further support for the separation of in-person and digital-based social support as separate constructs. Further research can continue to investigate social support between in-person and digital contexts, as well as within unique contexts such as the COVID-19 pandemic. COVID-19 facilitated rapid and dramatic changes to the world and how individuals interact socially. These changes had many negative effects on people’s perceptions of support, perceptions of loneliness, and experiences with stress. As progress is made to heal the damage that was done, important lessons learned within the context of the pandemic will remain valuable in future contexts.

Discussion

Social support is an important factor for health and psychological outcomes, and is often present in many health-related interventions. However, the specific role that social support plays is often overlooked or unexamined due to a lack of direct assessment. Additionally, societal changes have also presented new contexts that also remain understudied. With this in mind, the present pair of studies demonstrated the positive role of social support in the context of the Diabetes Prevention Program, and demonstrated the capability of a brief digital social support intervention to impact perceptions of digital social support in the context of the COVID-19 pandemic.

The Diabetes Prevention Program is one of the most well-supported lifestyle interventions. An important aspect of the program is its group-based design. This design allows for the exchange of social support amongst participants in a variety of ways. Previously, the role that this social interaction played in driving outcomes remained unstudied. The present results demonstrated the positive impact that social support may have on the primary outcome of weight. While not causal, these results potentially suggest that more weight loss could potentially be garnered by individuals who have larger increases in perceived social support across the trajectory of the program. Future research should be conducted to investigate this causal relationship. However, the present findings suggest that potential benefits may be seen from the social aspects within the Diabetes Prevention Program, as well as within other similar lifestyle interventions.

This finding is particularly relevant for implementations of the Diabetes Prevention Program that take place digitally. In recent years the Diabetes Prevention Program has increasingly been offered as a fully digital experience. Some of these implementations still offer a social component. However, in a digital context, maintaining social opportunities that are equivalent to in-person implementations is difficult. Given the present finding, social aspects of the program should be prioritized in digital contexts. While digital implementations have been increasing for several years, the COVID-19 pandemic has accelerated that adoption. In a time when in-person relationships are already disrupted, the importance of emphasizing the social aspects of interventions is even more relevant.

Building on this, the second study investigated the impact that virtual social support can have within the context of the COVID-19 pandemic. As discussed, a direct symptom of the pandemic was an accelerated adoption of digital communication behaviors. Much of this adoption was driven by restriction of other social opportunities. While the physical health benefits of social/physical distancing are clear, there are certainly secondary effects on psychological outcomes that have followed. There is a clear need for methods to connect individuals in a supportive manner within contexts where in-person social interaction is sparse. Specifically, within the context of the pandemic, individuals that engage in stricter distancing practice share this sparse in-person network. The present study demonstrated the relationship between strictness of distancing and negative psychological outcomes. However, other contexts such as fully remote workplaces or purely online communities also share similar characteristics. The present study demonstrated the ability for a brief digital social support intervention to positively impact perceptions of digital social support. This intervention was low-intensity, brief, and requires few resources to deploy, making it ideal for fast and wide deployment in a variety of contexts.

Together these studies both show the importance that social support can play in interventions and for health. Humans rely heavily on social relationships and social support in our everyday lives. As the world around us continues to change, and as we make efforts to improve our psychological and physical health within these shifting contexts, a deeper understanding of the role that social support plays will remain important. Future research should focus on how social support can be better leveraged to drive positive health outcomes in intervention research. Additionally, the world will continue to change as COVID-19 wanes, but our need for social interaction and social support will remain. It will become increasingly important to specifically understand how social support in the digital context operates, and how it can be used to drive more positive outcomes for a variety of individuals.

Table 1

UCLA Diabetes Prevention Program Sessions and Measures

Session	Week	Session Topic	Measures
1	1	Class introduction	Demographics
2	2	Getting active to prevent T2	Perceived Social Support
3	3	Tracking activity	Self-Efficacy
4	4	Eating well to prevent T2	
5	5	Tracking food	
6	6	Getting more active	
7	7	Burning more calories than you take in	
8	8	Shopping and cooking to prevent T2	
9	9	Managing stress	
10	10	Eating well away from home	Perceived Social Support
11	11	Coping with triggers	Self-Efficacy
12	12	Keeping your heart healthy	
13	13	Finding time for fitness	
14	14	Taking charge of your thoughts	
15	15	Getting social support	
16	16	Staying motivated to prevent T2	
17	18	more about carbs	
18	20	Staying active away from home	Perceived Social Support
19	23	When weight loss stalls	Self-Efficacy
20	28	Have healthy food you enjoy	
21	32	Getting enough sleep	Perceived Social Support
22	36	Staying active to prevent T2	Self-Efficacy
23	40	More about T2	
24	45	Getting back on track	
25	49	Preventing T2 for Life	Perceived Social Support

Table 2

Social Aspects of the Diabetes Prevention Program

Social Component	Description	Examples	Frequency
Social Skills Information	Educational information about getting social support and managing social cues	• Offered as a part of the DPP class curriculum	Select DPP sessions (one per topic)
Social Comparison	Active and passive presence of others that allow for comparisons to be drawn between individuals	• Explicit comparisons made by the coach • Implicit comparisons made while others are sharing • Comparisons made about progress in the program to individuals outside of the program	Available at every DPP session
Social Reward	Positive reinforcement explicitly exchanged socially or through the presence of others	• Coach and group recognition when milestones are achieved. • Coach and group recognition when anecdotal successes are shared. • Recognition from individuals outside of program for progress made in the program • Access to supportive others when program is attended	Available at every DPP session, as well as outside the program sessions
Exchange of Social Support	The active exchange of informational, emotional, esteem, tangible support, etc.	• Information provided to participants from the program coach (informational support) • Information provided to participants from other program participants (informational support) • Sympathy and empathy shared from the coach and peers when personal stories are shared • Presence of others that allow one to view themselves positively (esteem support). • Offers to directly help someone achieve their goals (tangible support)	Available at every DPP session, as well as outside the program sessions

		• Support and encouragement from friends, family, and close others who want someone to succeed in the program.	
Restructuring of the social environment	Adjustment to social network and environment such that individuals are exposed to new relationships and new opportunities for growing those relationships	• Access to new social relationships within the program • Increased time dedicated to socially interacting with other individuals	Available at every DPP session
Professional workplace identity*	Perceptions of social standing and identity in the workplace	• Workplace acknowledges the employee's value for participating in the program • Program coach facilitates feelings of cohesion amongst fellow employees in the program	Available at every DPP session, as well as outside the program sessions

Note. * Professional workplace identity is not an official component of DPP, but is present in this particular implementation of the program.

Table 3

Cronbach's Alphas at Each DPP Wave

Variables	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5
ISEL Overall	0.84	0.85	0.83	0.82	0.81
ISEL Appraisal	0.86	0.85	0.87	0.86	0.88
ISEL Belonging	0.82	0.83	0.83	0.82	0.80
ISEL Tangible	0.80	0.82	0.79	0.81	0.78
GSE Overall	0.84	0.88	0.91	0.82	---

Table 4

Variable Means and Standard Deviations at Each DPP Wave

	Wave 1		Wave 2		Wave 3		Wave 4		Wave 5	
Variables	M	SD	M	SD	M	SD	M	SD	M	SD
Social Support	25.17	5.77	25.86	5.60	26.31	6.36	27.26	5.69	28.34	5.84
Self-Efficacy	19.85	3.58	21.38	3.90	23.00	3.29	23.58	3.76	--	--
Weight (Pounds)	201.2	38.8	197.0	38.2	196.6	37.7	197.7	35.8	199.6	35.0
Activity (Minutes)	124.7	110.3	131.6	90.3	183.6	204.9	195.5	204.9	276.6	315.0
Age	44.6	11.01	--	--	--	--	--	--	--	--
Income (USD)	54253.85	25360.96	--	--	--	--	--	--	--	--

Note. Averages at each wave only include participants with values present in that wave.

Table 5

Wave 1 to Wave 2 Changes for Dropped Participants Vs. Adhered Participants

	Social Support		Self-Efficacy		Weight		Physical Activity	
Variables	M	SD	M	SD	M	SD	M	SD
Dropped by wave 3 (N = 28)	1.73	7.55	1.00	2.83	-1.88	6.09	11.73	150.51
Adhered past wave 3 (*N = 51)*	1.34	3.06	1.12	2.16	-2.82	4.87	3.15	113.92

Table 6

DPP Variable Baseline and Variable Change Pearson Correlations

Variables	1	2	3	4	5	6	7	8	9	10
1. Support Baseline	---									
2. Support Change	-.47***	---								
3. Efficacy Baseline	.27	-.08	---							
4. Efficacy Change	-.12	.38**	-.34*	---						
5. Weight Baseline	.04	.05	.10	-.09	---					
6. Weight Change	.13	-.40***	-.09	-.59***	-.17	---				
7. Activity Baseline	.07	-.29	.22	-.27*	.10	.09	---			
8. Activity Change	.17	-.13	-.08	.20	-.08	-09	-.19	---		
9. Age	-.14	.03	-.29	.18	-.13	-.18	-.01	.10	---	
10. Sex	.18	-.06	-.02	-.06	-.29*	-.06	-.03	.09	-.06	---
11. Income	.20	-.07	-.15	.14	.26	-.08	.13	-.11	.39**	.08

Note. Change variables were derived from the difference in score from a participant's first instance of that measure to their last. For sex, male was dummy coded as 0, and female was coded as 1.

Table 7

Social Support and Weight Parallel Process Latent Growth Curve Model Results

Model Fit: $\chi 2$ (35) = 99.62, p < .001; RMSEA = .13, 90% CI: 0.12-0.19; CFI = 0.94; SRMR = 0.13

Support Process Growth Factor Loadings	Initial Status	Growth Estimate	Standard Error
Support Wave 1	0	0.00	0.00
Support Wave 2	*	0.44	0.10
Support Wave 3	*	0.60	0.07
Support Wave 4	*	0.82	0.06
Support Wave 5	1	1.00	0.00
Weight Process Growth Factor Loadings	Initial Status	Growth Estimate	Standard Error
Weight Wave 1	0	0.00	0.00
Weight Wave 2	*	0.19	0.12
Weight Wave 3	*	0.52	0.27
Weight Wave 4	*	0.76	0.09
Weight Wave 5	1	1.00	0.00
Latent Factors Means	Estimate	Standard Error	P-Value
Support Intercept	25.01***	0.73	< 0.001
Support Slope	12.46*	5.61	0.026
Weight Intercept	200.30***	4.29	< 0.001
Weight Slope	3.42	7.79	0.661
Latent Factor Relationships	Estimate	Standard Error	P-Value
Weight Intercept ←→ Support Intercept	6.91	29.49	0.82
Weight Intercept → Weight Slope	-0.06	0.03	0.06
Weight Intercept → Support Slope	0.01	0.02	0.58
Support Intercept → Weight Slope	0.12	0.20	0.55
Support Intercept → Support Slope	-0.46**	0.18	0.01
Support Slope ←→ Weight Slope	-26.71***	7.89	< 0.001

Table 8

Social Support and Physical Activity Parallel Process Latent Growth Curve Model Results

Model Fit: $\chi2$ (35) = 51.23, p < .04; RMSEA = .08, 90% CI: 0.02-0.12; CFI = 0.96; SRMR = 0.12

Support Process Growth Factor Loadings	Initial Status	Growth Estimate	Standard Error
Support Wave 1	0	0.00	0.00
Support Wave 2	*	0.32	0.10
Support Wave 3	*	0.55	0.08
Support Wave 4	*	0.79	0.06
Support Wave 5	1	1.00	0.00
Activity Process Growth Factor Loadings	Initial Status	Growth Estimate	Standard Error
Activity Wave 1	0	0.00	0.00
Activity Wave 2	*	0.10	0.06
Activity Wave 3	*	0.51	0.08
Activity Wave 4	*	0.52	0.11
Activity Wave 5	1	1.00	0.00
Latent Factors Means	Estimate	Standard Error	P-Value
Support Intercept	31.33***	6.54	< 0.001
Support Slope	24.23**	9.14	0.008
Activity Intercept	0.205	0.12	0.083
Activity Slope	3.81	2.41	0.114
Latent Factor Relationships	Estimate	Standard Error	P-Value
Activity Intercept ←→ Support Intercept	0.44	0.64	0.49
Activity Intercept → Activity Slope	1.66	2.32	0.48
Activity Intercept → Support Slope	-3.98	3.78	0.29
Support Intercept → Activity Slope	0.18	0.10	0.06
Support Intercept → Support Slope	-0.26	0.19	0.18
Support Slope ←→ Activity Slope	-1.39	3.40	0.68

Note. Participant physical activity data were standardized to account for outliers.

Table 9

Social Support, Self-Efficacy, and Weight Mediated Parallel Process Latent Growth Model

Model Fit: $\chi 2$ (70) = 145.48, p < .001; RMSEA = .12, 90% CI: 0.09-0.14; CFI = 0.94; SRMR = 0.11

Support Process Growth Factor Loadings	Initial Status	Growth Estimate	Standard Error
Support Wave 1	0	0.00	0.00
Support Wave 2	*	0.39	0.11
Support Wave 3	*	0.57	0.08
Support Wave 4	*	0.80	0.07
Support Wave 5	1	1.00	0.00
Weight Process Growth Factor Loadings	Initial Status	Growth Estimate	Standard Error
Weight Wave 1	0	0.00	0.00
Weight Wave 2	*	0.33	0.07
Weight Wave 3	*	0.69	0.21
Weight Wave 4	*	0.83	0.06
Weight Wave 5	1	1.00	0.00
Self-Efficacy Growth Factor Loadings	Initial Status	Growth Estimate	Standard Error
Self-Efficacy Wave 1	0	0.00	0.00
Self-Efficacy Wave 2	*	0.35	0.04
Self-Efficacy Wave 3	*	0.59	0.04
Self-Efficacy Wave 4	1	1.00	0.00
Latent Factors Means	Estimate	Standard Error	P-Value
Support Intercept	24.97***	0.73	< 0.001
Support Slope	13.18*	6.61	0.046
Weight Intercept	201.08***	4.35	< 0.001
Weight Slope	1.30	8.67	0.88
Efficacy Intercept	20.09***	0.46	< 0.001
Efficacy Slope	10.63***	3.25	0.001
Latent Factor Relationships	Estimate	Standard Error	P-Value
Support Intercept → Support Slope	-0.37*	0.18	0.04
Weight Intercept → Support Slope	0.01	0.02	0.81
Efficacy Intercept → Support Slope	-0.08	0.24	0.73
Support Intercept → Weight Slope	0.02	0.21	0.91
Weight Intercept → Weight Slope	-0.05	0.03	0.08
Efficacy Intercept → Weight Slope	0.11	0.30	0.71
Support Intercept → Efficacy Slope	0.09	0.08	0.24
Weight Intercept → Efficacy Slope	0.01	0.01	0.50
Efficacy Intercept → Efficacy Slope	-0.53***	0.12	< 0.001
Weight Intercept ←→ Slope Intercept	13.86	30.17	0.65
Support Slope ←→ Weight Slope	-21.18**	7.21	0.003
Support Intercept ←→ Efficacy Intercept	6.03*	2.93	0.04
Weight Intercept ←→ Efficacy Intercept	8.69	18.50	0.64
Support Slope ←→ Efficacy Slope	5.05*	2.56	0.048
Efficacy Slope ←→ Weight Slope	-17.10***	4.04	< 0.001

Table 10

Social Support, Self-Efficacy, and Activity Mediated Parallel Process Latent Growth Model

Model Fit: $\chi 2$ (70) = 92.05, $p < .04$; RMSEA = .06, 90% CI: 0.02-0.10; CFI = 0.96; SRMR = 0.12

Support Process Growth Factor Loadings	Initial Status	Growth Estimate	Standard Error
Support Wave 1	0	0.00	0.00
Support Wave 2	*	0.27	0.11
Support Wave 3	*	0.47	0.08
Support Wave 4	*	0.71	0.05
Support Wave 5	1	1.00	0.00
Activity Process Growth Factor Loadings	Initial Status	Growth Estimate	Standard Error
Activity Wave 1	0	0.00	0.00
Activity Wave 2	*	0.10	0.06
Activity Wave 3	*	0.50	0.07
Activity Wave 4	*	0.52	0.10
Activity Wave 5	1	1.00	0.00
Self-Efficacy Growth Factor Loadings	Initial Status	Growth Estimate	Standard Error
Self-Efficacy Wave 1	0	0.00	0.00
Self-Efficacy Wave 2	*	0.35	0.05
Self-Efficacy Wave 3	*	0.60	0.04
Self-Efficacy Wave 4	1	1.00	0.00
Latent Factors Means	Estimate	Standard Error	P-Value
Support Intercept	32.50***	6.68	< 0.001
Support Slope	20.55**	6.94	0.003
Activity Intercept	0.20	0.12	0.089
Activity Slope	2.35	3.32	0.479
Efficacy Intercept	13.75***	2.42	< 0.001
Efficacy Slope	8.76**	3.20	0.006
Latent Factor Relationships	Estimate	Standard Error	P-Value
Support Intercept → Support Slope	-0.27	0.17	0.11
Activity Intercept → Support Slope	-3.96	4.71	0.40
Efficacy Intercept → Support Slope	-0.01	0.35	0.97
Support Intercept → Activity Slope	0.22*	0.10	0.03
Activity Intercept → Activity Slope	3.27	3.72	0.38
Efficacy Intercept → Activity Slope	-0.39	0.26	0.13
Support Intercept → Efficacy Slope	0.12	0.102	0.23
Activity Intercept → Efficacy Slope	-4.17	3.63	0.25
Efficacy Intercept → Efficacy Slope	-0.36	0.27	0.19
Activity Intercept ←→ Slope Intercept	3.78	0.65	0.56
Support Slope ←→ Activity Slope	-2.36	3.68	0.52
Support Intercept ←→ Efficacy Intercept	5.50	2.92	0.06
Activity Intercept ←→ Efficacy Intercept	0.85*	0.37	0.02
Support Slope ←→ Efficacy Slope	4.09	3.61	0.26
Efficacy Slope ←→ Activity Slope	3.51	2.47	0.16

Note. Participant physical activity data were standardized to account for outliers.

Table 11

Cronbach's Alphas at Each Intervention Session

Variables	Session 1	Session 2	Session 3
DS3 Overall	0.79	0.84	0.84
DS3 Appraisal	0.92	0.93	0.94
DS3 Response	0.81	0.82	0.79
DS3 Esteem	0.51	0.53	0.61
DS3 Tangible	0.63	0.68	0.69
ISEL Overall	0.87	0.87	0.85
ISEL Appraisal	0.75	0.77	0.72
ISEL Belonging	0.83	0.81	0.74
ISEL Tangible	0.67	0.69	0.69
PSS Overall	0.88	0.91	0.90
Loneliness Overall	0.79	--	--
Distancing Overall	0.73	--	--

Note. DS3 assesses digital social support, ISEL assesses general social support, and PSS assesses perceived stress.

Table 12

Condition Variable Means and Standard Deviations at Each Intervention Session

		Session 1		Session 2		Session 3	
Variables	Condition	M	SD	M	SD	M	SD
DS3	Intervention	21.80	5.05	23.52	5.51	24.48	5.44
DS3	Control	21.24	6.61	21.72	5.97	21.82	6.10
ISEL	Intervention	26.43	7.39	25.70	6.86	25.49	6.63
ISEL	Control	25.51	6.56	24.06	6.42	24.23	6.01
PSS	Intervention	19.24	6.97	18.22	7.50	17.87	7.55
PSS	Control	21.91	8.06	21.03	7.67	20.06	8.12
Loneliness	Combined	24.30	13.84	--	--	--	--
Distancing	Combined	12.65	2.39	--	--	--	--
Age	Combined	20.87	3.88	--	--	--	--
Income	Combined	12,417.21	52,226.77	--	--	--	--

Note. Averages at each wave only include participants with values present in that wave. DS3 assesses digital social support, ISEL assesses general social support, and PSS assesses perceived stress.

Table 13

COVID-19 Distancing and Baseline Digital Social Support Regression

$F(1, 137) = 4.43$	Estimate	SE	95% CI		p
$R^2 = 0.03$			*LL*	*UL*	
Intercept	14.14	0.75	12.65	15.63	< 0.001
Baseline Digital Support	-0.07	0.03	-0.19	-0.00	0.04

Table 14

COVID-19 Distancing and Baseline General Social Support Regression

$F(1, 139) = 3.95$	Estimate	SE	95% CI		p
$R^2 = 0.03$			*LL*	*UL*	
Intercept	14.13	0.77	12.61	15.66	< 0.001
Baseline General Support	-0.06	0.03	-0.11	-0.00	0.049

Table 15

COVID-19 Distancing and Baseline Loneliness Regression

$F(1, 139) = 3.97$	Estimate	SE	95% CI		p
$R^2 = 0.03$			*LL*	*UL*	
Intercept	11.95	0.40	11.16	12.16	< 0.001
Baseline Loneliness	0.03	0.01	0.00	0.06	0.048

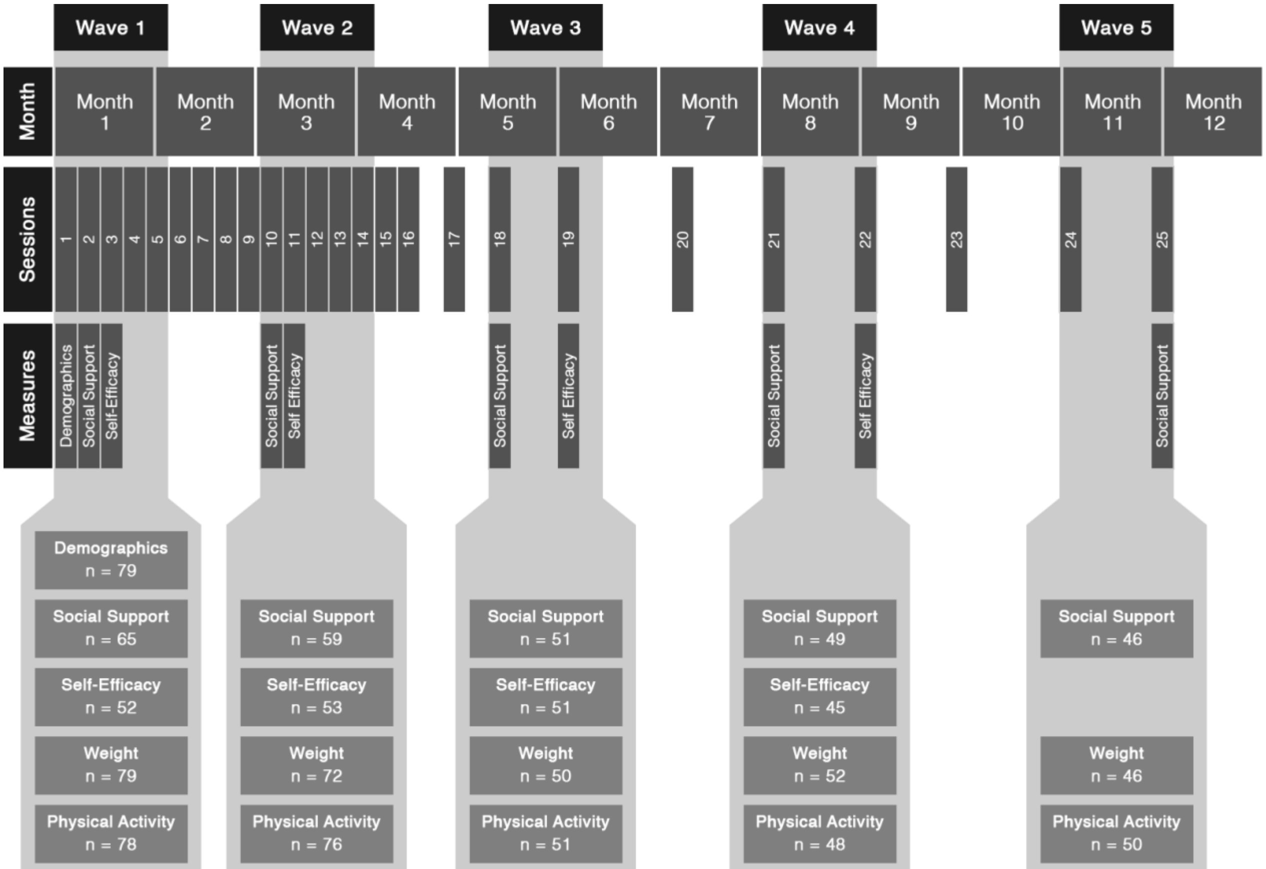
Table 16

Social Support Intervention Multilevel Models

	Digital Support			General Support			Perceived Stress		
	β	*SE*	*p*	*β*	*SE*	*p*	*β*	*SE*	*p*
Intercept	2.67	0.72		4.43	0.83		4.98	1.09	
Condition	-0.90	0.68	0.19	0.30	0.80	0.71	-0.91	1.15	0.43
Session	0.26	0.20	0.2	-0.59	0.24	0.02	-0.98	0.35	0.01
Condition * Session	1.01	0.29	< 0.001	0.14	0.35	0.7	0.32	0.50	0.53
Baseline	0.86	0.03	< 0.001	0.84	0.02	< 0.001	0.82	0.03	< 0.001

Figure 1

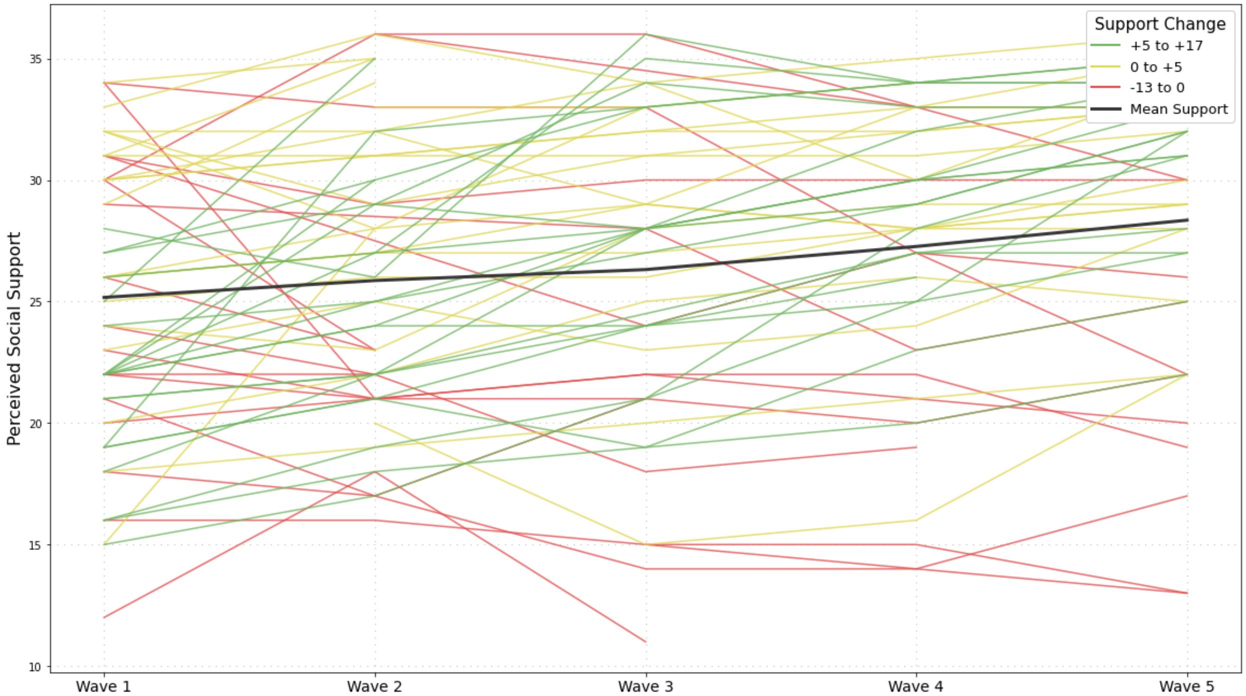
Timeline of Diabetes Prevention Program Sessions and Collection of Measures



Note. Progression of intervention sessions across the trajectory of the diabetes prevention program. Sample sizes and timing of each collected study measure. For each weight and physical activity outcome, the first instance of the measure at each wave was selected for each participant.

Figure 2

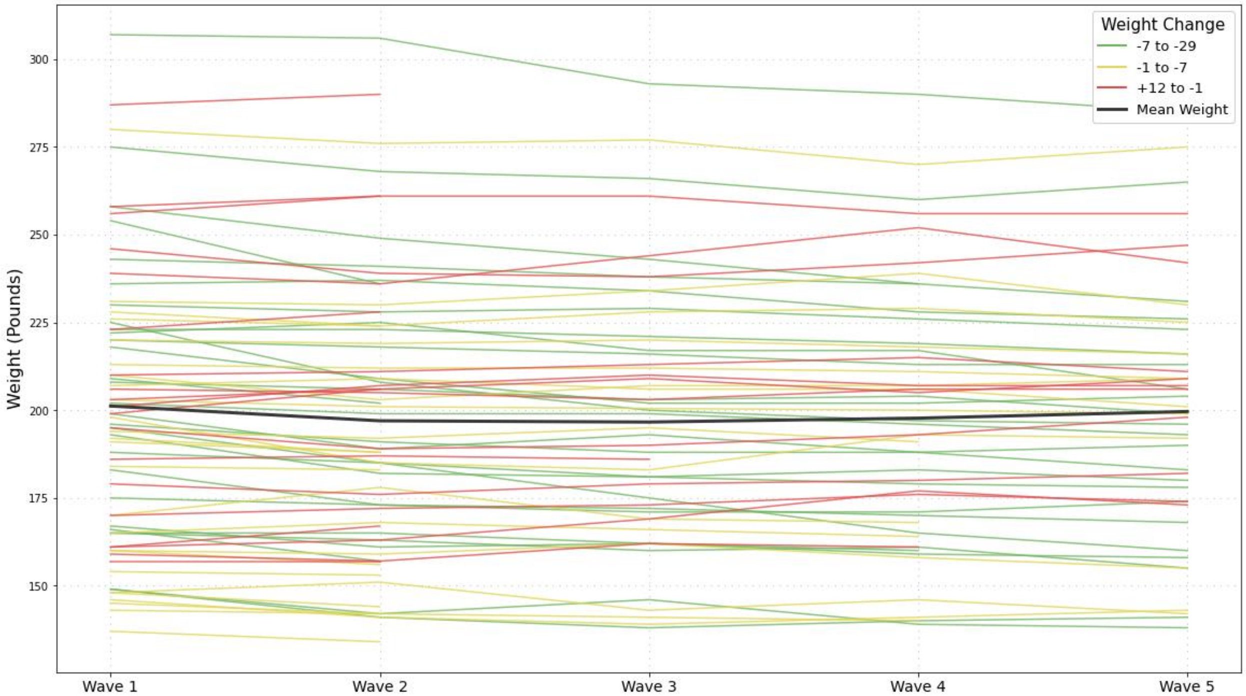
Participant Social Support Ratings Across DPP Waves



Note. Depicting individual participant ratings of perceived social support across each wave of the study. Participants are categorized based on a tertile split of their overall change in social support. Overall change in social support represents the difference between a participant's first and last rating of social support across the study waves.

Figure 3

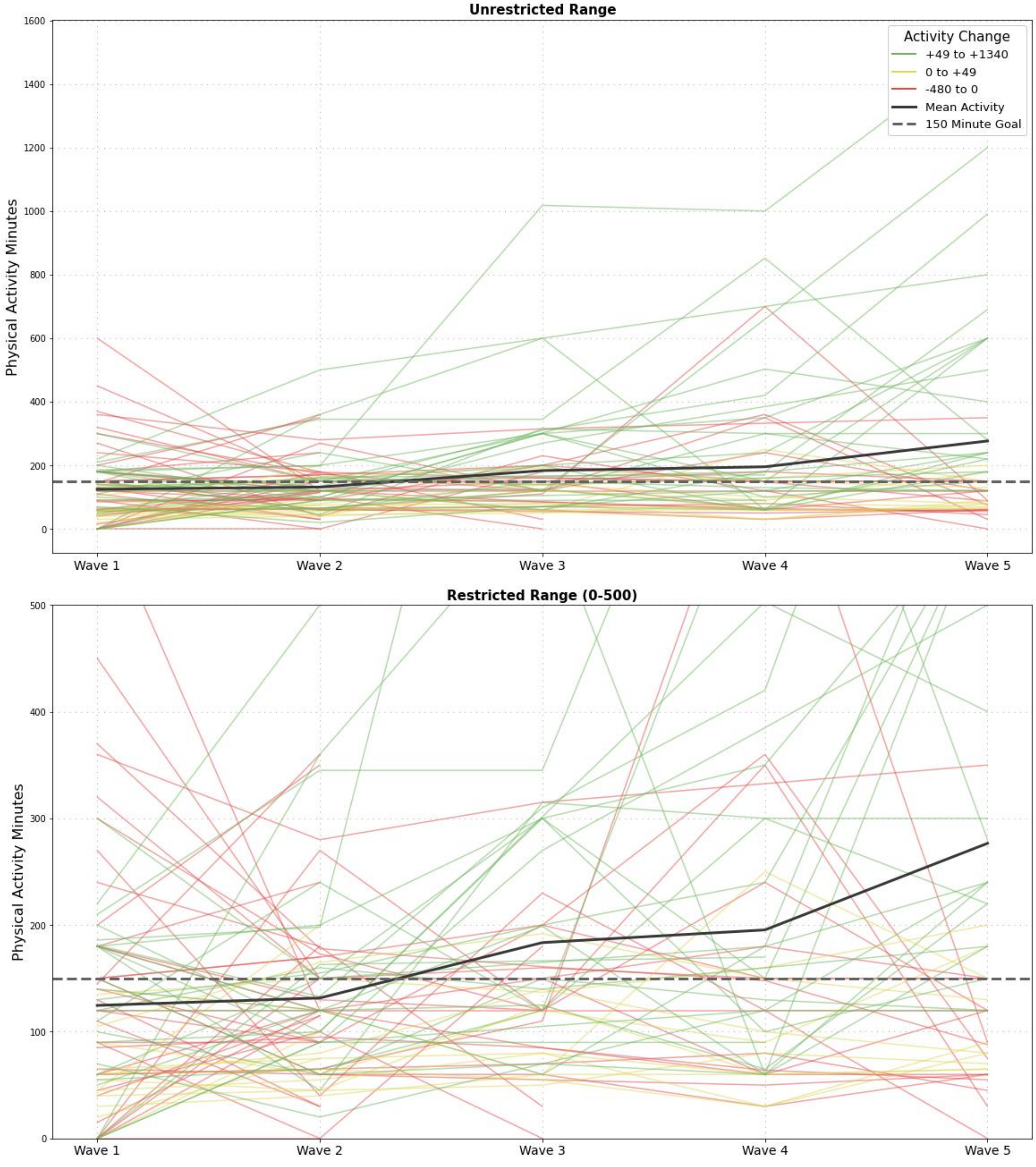
Participant Weight Ratings Across DPP Waves



Note. Depicting individual participant weights across each wave of the study. Participants are categorized based on a tertile split of their overall change in weight. Overall change in weight represents the difference between a participant's first and last rating of weight across the study waves.

Figure 4

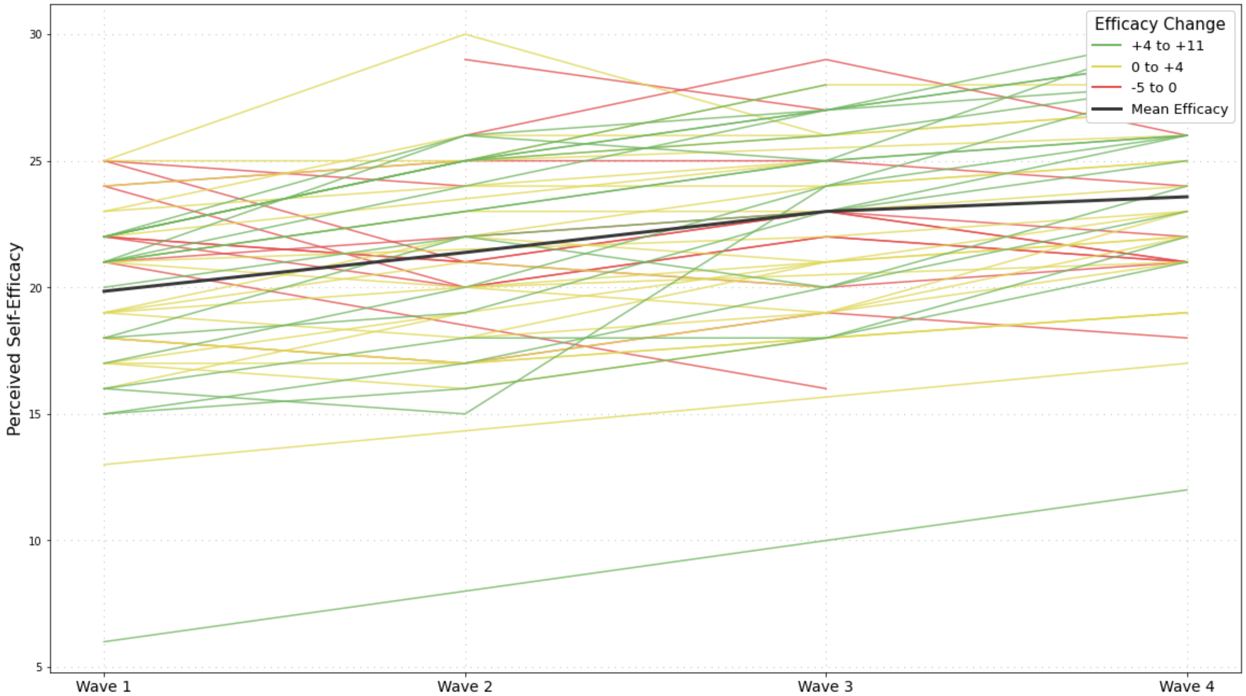
Participant Physical Activity Minutes Across DPP Waves



Note. Depicting individual participant physical activity minutes ratings across each wave of the study with both an unrestricted range, and a restricted range. Participants are categorized based on a tertile split of their overall change in physical activity minutes. Overall change in physical activity minutes represents the difference between a participant's first and last rating of physical activity minutes across the study waves.

Figure 5

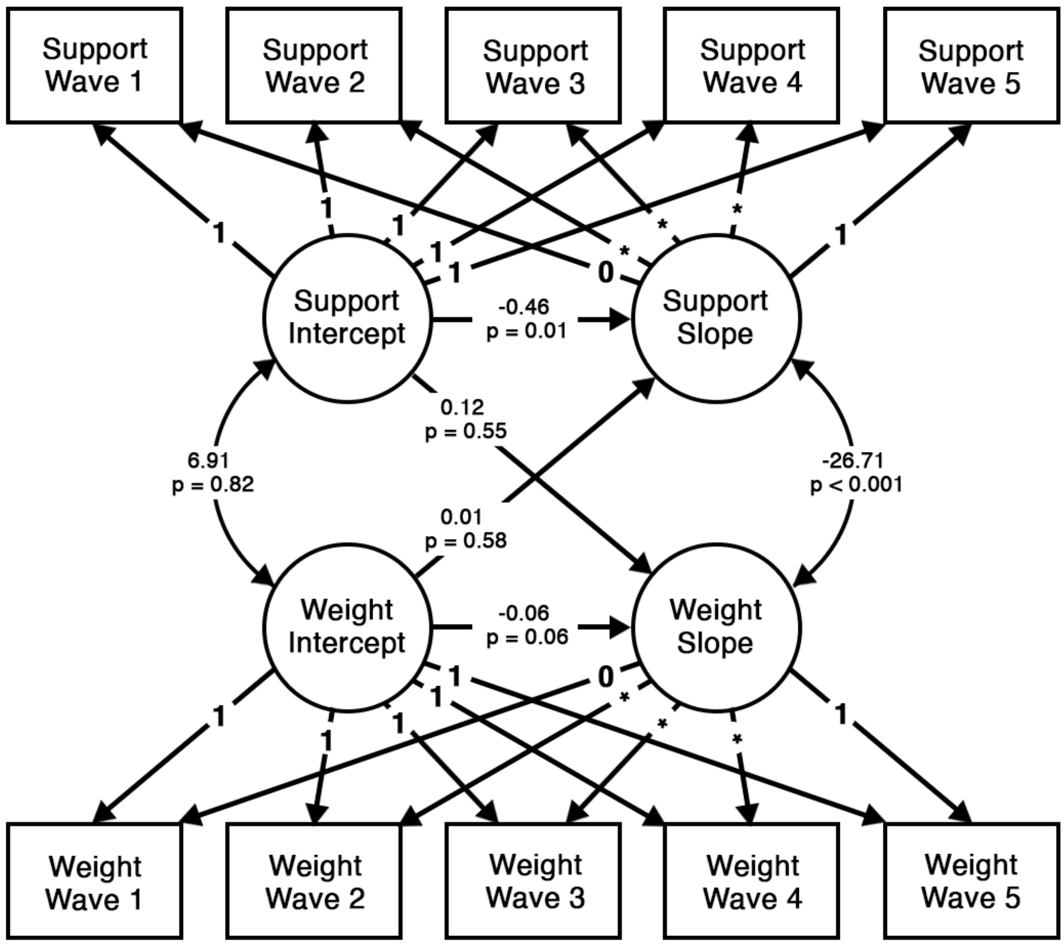
Participant Self-Efficacy Ratings Across DPP Waves



Note. Depicting individual participant self-efficacy ratings across each wave of the study. Participants are categorized based on a tertile split of their overall change in self efficacy. Overall change in self-efficacy represents the difference between a participant's first and last rating of self-efficacy minutes across the study waves.

Figure 6

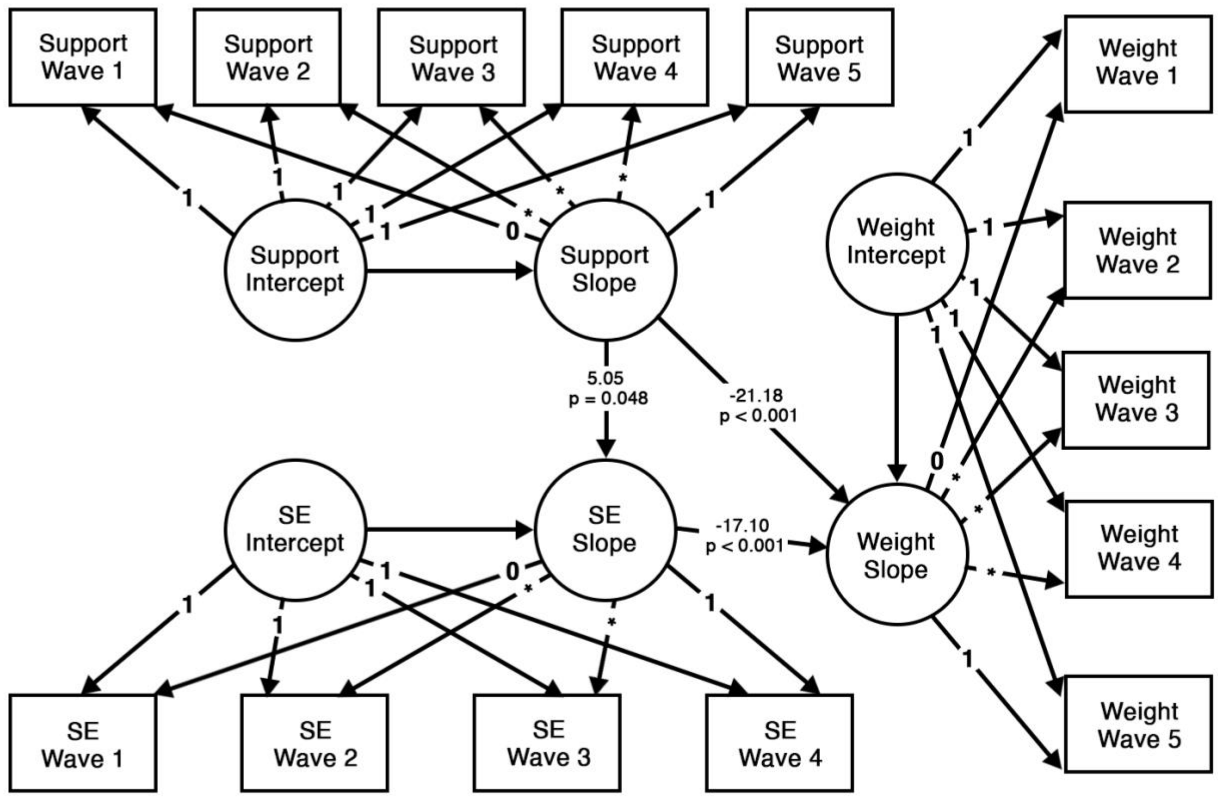
Conceptual Parallel Process Latent Growth Curve Model Path Diagram



Note. Conceptual parallel process latent growth curve model path diagram representing growth in perceived social support and weight. Intercepts were given a factor loading of 0, mid-treatment loadings were freely estimated (*), and final wave scores were given a loading of 1.

Figure 7

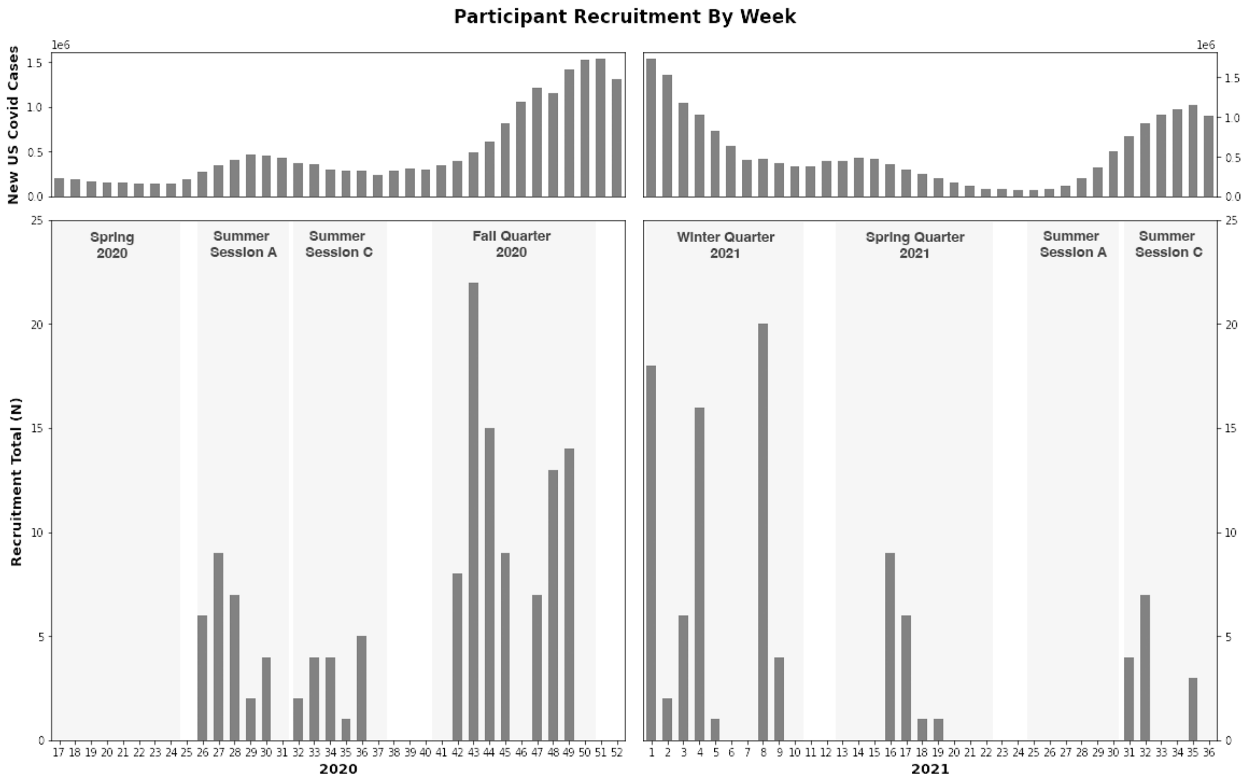
Conceptual Mediated Parallel Process Latent Growth Curve Model Path Diagram



Note. Conceptual mediated parallel process latent growth curve model path diagram representing growth in perceived social support, self-efficacy, and weight. Intercepts were given a factor loading of 0, mid-treatment loadings were freely estimated (*), and final wave scores were given a loading of 1.

Figure 8

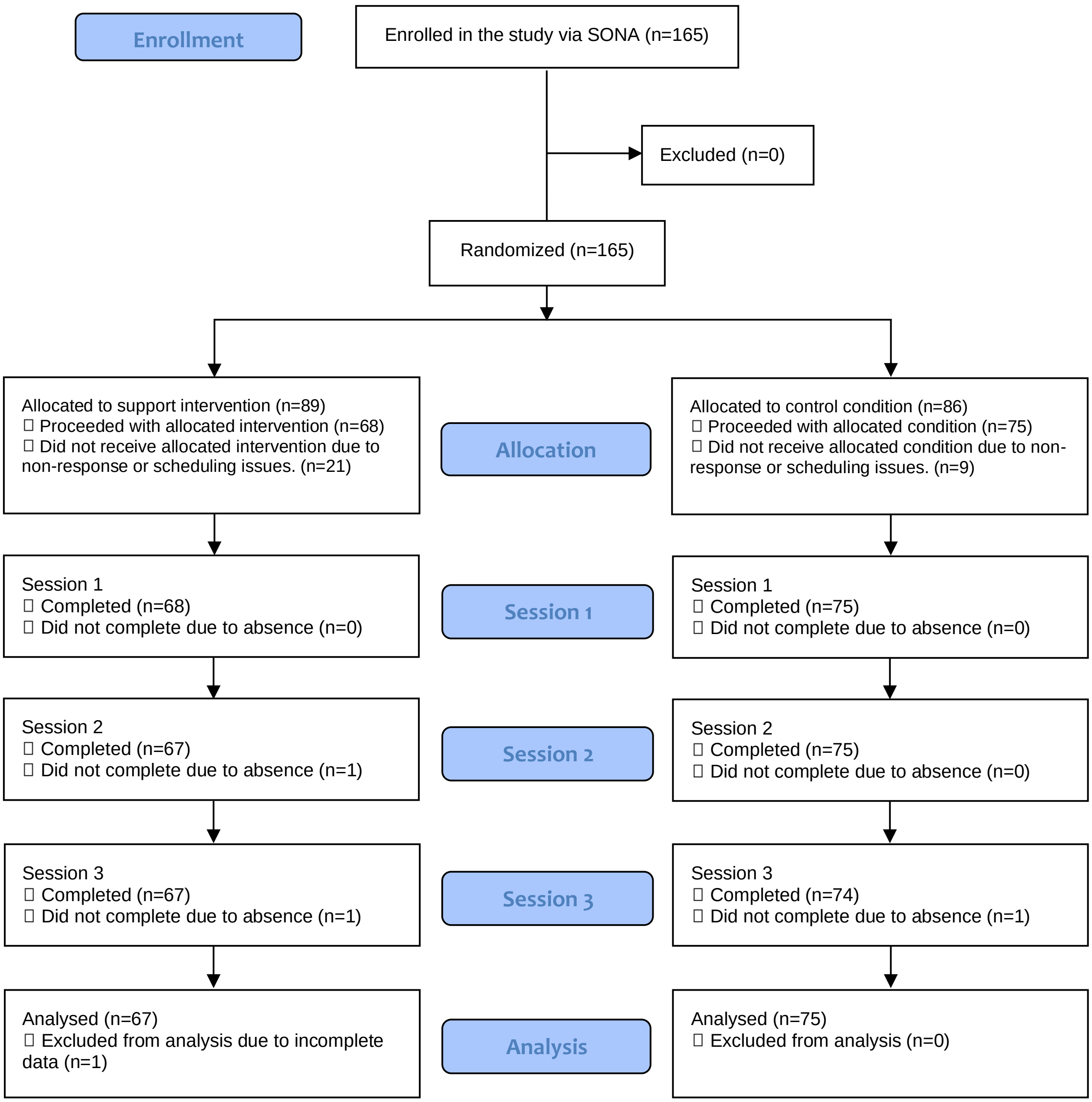
Support Intervention Participant Recruitment and New COVID-19 US Case



Note. Volume of recruited participants across recruitment period compared to volume of new COVID-19 cases in the United States.

Figure 9

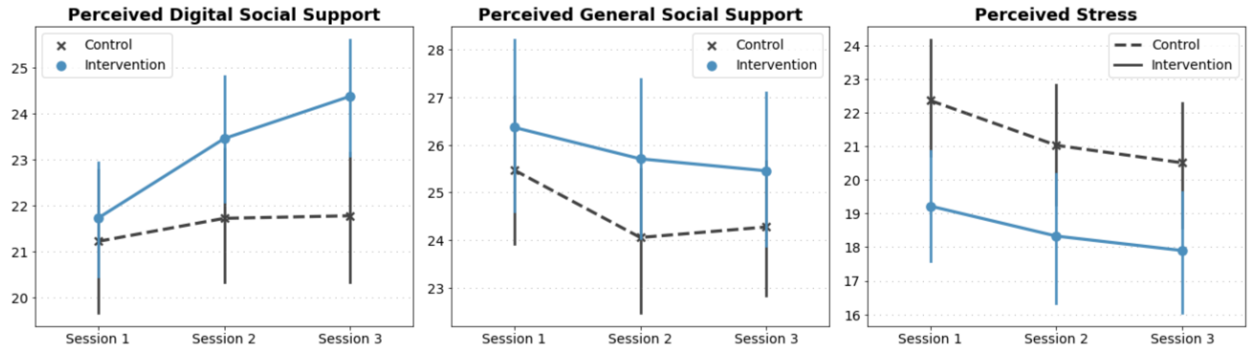
Social Support Intervention CONSORT Diagram



Note. CONSORT diagram showing flow of participants through the intervention.

Figure 10

Support and Stress Outcomes Across Intervention Sessions



Note. Changes of perceived digital social support, general social support, and perceived stress across the sessions of the study for intervention and control groups. Error bars indicate 95% confidence intervals.

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