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Determinants of physical activity maintenance during the Covid-19 pandemic: a focus on fitness apps

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Abstract

There are various health benefits of regular physical activity (PA) and health risks of sedentariness. The Covid-19 pandemic may have decreased PA and increased sedentariness for several reasons (e.g., closure of gyms, family-related time constraints, and reduced outdoor mobility). Yet, to date, there are no longitudinal studies that examined whether the pandemic affects PA levels and what factors help people remain physically active during lockdown. This study aims to investigate changes in U.S. residents' PA during (vs. before) the Covid-19 pandemic and predictors of changes, with a focus on PA smartphone applications (apps) and their features (i.e., motivational, educational, or gamification related). The study utilized a two-wave longitudinal survey design with an online panel. Healthy adults (N = 431) from 45 U.S. states self-reported their PA levels before and during lockdown. PA app use and app feature ratings were assessed. t-tests and regression analyses were conducted. Moderate PA, vigorous PA, and PA measured in metabolic equivalent of task (MET) minutes per week decreased during lockdown (all p < .01). Controlling for PA before lockdown and individuals' PA intentions, PA app use was positively related to overall change in PA, measured in MET minutes per week (β = 15.68, standard error = 7.84, p < .05). PA decreased less with increasing app use frequency. When app features were added to the model, a buffering effect for gamification features was identified. The Covid-19-caused lockdown decreased U.S. residents' PA levels by 18.2%. The use of PA apps may help buffer the decline, and gamification-related app features may be particularly helpful in this context.

Keywords

Exercise, Smartphone, Applications, Mobile Internet

INTRODUCTION

Regular physical activity (PA) promotes people's health and is a protective factor for many leading noncommunicable diseases [1, 2]. The World Health Organization recommends 150 min of moderate PA or 75 min of vigorous PA per week, or 500−1,000 metabolic equivalent of task (MET) minutes per week for adults [3]. Despite the importance of PA, around 31% of adults fail to achieve sufficient PA [4]. The global outbreak of the coronavirus disease 2019 (Covid-19) may have decreased PA levels further [5].

Since Covid-19 first emerged in Wuhan (China) in 2019, it has infected more than 21.9 million people and resulted in at least 775,439 deaths worldwide [6]. In response to Covid-19, restricting regulations

Implications

Practice: Individuals and health professionals can be recommended to use physical activity (PA) applications (apps), particularly gamification features, to promote PA during a pandemic.

Policy: Policymakers in public health can be recommended to fight decreases in PA during Covid-19 lockdown via collaboration with actors from the digital world, such as smartphone and PA app providers.

Research: The study is the first to show that app usage helps buffer the pandemic-caused decline in PA over and above baseline PA and behavioral intentions.

(e.g., stay-at-home policies; closure of gyms; reduced access to outdoor sport facilities; and home office regulations) may have forced many people to break their normal PA routines. Most importantly, they may have had fewer opportunities to remain physically active [5, 7].

To date, there is only suggestive evidence on whether PA levels have changed during Covid-19, and the determinants of potential changes are unclear. For example, Fitbit (a wearables provider) reported a statistically significant decline in average steps during the pandemic compared to the same time in 2019 [8]. Still, wearables or PA smartphone applications (apps) may have helped individuals remain active during restricting circumstances of Covid-19, such as lockdown [7]. Particularly, PA apps that do not require the adoption of new hardware have the potential to be cost-effective ways to promote PA, given that the users adhere to utilize the apps [9] (or, in the context of the Covid-19-caused lockdown, to reduce PA declines). To date, however, there is no evidence on whether PA levels have changed during Covid-19-caused lockdown; whether PA app use helps prevent declines in PA; and which app features are particularly helpful in this context. This study aims to fill this void of research and investigates the change in PA during

the Covid-19-caused lockdown and the determinants for the maintenance of PA, with a focus on PA app use and the features of these apps.

Covid-19 and PA

Several viral epidemics have occurred in the past two decades, such as severe acute respiratory syndrome in 2003 [10], influenza A virus subtype H1N1 in 2009 [11], and Ebola virus in 2014 [12]. Covid-19 is unique in the sense that it spread quickly around the world and infected more people outside than inside China (i.e., the outbreak country). The USA is the leading country with regard to the number of infected people and Covid-19-attributed deaths [6].

Covid-19 forced governments around the world to limit the spread of the disease by implementing restrictions (e.g., closures of shops, schools, and manufactures; closure of borders to limit traveling; and implementation of social distancing rules). These restrictions may have led people to break their PA routines and become less physically active [5, 7]. Importantly, sustained low levels of PA and high levels of sedentariness are associated with poor physical and mental health and hold the potential to increase disease-specific and all-cause mortality risks [13].

Industry actors that analyzed people's mobility via wearables or smartphones found a significant decline in average step count during the Covid-19 pandemic (e.g., Fitbit Inc. [8] and Apple Inc. [14]). Additionally, cross-sectional studies showed reduced PA and increased sedentariness during Covid-19-caused lockdown among people of all ages in China [15], Italy [16], Canada [17], and Australia [18]. Those studies provide descriptive information on patterns of PA and the associated negative health effects. However, to the best of our knowledge, there are no longitudinal studies (with one exception, which recruited 70 out of 631 participants for a follow-up [15]) and none of the studies examined PA app use-related determinants that might have been helpful to residents to remain physically active during Covid-19-caused lockdown. In what follows, we briefly review the existing literature on PA apps and their potential to buffer the decline in PA during Covid-19-caused lockdown.

Smartphone apps and their potential to buffer the decline in PA

With the rapid development of technology, mobile health apps (e.g., smartphone PA apps) present cost-effective means to promote PA and prevent sedentariness [9]. Studies have emphasized the importance of such apps for remaining physically active during the critical period of Covid-19 [7, 19]. For instance, PA apps can be appealing to users, can be tailored to many people, and can be used in small spaces during lockdown. However, adherence to PA apps tends to be rather poor [9] and is influenced by as many as 89 factors [20]; among these, the perceived playfulness of PA apps might be particularly important [20].

To date, it remains largely unknown which app features help people remain physically active. Conroy et al. have cluster-analyzed PA apps and found two broad features: motivational and educational features [21]. Motivational app features emphasize social and self-regulation of PA (e.g., feedback, social support, and goal setting); educational app features focus on PA tutoring (e.g., instructions, coaching, and learning) [21]. Furthermore, gamification-related features are increasingly being used in PA apps to help individuals improve their health and fitness [22]. Gamification describes the use of game design elements, such as points, levels, and badges, to make the experience more playful and enjoyable [23, 24]. In the present study, we consider gamification-related features besides motivational and educational features of PA apps as factors to describe three relevant clusters of app features that might help predict the maintenance of PA.

Research questions of the present study

Three research questions guided the presented study:

(1) Do PA levels change during Covid-19-caused lockdown?
(2) Does the use of smartphone PA apps help individuals remain physically active during Covid-19-caused lockdown?
(3) Which PA app features support individuals in remaining physically active during Covid-19-caused lockdown?

METHODS

Study design and participants

This study utilized a two-wave longitudinal survey design with an online panel. The survey was delivered via Qualtrics and Amazon Mechanical Turk; the latter has been shown to be a reliable and useful platform to conduct behavioral research [25, 26]. The results were reported according to the CHERRIES statement for web-based surveys [27].

Participants were recruited online. Inclusion criteria were the following: healthy adults aged between 18 and 65 years old, who own a smartphone and have downloaded at least one PA app. Furthermore, participants were required to be U.S. residents who are able to read and understand English. All participants were informed about the study procedures and provided informed consent prior to the survey. Participation was voluntary and participants were informed about the confidentiality of personal information. The study was carried out in accordance with the World Medical Association Declaration of Helsinki.

Procedures

The first-wave (T0) data collection was conducted between March 12 and March 17, 2020, a time when no restricting regulations (e.g., stay-at-home order) were imposed at the U.S. state level. At T0, 867 respondents participated in the survey, and 839 were eligible after a quality check (e.g., after having eliminated incomplete surveys).

The second wave of the survey (T1) took place after the U.S. government and the states responded to the Covid-19 pandemic with restricting regulations to slow its progression (e.g., California first imposed a stay-at-home order on March 19 [28]; South Carolina did so on April 7; see Supplementary Table 1) and after these restrictions had been in place for at least 4 weeks. For example, T1 started on April 16 in California and on May 5 in South Carolina, both exactly 28 days after the lockdown. The average duration between T0 and T1 was 43.7 days (standard deviation = 4.7). Four hundred and fifty-nine participants filled in the survey at T1 and 431 were eligible after a quality check, which yields an attrition rate of 49%. We expected that those stringent regulations would reduce individuals' PA levels [29]. We further expected that the use of PA apps (and their features) would help prevent the potential decline in PA (see Research questions of the present study).

Measures

PA and intention to be physically active

PA was measured at both T0 and T1 with the International Physical Activity Questionnaire Short Form (IPAQ-SF) [30]. The IPAQ-SF asks about participants' types of PA and sedentary time during the last 7 days. Three types of PA (i.e., walking, moderate PA, and vigorous PA duration) were assessed and active PA (i.e., the sum of walking, moderate PA, and vigorous PA) and total MET were calculated (PA MET, MET minutes per week). PA MET was calculated by multiplying each activity by a weighting (i.e., 3.3 for walking, 4.0 for moderate PA, and 8.0 for vigorous PA [31]). Change in PA indicates the change in PA MET between Waves 2 and 1. The reliability and validity of the IPAQ-SF have been evidenced across 12 countries [30]. The data were processed following existing IPAQ-SF guidelines [32]. To measure individuals' intentions to be physically active at T0, similar items as the IPAQ-SF items (covering a time span of 4 weeks into the future) were used.

Smartphone app features

Participants were asked to name their most preferred PA app and then respond to questions about how they perceive the features of this particular app. Educational, motivational, and gamification-related app features were measured with a nine-item scale (i.e., three items each). Participants were asked to rate the importance of app features on a scale from 1 = "not at all important" to 7 = "extremely important" (e.g., "How important are app features that motivate you to be physically active to you?," for a motivational feature item; "How important are app features that educate yourself about how to exercise best to you?," for an educational feature item; and "How important are app features to enjoy yourself while exercising to you?," for a gamification-related feature item). Cronbach's alpha was .91 for educational, .84 for motivational, and .86 for gamification-related app features.

Usage of PA apps

PA app use was measured by assessing the frequency of use ("How often did you use [brand name; *participants' most preferred PA app was entered here*] during the past four weeks?") [33].

Sociodemographic information

Sociodemographic information was collected at T0. In particular, height (feet, inches; converted to meters) and weight (pounds, lbs; converted to kilograms) were collected and the body mass index (BMI, kg/m^2) was calculated. The educational level was classified as high school degree or below; associate's college degree; bachelor's degree; master's degree; or doctorate. Furthermore, information on marital status (single, married, divorced, or widow/widower), personal annual gross income (under U.S. $15,000; $15,000–24,999; $25,000–34,999; $35,000–49,999; $50,000–64,999; $65,000–79,999; or $80,000 and more), employment status (employed; self-employed; or unemployed), and ethnicity (White/Caucasian; Black/African American; Asian; or Other) were collected.

Sample size consideration

We conducted an a priori power analysis using G*Power Version 3.1 [34] (*F*-tests, multiple regression with six predictors, and R^2 deviation from 0). The analysis revealed a sample size of at least $N = 146$ to determine a medium effect size of $f^2 = .15$ (alpha = .05; power = .95; noncentrality parameter = 21.90, critical $F = 2.16$). Allowing for an attrition rate of 50% at T1, a sample size of 292 is needed. The final sample size was $N = 431$ (i.e., 48% bigger than the recommended minimum sample size [to be able to include control variables in the analyses]).

Statistical analyses

Descriptive statistics were computed for sociodemographic information. Paired samples *t*-tests were used to compare the differences between T0 and T1. Three ordinary least squares linear regression analyses were performed to predict the maintenance of PA during lockdown. A first model tested the relationship between change in PA (T1–T0, dependent variable, *Y* in the regression equation,

unit: MET minutes per week) and PA app use measured at T1 (independent variable, X, unit: frequency of use in the past 4 weeks), as well as PA measured at T0 and individuals' intentions to be physically active measured at T0 (further independent variables, X, unit: rating scale and MET minutes per week, respectively). In a second model, PA app features (i.e., motivational, educational, and gamification-related; X, unit: rating scales) were added to the model. In a third model, age, gender, BMI, education, income, marital status, employment, and ethnicity were added. The data were analyzed using R (RStudio, V1.2.5019, Boston, MA) and the level of significance was set at $p < .05$ (two tailed).

RESULTS

Characteristics of participants

Four hundred and thirty-one participants were included in the analysis (49% females). Participants lived in 45 states (with frequencies between 1 (Hawaii) and 37 (New York); median of 6 participants per state). They were mostly young adults (75% of the participants were aged between 21 and 45 years). About 47% of them were overweight or obese. About 69% of the participants had a college bachelor's or a higher degree and 84% were employed. Table 1 shows the characteristics of the sample.

Descriptive statistics and difference testing between waves

While self-reports of PA might be subject to overreporting [35] (this might also be true for the present study), the within-participant design allowed us to assess differences between the two waves. The changes in PA and sedentariness between the two waves are shown in Table 2. From T0 to T1, there was a significant decrease in moderate PA (-10.4 ± 51.5 min/day, $p < .01$) and vigorous PA (-8.5 ± 46.0 min/day, $p < .001$). There was no significant difference in walking (-4.5 ± 51.5 min/day, $p = .067$) and sedentary time (1.6 ± 170.1 min/day, $p = .85$). Both active PA (-23.4 ± 93.3 min/day, $p = .003$) and PA MET ($-605.1 \pm 2,453.5$ MET min/week, $p < .001$, indicating a decline by 18.2%) decreased significantly. These results, thus, provide an answer to Research Question 1: PA decreased significantly during lockdown.

Predictors of change in PA

Change in PA MET was used as the dependent variable in the three models. The results for the regression analyses are shown in Table 3. The predictors included in Model 1 explain 37% of the variance in the change in PA MET. With regard to Research Question 2, PA app use was positively related with change in PA ($\beta = 15.68$, standard error [SE] = 7.84, $p = .04$) such that the more often the app was used, the more positive was the change in PA. The model controls for PA at T0 (i.e., before the lockdown)

and individuals' stated PA intentions (i.e., their stated willingness to be active; if individuals are not intending to be active, it would be no surprise if PA declined during lockdown). PA at T0 was negatively

Table 1 | Sociodemographic characteristics of participants

Variables	$N = 431$
Age (years)	39.1 ± 10.6
Gender (F%)	211 (49.0%)
BMI (kg/m²)	25.1 ± 5.6
Underweight	34 (7.9%)
Normal	227 (44.8%)
Overweight	136 (31.6%)
Obese	68 (15.8%)
Education levels	
High school degree or below	56 (13.0%)
Associate's degree	79 (18.3%)
College Bachelor's degree	206 (47.8%)
Master's degree	80 (18.6%)
PhD	10 (2.3%)
Marital status	
Single (never married)	168 (39.0%)
Married	227 (52.7%)
Divorced	32 (7.4%)
Widowed	4 (0.9%)
Income (gross, per year)	
Under $15,000	39 (9.1%)
$15,000–24,999	29 (6.7%)
$25,000–34,999	54 (12.5%)
$35,000–49,999	94 (21.8%)
$50,000–64,999	70 (15.2%)
$65,000–79,999	61 (14.2%)
$80,000 and above	84 (19.5%)
Employment	
Employed	362 (84.0%)
Self-employed	39 (9.1%)
Unemployed	30 (7.0%)
Ethnicity	
White/Caucasian	354 (82.1%)
Black/African American	33 (7.7%)
Asian	28 (6.5%)
Other	16 (3.7%)
Covid-19 related symptoms (assessed at Wave 2)	13 (3.0%)
Tested for Covid-19 (assessed at Wave 2)	14 (3.2%)

Data are presented as means ± standard deviation or numbers (%) if they are at the category level. Body mass index (BMI) was classified according to the U.S. Centers for Disease Control and Prevention's BMI weight status categories: underweight (below 18.5 kg/m²); normal or healthy weight (18.5–24.9 kg/m²); overweight (25.0–29.9 kg/m²); and obese (30.0 kg/m² and more).

Table 2 | Changes in physical activity and sedentariness between Waves 1 and 2

Variables	Wave 1		Wave 2			
	Mean	SD	Mean	SD	t (430)	p-value
PA MET (MET min/week)	3,323	2,451	2,718	2,205	5.12	<.001
Moderate PA (min/day)	57.15	42.67	46.77	41.37	2.15	<.01
Vigorous PA (min/day)	47.94	41.91	39.47	40.00	3.82	<.001
Active PA (min/day)	157.80	92.73	134.45	90.89	2.97	.003
Walking (min/day)	52.71	47.70	48.21	44.41	1.83	.067
SED (min/day)	367.99	167.01	369.55	152.85	−0.19	.85

p-value refers to t-tests between Waves 1 and 2.

Active PA sum of walking, moderate PA, and vigorous PA; *PA* physical activity; *PA MET* PA calculated as metabolic equivalent of task minutes per week; *SD* standard deviation; *SED* sedentary time.

and PA intention was positively related with the change in PA MET.

Model 2 was run to answer Research Question 3. The predictors explain 38% of the variance in the change in PA MET. The relationships between the Model 1 variables and change in PA MET remained significant, while gamification-related features (β = 235.40, *SE* = 90.75, *p* = .01) were positively associated with the change in PA MET. With increasing perceived importance of gamification-related features of apps, there was a more positive change (i.e., people's activity rather increased). Both motivational and educational features did not predict the change in PA MET (β = −183.00, *SE* = 105.20, *p* = .083 and β = 81.34, *SE* = 87.84, *p* = .36, respectively).

To test the robustness of the results, Model 3 further included participants' age, gender, BMI, education, income, marital status, employment, and ethnicity. The model explains 38% of the variance in the change in PA MET. None of the variables that were added to the model had an influence on the change in PA MET, while the same predictors as in Model 2 remained significant.

DISCUSSION

The purpose of the study was to investigate changes in PA during (vs. before) Covid-19-caused lockdown and to assess the relevance of predictors of change, with a focus on PA smartphone apps and their features. The results showed a decrease in PA MET by 18.2%. While PA MET levels were still high during lockdown in our U.S. resident sample against the background of health-enhancing PA recommendations [3], the assessment might have been biased due to overreporting tendencies [35]. The results of the present study also revealed that the use of PA apps may help buffer the decline in PA MET and that gamification-related app features may be particularly helpful.

Theoretical contribution

Given that physical inactivity has been considered as a pandemic itself, one could argue that the world is currently facing two pandemics at the same time [5]. Mobile health technology, such as smartphone PA apps, might help tackle the inactivity pandemic [9, 36], particularly in the light of restrictions in people's access to PA-enhancing sites (e.g., fitness clubs, parks) during Covid-19-caused lockdown. The study provides evidence on whether PA levels have changed during Covid-19-caused lockdown, whether PA app use helps prevent declines in PA, and which app features are particularly helpful in this context.

First, to fill the void of research into how PA is affected by Covid-19-related restrictions [37], we designed a longitudinal study that was timed so that each individual had experienced the lockdown for at least 28 days before they participated in the second-wave survey. The first-wave survey took place before the lockdown. The results of the study showed that moderate PA and vigorous PA decreased (but sedentary times did not increase) during lockdown—despite the fact that several recommendations were issued that aim to encourage people to stay physically active during Covid-19 [7, 29, 38]. While previous studies have reported similar decreases in PA during Covid-19 [15−18], these studies were largely cross-sectional in nature. The studies cannot rule out that within-participant differences drive the change over time. Thus, it remains unclear what contribution the Covid-19 lockdown made to the change in PA. Our study addresses these limitations, using a longitudinal design, and it revealed a decrease of 18.2% when PA is measured in MET. In the present study, there was no increase in sedentariness, despite the fact that home environments may have made it more convenient for people to be sedentary during Covid-19-caused lockdown [5]. The results could be explained by a potential increase in tasks that require nonsedentary behaviors at home.

Second, while the determinants for PA maintenance have been extensively explored [39, 40], studies have rarely considered the role of PA app use, controlling for intentions to be physically active and baseline PA. Controlling for these variables is important because a lack of intent to be active might explain low PA levels (in particular, when there

Table 3 | Predictors of Change in Physical Activity Between Waves 1 and 2: Results of Regression Analyses

	Model 1 (adjusted R^2 = .37)				Model 2 (adjusted R^2 = .38)				Model 3 (adjusted R^2 = .38)			
	β	SE	t	p-value	β	SE	t	p-value	β	SE	t	p-value
PA (T0)	-0.71	0.06	-12.87	<.001	-0.72	0.05	-13.08	<.001	-0.72	0.06	-12.95	<.001
PA intention (T0)	0.13	0.05	2.66	.008	0.13	0.05	2.51	.012	0.12	0.05	2.44	.015
PA app use	15.68	7.84	2.00	.046	16.82	8.25	2.04	.042	16.60	8.43	1.97	.049
PA app features												
Motivational					-183.00	105.2	-1.74	.083	-178.7	108.5	-1.65	.99
Educational					81.34	87.84	0.93	.355	86.3	89.80	0.96	.34
Gamification related					235.40	90.75	2.59	.010	214.9	95.57	2.25	.025
Age									13.36	10.19	1.31	.19
Gender									-118.3	195.8	-0.96	.34
BMI									-18.98	17.45	-1.09	.28
Education												
Dummy 1									-63.90	364.0	-0.18	.86
Dummy 2									-57.52	322.1	-0.18	.86
Dummy 3									-123.9	376.1	-0.33	.74
Dummy 4									-493.7	705.9	-0.70	.49
Marital status												
Dummy 1									-65.62	228.0	-0.29	.77
Dummy 2									403.5	424.8	0.95	.34
Dummy 3									-399.7	1,017.6	-0.39	.70
Income												
Dummy 1									363.1	443.9	-1.16	.25
Dummy 2									40.82	410.8	0.10	.92
Dummy 3									206.3	434.5	0.47	.64
Dummy 4									591.3	459.4	1.29	.20
Dummy 5									589.9	437.2	1.35	.18
Employment												
Dummy 1									346.6	361.1	0.96	.34
Dummy 2									-215.1	399.8	-0.54	.59
Ethnicity												
Dummy 1									-179.9	366.3	-0.49	.62
Dummy 2									-389.2	393.3	-0.99	.32
Dummy 3									-380.6	514.0	-0.74	.46

Dummy variables were created for categorical and ordinal variables (education: Dummy 1 was coded 1 for Associate's degree, Dummy 2 for College Bachelor's degree, Dummy 3 for Master's degree, and Dummy 4 for PhD; marital status: Dummy 1 was coded 1 for married, Dummy 2 for divorced, and Dummy 3 for widowed; income: Dummy 1 was coded 1 for $25,000–34,999, Dummy 2 for $35,000–49,999, Dummy 3 for $50,000–64,999, Dummy 4 for $65,000–79,999, and Dummy 5 for $80,000 and above; employment: Dummy 1 was coded 1 for self-employment and Dummy 2 for unemployment; ethnicity: Dummy 1 was coded 1 for Black/African American, Dummy 2 for Asian, and Dummy 3 for others).
β regression coefficient; *BMI* body mass index; *PA* physical activity; *SE* standard error; *T0* Wave 1.

are few opportunities to be active, such as during lockdown [5]) and because the baseline level of PA might influence how individuals respond to changes in the environment [41]. Our study revealed a positive effect of the usage of PA apps. Although previous meta-analyses indicated poor adherence and modest effects by using PA apps to increase PA in the long run [9, 42], any increase of PA, regardless of the intensity, was shown to be associated with reduced health risks [43].

Lastly, while there is research on the general effectiveness of PA apps [9, 42, 44] there are few answers to the question regarding which app features are effective to maintain PA. The present study revealed that gamification-related app features particularly helped individuals remain active during Covid-19-caused lockdown. The findings thus help deepen our understanding of the role of app features for helping people maintain their PA during pandemics.

Practical contribution

The study provides implications for individuals and health professionals, as well as policymakers. With regard to individuals, they can be recommended to use PA apps, and particularly those with gamification features, to maintain their PA levels during a pandemic; this reduces health risks and increases well-being [45]. With regard to health professionals, they can be recommended to use apps to engage with their customers. Gamification-related features might need constant updates to arouse individuals, so health professionals might look for gamification elements that help people to both use the app and remain active. Lastly, regarding policymakers in public health, they can be recommended to fight decreases in PA during lockdown to establish a healthy environment during Covid-19 [7] by collaborating with stakeholders from the digital world, such as smartphone and PA app providers. These collaborations might be directed at increasing the pleasure of using technology and being physically active when access to PA-enhancing external resources is limited.

Limitations and future research

This study has some limitations. First, we relied on self-reports to assess PA. Studies have reported substantial differences between self-reports and objective measures for several reasons (e.g., biases and lack of memory) [46]. In a systematic review, it was shown that the IPAQ-SF overestimated actual PA levels by around 84% [35]. Similar arguments can be made for the assessment of app usage. Second, we used a nonrepresentative sample (surveyed online) and only about half of the participants could be recruited in the second wave. While online surveying is an eligible tool during times of social distancing, the generalizability of the results is limited. Also, the results might be biased, because individuals who could not be recruited again may have displayed different behaviors than individuals who participated in both waves. Lastly, the study did not consider the long-term effects of Covid-19 on PA and focused on the time period of lockdown. Previous studies have considered longer time frames. For example, the lasting impact of the 2011 earthquake in East Japan on PA was assessed in a longitudinal study over a time period of 3 years [47]. Future research may look at how PA opportunities have changed in response to the Covid-19 pandemic and how PA levels are affected in the long run.

CONCLUSION

The Covid-19 lockdown decreased U.S. residents' PA MET levels by 18.2%. Using PA apps (and particularly those rated highly on gamification-related features) may help buffer the decline over a time period of several weeks. The robustness of these findings should be tested using objective PA assessments, as well as actual usage behavior of apps and their features.

SUPPLEMENTARY MATERIAL

Supplementary material is available at *Translational Behavioral Medicine* online.
Supplementary Table 1. Start and end dates of the two-wave data collection, based on the U.S. state-level lockdown orders.

Compliance with Ethical Standards

Conflicts of Interest: The authors declare that they have no conflict of interest.

Authors' Contributions: Y.Y. contributed to the study design, data collection, processing, and analysis and wrote the first draft. J.K. contributed to the study design, data analysis, and edited drafts and served as the principal investigator of this study.

Ethical Approval: All procedures performed in studies involving human participants were in accordance with the ethical standards of the Faculty Board of the TUM Germany, which acts as the local ethics committee for studies outside the TUM Faculty of Medicine, and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. This article does not contain any studies with animals performed by any of the authors.

Informed Consent: Informed consent was obtained from all individual participants included in the study.

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