THESIS

MOTIVATIONAL PROFILES AS A PREDICTOR FOR PHYSICAL ACTIVITY DURING EARLY MONTHS OF THE COVID-19 GLOBAL PANDEMIC

Submitted by

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In partial fulfillment of the requirements

For the Degree of Master of Science

Colorado State University

Fort Collins, Colorado

Spring 2021

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ABSTRACT

MOTIVATIONAL PROFILES AS A PREDICTOR FOR PHYSICAL ACTIVITY DURING COVID-19 GLOBAL PANDEMIC

The COVID-19 Global pandemic resulted in United States officials mandating stay-at-home, shelter in place, and quarantine ordinances starting in March 2020, limiting opportunities for physical activity (PA) during this period. Motivational profiles use controlled and autonomous attributes of motivation to predict PA maintenance; however, the effect of motivational profiles on PA during the COVID-19 pandemic is unknown. Therefore, the current study used Ecological Momentary Assessment (EMA) to examine the relationship between motivational profiles and daily PA during the COVID-19 pandemic.

A convenience sample of 481 U.S. adults (M_{age}=34.9 years, 78.1% female) participated in a 28-day smartphone-based EMA study during the early months of the COVID-19 pandemic (April – June 2020). EMA surveys assessed number of PA bouts (> 10 mins), length of PA bout, and types of PA completed during the day, which was used to calculate daily PA mins and daily PA metabolic equivalent (METs) mins. A baseline online survey assessed motivation for PA, using the Behavioral Regulation for Exercise 3 (BREQ-3) questionnaire, and demographic information.

Latent Profile Analysis (LPA) of the BREQ-3 identified motivational profiles for PA. Separate multi-level linear regression models examined motivational profiles as predictors of average daily PA mins and daily PA MET mins as well as interactions of motivational profile x time (i.e., days in the study). Models controlled for age, sex, ethnicity, income, employment status, body mass index, study site, and start date LPA revealed four distinct motivational profiles for PA including: Class 1) High amotivation (n=102, 21.5%), Class 2) Low controlled motivation (n=55, 11.6%), Class 3) High external regulation (n=47, 9.9%), and Class 4) Moderate autonomous motivation (n=271 57.1%). There were significant negative main effects of motivational profile and time on daily PA mins and daily PA MET mins (b= -0.32, $p<.001$, b= -1.4, $p<.001$, respectively). Significant interaction effects of class and time were also detected. Class 2 showed greater decreases in daily PA mins (b=-0.31, $p<.01$) over time than Class 1. Class 2 and Class 4 also showed significantly greater decreases in daily PA MET mins (b=-1.81, $p<.05$, and b =-1.49, $p<.01$, respectively) than Class 3.

Motivational profiles for PA predicted mean PA engagement and PA engagement over time during early months of the COVID-19 pandemic. Contrary to previous research, more autonomous/less controlled motivational profiles showed the steepest declines in PA over time; whereas, more amotivated/externally regulated motivational profiles reported lesser declines over time. These findings suggest that COVID-19 restrictions for PA participation may have mitigated the influence of autonomous/less controlled motivation on maintaining PA over time among this sample.

ACKNOWLEDGEMENTS

This project could never have happened without the support I've received from folks inside and outside of the HES department First, I would also like to thank my thesis committee Dr. Daniel Graham from the Department of Psychology here at CSU Dr. Genevieve Dunton from the University of Southern California. Dr. Dunton and the REACH lab at USC were fundamental to this data collection and analysis. I thoroughly enjoyed collaborating with their team and learning from these impressive scientists Bridgette Do and Shirlene Wang.

I would also like to thank my mentor Dr. Kaigang Li and the entire APPAH lab for the support you've all showed me over these past two years.

Dr. Jimikaye Courtney and Dr. Kayla Nuss- this project could not have happened without you two. Jimikaye wrote an IRB proposal in record timing to get this project off the ground last year and from there she has been involved in every step. Jimikaye was always available to discuss statistics and keep me on track and she has really been the backbone to the CSU side of this project. Dr. Nuss has been another amazing mentor and friend to me throughout this process. She was always available for a zoom call and willing to help me navigate the graduate school process from day 1.

I want to thank my friends inside and outside of the department. You've made these last two years unforgettable.

And finally, I would like to thank my family for their ongoing love and support. They always push me to work hard and accomplish things that feel impossible.

DEDICATION

Dedicated to my parents Kevin L. Moore and Tina L. Moore.

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CHAPTER 1: INTRODUCTION

1.1 Background

As life expectancy increases, so does the proportion of humans encountering chronic diseases [1]. Chronic diseases such as cardiovascular disease (CVD), cancer, and diabetes represent the shared leading causes of mortality in the United States and worldwide [2]. In the year 2017, 1.4 million individuals died from diabetes worldwide, whereas cancer killed nearly 9.5 million. CVD was responsible for a 17.2 million deaths globally [3]. These illnesses pose an extreme threat to our modern world and, therefore, require immediate attention from researchers, clinicians, public health practitioners, and professionals alike in terms of both disease treatment and disease prevention.

Prior to the recent coronavirus (COVID-19) pandemic, acute diseases such as tuberculosis, measles, polio, and other short-term manifesting illnesses had not posed as much of a threat to our advanced modern medical system as chronic diseases [4]. Though the infectious nature of COVID-19 poses an acute risk to many, the onset and manifestation of this disease is far more dangerous for those already suffering from preexisting conditions [2]. The comorbid nature of chronic diseases and COVID-19 puts many Americans at elevated risk of mortality [2]. Due to the immediate and long-term risks associated with chronic illnesses, it is of utmost importance that preventative practices for such diseases are implemented to mitigate deaths from both chronic illnesses and acute illnesses such as COVID-19.

1.2 Timeline of COVID-19

On December 31, 2019, the Wuhan Municipal Health Commission reported a cluster of pneumonia cases in the Wuhan, Hubei Province of China [2]. United States (U.S.) officials were made aware of this deadly coronavirus (later termed COVID-19) on January 3, 2020 via Robert Redfield, Director of the Center for Disease Control and Prevention [4]. On January 21, 2020 the first COVID-19 case in the U.S. was confirmed in Washington State using test kits developed in the U.S. [5].

Cases began to rise at an alarming rate in the U.S. when 44 passengers of a Diamond Princess Cruise tested positive for COVID-19 on February 1, 2020 [6]. On February 29, 2020, the state of Washington officially declared a state of emergency following the first COVID-19 death on U.S. soil. Following Washington, California declared a state of emergency on March 4, 2020 [7]. On March 7, 2020 Italy locked down a quarter of their national population to contain the virus [5]. Ohio declared a state of emergency on March 9, 2020 followed by New York and Colorado on March 10, 2020 [8]. On March 11, 2020, COVID-19 was declared a global pandemic by the World Health Organization [2], and on March 13, 2020 the United States officially declared a national state of emergency [2]. Following the nationally declared state of emergency, many federal and state policies began to take shape aiming to mitigate the disease's spread. On March 19, 2020 California governor Gavin Newson issued a stay-at-home-order mandating citizens to only leave their homes for essential errands [7]. Governors from both political parties mutually insisted on mandates which instated lockdown protocols [5]. From this point on, stay-at-home and shelter-in-place orders in a number of states, including Colorado and California, were set in place [8]. Such ordinances required all non-essential businesses to close. This included nail and hair salons, retail and clothing stores, gyms or other fitness facilities, along with "non-essential" medical practices like dentistry, chiropractic care and physical therapy [7]. Despite these efforts, by March 26, 2020 the U.S. reported the most COVID-19 cases worldwide [4].

1.3 COVID-19 and Chronic Disease

Many of those infected with COVID-19 develop only mild-symptoms including a cough, high temperature, and loss of smell; while others may develop no symptoms at all [5]. However, some experience much more severe, life-threatening symptoms affecting the lungs and other vital organs including the heart and brain [4].

Six in ten Americans currently suffer from a chronic disease and four in ten currently suffer from two or more chronic diseases [9]. Pre-existing cardiovascular disease (CVD) seems to be linked with worse outcomes and increased risk of death in patients with COVID-19, whereas COVID-19 itself can also induce myocardial injury, arrhythmia, acute coronary syndrome and venous thromboembolism [10]. Chronic disease states exacerbate the symptoms of COVID-19 leaving many Americans vulnerable to severe outcomes, including death, as a result of contracting this virus [4]. Mitigation of certain chronic diseases can drastically reduce the risk of mortality by way of COVID-19 when considering the bodily systems and tissues targeted by this virus [11].

1.4 Physical Activity, Chronic Disease, and COVID-19

Physical activity (PA) may be protective against the effects of COVID-19 infection when considering both the short-term and long-term benefits of routine PA engagement. For example, moderate PA has been associated with acute enhancements in immune function from a cellular standpoint [12]. Therefore, the immune enhancements produced by PA likely provide protection against contracting or dying from COVID-19 [11].

PA has been negatively correlated with the risk of cardiovascular mortality independently from age, sex, and presence or lack of pre-existing cardiovascular disease [13]. Regular PA improves weight control and prevents a number of chronic diseases including: diabetes, cardiovascular disease, and even some cancers [9]. According to the CDC, such benefits have been observed through the lifespan beginning in youth and continuing into older adulthood [4].

Unfortunately, worldwide reductions in PA have been observed as a result of the COVID-19 global pandemic and the accompanying policy changes [14]. Lockdown measures have fundamentally changed work and transport related PA for the non-essential working population [15]. Furthermore, closures of gyms, fitness facilities, and some outdoor spaces pose a barrier for Americans who regularly use such spaces for recreational PA participation.

As the COVID-19 pandemic persists, public health practitioners and exercise scientists have sought to better understand PA trends during COVID-19. Researchers have identified reductions in daily self-reported PA among healthy adults in Spain [16], as well as profoundly negative impacts on physical and psychological health and well-being among healthy adults in Italy [17]. According to the literature, these unfortunate trends also pertain to clinical populations. Similar COVID-19 related PA reductions were reported among patients suffering from neuromuscular disease [18] and among children with congenital heart failure [19]. Though these data provide important insight for PA levels during the pandemic, it is still unclear how personal or psychological mechanisms may influence PA.

Because the COVID-19 pandemic has only persisted for a year, little data exists pertaining to the relationship between certain psychological mechanisms that are associated with PA in the context of this pandemic. Evidence of an association between psychological distress and PA [17] during the COVID-19 pandemic does exist, but there is little information on the relationship between motivation for PA and PA outcomes during this time. Researchers in Italy [42] assessed motivation and PA during COVID-19, however, this particular project took a cross-sectional approach and did not measure these influences over time. Currently, no evidence exists regarding motivation for PA over time during the COVID-19 pandemic.

1.5 Physical Activity and Motivation

In the wake of gym and fitness facility closures, fitness professionals offered creative at-home options like free or reduced cost online or stream able group fitness classes. Some gyms and personal trainers turned to Zoom and other video conferencing software in attempts to offer real time training and workout sessions [20]. The demand for at-home fitness equipment increased as supply chain disruptions caused items such as dumbbells, kettlebells, and jump ropes to sell out nationwide [21]. Peloton, a popular aerobic fitness equipment company, recorded a record breaking 66% increase in revenue as a result of COVID-19 related gym closures [22]. These conflicting data suggests that, on one hand PA levels were at an all-time low during the global pandemic, while on the other hand fitness equipment sales soared [21]. These two seemingly contradictory trends raise many questions in terms of who has remained active during the COVID-19 global pandemic and why.

We believe that motivational differences may drive this trend to an extent. A wealth of psychological information exists attempting to answer the questions behind motivation and why people do or do not participate in certain behaviors. According to Self-Determination Theory (SDT), motivation is influenced by three fundamental needs: autonomy, competence, and relatedness [23]. The need for autonomy refers to the experience of behavior as volitional and reflectively self-endorsed. Competence is the experience of a behavior as effectively enacted. Finally, relatedness facilitates the process of internalization and allows individuals to feel connected to others through values and practices [23]. When these three psychological needs are fulfilled, individuals can progress along a motivational continuum ranging from amotivation to intrinsic motivation. In between these two extremes lie 4 subtypes of regulatory style: external, introjected, identified, and integrated regulations which reflect extrinsic motivation (see figure 1) [23].

The subtypes closest to the amotivation end are termed "controlled" forms of motivation, whereas those closest to the intrinsic side are considered more "autonomous" forms of motivation [23]. In reference to PA, a review [24] indicates that more autonomous forms of motivation are associated with persistent PA engagement.

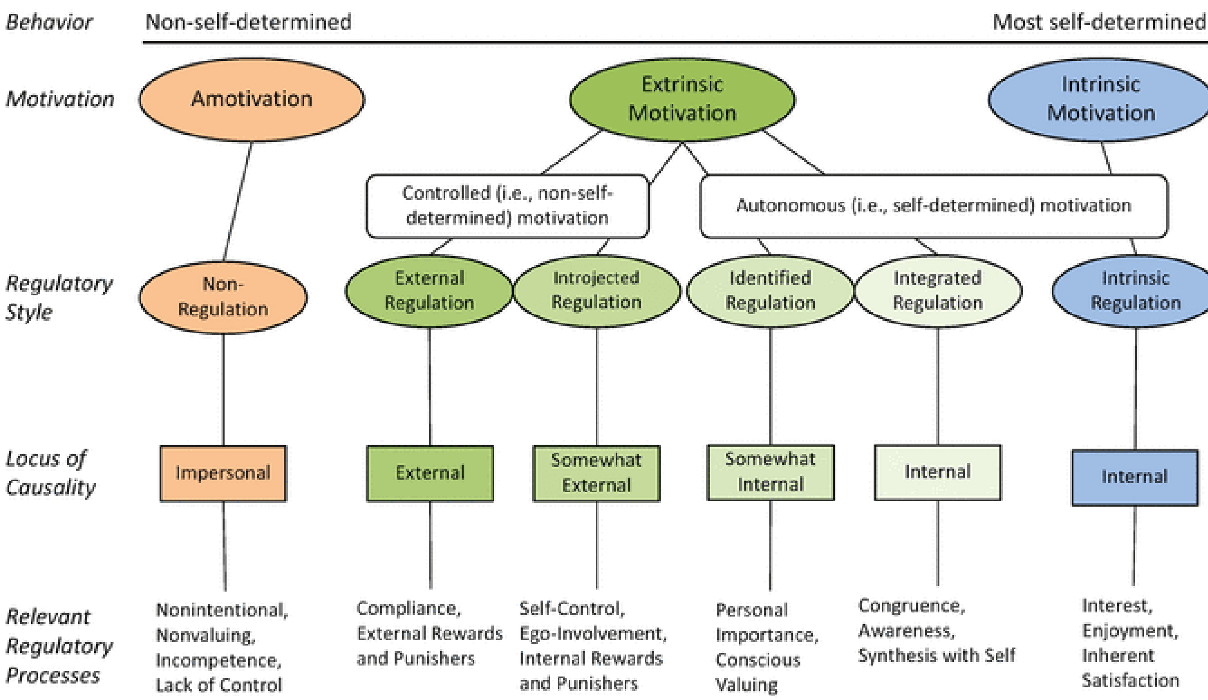

Figure 1: Self-Determination Theory (SDT) of motivation depicting SDT as well as the four subtypes of regulatory style along a continuum of motivation. [Adapted from Legault, et al, 2017[25]]

The intersection of SDT and PA has been widely studied and addressed with a common aim to understand and identify individual's motivation for PA. A systematic review of SDT found good evidence to support the value of SDT, and specifically autonomy, in understanding exercise behavior [24]. Theoretically, if we can improve autonomy we can improve PA behaviors. Gilson et al, (2019) found that competence and relatedness can also be improved among interventions targeting these mechanisms, subsequently enhancing PA behavior [26]. All three needs addressed through SDT (autonomy, relatedness, and competence) are plastic and, when fulfilled, can correlate with the adoption of a desired behavior.

1.6 BREQ-3 Questionnaire & Motivational Profiles

Many challenges come with measuring motivation as it cannot easily be quantified. In 1997 Mullan, Markland, and Ingledew [27] developed the Behavioral Regulation in Exercise Questionnaire (BREQ), to measure the continuum of behavioral regulation in exercise and PA contexts. The third version (BREQ-3) assesses external, introjected, identified, integrated and intrinsic regulations [27] pertaining to exercise or PA engagement. Non-regulation under the umbrella of amotivation lacks all intent for an activity [25]. External regulation refers to external rewards or punishments, whereas introjected regulation involves ego, thus relying on internal punishments and rewards. Identified regulation requires personal importance and value, internal regulation refers to self-awareness and congruence, and finally, intrinsic regulation involves enjoyment and satisfaction of an activity [25].

The BREQ-3 consists of a 24 question, four-point Likert scale, varying between 1 ("Strongly Disagree") and 4 ("Strongly Agree"). The items are grouped posteriorly into six factors (with four items each), that reflect the motivational continuum of SDT [28]. This questionnaire provides the most relevant and valid measure for determining motivational scales while sharing ideology with SDT [27].

The widely used BREQ-3 questionnaire measures all 6 subtypes of motivation outlined in SDT, which can complicate interpretation. The Relative Autonomy Index (RAI) uses a single numerical score for assessing motivation. The RAI uses negative values for controlled forms of motivation, and positive values for more autonomous forms. These values are then plugged into the following formula to yield a final score: Intrinsic+Integrated+Identified-Introjected-External-

Amotivation ([29]. However, some researchers argue that motivation may be more complex and that a single score cannot fully explain the nuances of these motivational subscales [30]. It is common for individuals to report a mixture of motivational subtypes rather than just adhering to one end of this continuum [30]. In fact, motivation is a multidimensional construct in which people have different, sometimes competing, reasons for engaging in PA [31], therefore, some instances require a different measurement style like motivational profiles [31]. Motivational profiles, derived from Latent Profile Analysis (LPA), are sample specific rather than participant specific, and attempt to explain common motivational characterizes that subsets of the sample share [31, 32].

Motivational profiles allow for a greater understanding of how a particular mixture of motivation subtypes may predict PA engagement and patterns [32, 33]. The purpose of identifying motivational profiles is to yield our best understanding of the sample by grouping characteristics of motivation and creating unique motivational profiles. Motivational profiles have also been used to identify PA engagement among a wide range of populations including adolescents [34], athletes [35] and clinical populations [31].

Motivational profiles have been used to successfully group classes of individuals and apply this information to PA engagement as an outcome. For example, a 2015 longitudinal study used motivational profiles for PA among adults with type 2 diabetes to determine perceived competence for PA program adherence [32]. Using these data, researchers retrospectively assessed motivational profiles for PA engagement over time to better understand the motivational attributes contributing to their PA intention and behavior using a SDT perspective [31]. Currently, no data exists pertaining to motivational profiles for PA and PA engagement during the COVID-19 global pandemic.

1.7 Ecological Momentary Assessment

With regard to measuring PA, COVID-19 stay-at-home and shelter-in-place restrictions have made it somewhat difficult not only for individuals to participate in PA, but also for that activity to be measured. With in-person non-essential research temporarily suspended on a federal and state level in response to the COVID-19 pandemic, an added layer of difficulty emerged in terms of adequately gathering data while keeping study participants safe. Through the use of modern technology, specifically smartphone devices, and EMA [31], it is still possible to gather accurate data while maintaining social distancing and safety for researchers and human participants.

EMA was developed in response to the limitations of retrospective data collection [36]. Memory retrieval is often subject to bias as humans tend to associate certain memories with their mood or mental state at the time of that occurrence [37]. Collecting data during (or directly after) a behavioral occurrence allows researchers to observe this behavior in the context of a subject's natural environment allowing for validity and generalizability to the subjects life and experiences [37]. Because EMA assesses data in real time, participants are less likely to succumb to recall biases associated with global or aggregate self-reporting [38].

EMA strategically selects moments for data capture in order to coincide with the behavior of interest. For instance, EMA has been adopted for the study of smoking cessation to predict and understand moments of relapse [39]. By assessing the context before, during, and after relapse occurs, EMA can help apply context to this momentary occurrence [39]. This is desired over an aggregate reflection of an occurrence as participants tend to overestimate feelings of distress and low self-efficacy, yielding unreliable framing of these data [39].

EMA is not a single method but rather an approach that encompasses a wide range of trusted methodological traditions and assessments [37]. Continuous monitoring of a behavior or physiological phenomenon provides a trusted and valid technique for data capture. Researchers have relied on ambulatory physiological monitoring [40] in the field of physiology and self-reported diaries in the field of psychology for many years [37]. EMA attempts to unify ambulatory monitoring and self-monitoring to better understand the contextual influences on a momentary phemonoma [36].

EMA allows subjects' to report current behaviors and experiences in real time, in subjects' natural environments, minimizing recall bias, maximizing ecological validity, and allowing for the study of micro processes that influence behavior in real-world contexts [37]. EMA studies have been widely administered in the field of psychology and behavioral research. EMA has successfully assessed anxiety, alcohol consumption, eating disorders, depression, exercise, physical activity, and many other health behaviors [37].

Accelerometer devices provide an accurate and widely validated tool for objectively measuring PA among human participants. Accelerometers use device positioning and acceleration to derive a number of PA based outcomes including steps, energy expenditure, and metabolic outputs and more. However, PA reported using EMA has also been widely assessed and validated among a number of participants and age groups [41, 42]. A 2017 validation study by Knell et al, [42] found EMA collected PA data to better correlate with objectively measured forms of PA than other self-reported techniques [42]. Current research suggests that EMA provides a useful and reliable tool for reporting PA [43].

1.8 Summary

During the early months of the COVID-19 global pandemic workplaces, schools and fitness facilities were forced to temporarily shut their doors in an effort to combat exposure to the COVID-19 virus. As a result, world-wide reductions in PA were reported [14]. However, a rise in at-home fitness equipment purchases and PA streaming services was observed [20-22]. These contradictory phenomena suggest a nuanced effect of the global pandemic on motivation and PA levels. Therefore, the purpose of this study was to examine motivational profiles as a predictor of PA engagement assessed using EMA during early months of the COVID-19 pandemic.

1.9 Statement of Purpose

This study (1) assessed physical activity engagement using ecological momentary assessment, and (2) examined motivational profiles as a predictor for physical activity engagement during the early months of the COVID-19 global pandemic. Specific research questions (RQs) and Hypotheses (Hs) are represented below.

RQ1: What types of motivational profiles can be identified among participants in this study?

H1: Substantively different motivational profiles (e.g., a predominately externally motivated group, a predominately intrinsically motivated group, and a group in between with equally extrinsic and intrinsic motivational components) will be derived from these data using latent profile analysis.

RQ2: Will motivational profiles predict mean physical activity engagement during early months of the COVID-19 global pandemic?

H2: Motivational profiles will predict mean physical activity engagement at the beginning of 28-day data collection during the early months of the COVID-19 global pandemic.

More specifically, participants with more controlled and externally motivated profiles will engage in less physical activity compared to the more autonomous profiles.

RQ3: Will motivational profiles predict physical activity over time during early months of the COVID-19 Pandemic?

H3: Motivational profiles will predict physical activity over time during early months of COVID-19. More specifically, participants with more intrinsically motivated groups will have better adherence (less decline) in physical activity across their 28-day data collection period compared to more external or controlled profiles.

CHAPTER 2: METHODS AND PROCEDURES

2.1 Study Design

2.1.1 Recruitment and Participants

Our research teams from Colorado State University (CSU) and the University of Southern California (USC) used university email platforms in addition to social media (Facebook, Twitter, Instagram, etc.) to recruit a convenience sample of adults living in the United States. Eligible participants were 18 years or older, able to speak and read English, lived in the U.S., owned and regularly used an Android or iPhone smartphone, were willing to use their smartphone to complete app-based surveys for the entire study period, and were willing to comply with the entire study protocol. Participants enrolled in other PA studies were excluded from this study. The Institutional Review Boards (IRB) of CSU (Protocol #20-9987H) and USC (Protocol # HS-20-00304) approved the study protocol.

2.1.2 Procedures

Eligible participants completed a 30-minute electronic baseline, survey that included the BREQ-3 questionnaire, and demographic questions. After completing the baseline survey, participants completed a 28-day EMA protocol. The dates of the 28-day data collection periods differed by participant as study recruitment and enrollment were completed on a rolling basis between March 2020 and May 2020.

CSU participants used the Ilumivu mEMA mobile application and USC participants used the RealLife Exp mobile application, by LifeData, downloaded to their personal smartphones to complete the EMA protocol. Participants received two 3-minute surveys per day, one in the morning and one in the evening. The morning survey was available from 8AM – 10AM and the evening survey available from 7PM – 9PM at both sites, giving participants two-hours to complete each survey. CSU participants were sent a notification at 9AM MST and 8PM MST for the morning and evening surveys, respectively whereas USC participants were sent a notification at 8AM PST and 7PM PST. Non-responders were sent up to two reminders (five minutes apart at CSU and forty-five minutes apart at USC) to complete the survey. EMA data were collected between April 2, 2020 and June 9, 2020.

2.2 Measures

2.2.1 Demographic variables

Subjects reported demographic information including biological sex, ethnicity, race, education level, age, height, weight, and income. Categories for sex included male and female sex at birth; for ethnicity: Hispanic or non-Hispanic heritage; for race: American Indian/Alaska Native, Asian, Native Hawaiian/Pacific Islander, Black, and White. Education level was self-reported with the following response options: 12th grade or less, high school graduate or GED, some college/technical school/Associate's degree, Bachelor's degree, or graduate degree. Current school status: not in school, high school/GED program, community college/technical school, 4-year University, or graduate/professional school, was also reported through the baseline survey. Age, was reported as a continuous variable and then collapsed into three categories: <40 years old, 40-59 years old, and ≥60 years old. Height and weight were self-reported as continuous variables and later used to calculate Body Mass Index (BMI) using the equation kg/m^2 [44]. Work status was also collapsed into three categories: employed full-time, employed part-time, or unemployed/retired. Income was collapsed into four categories: <\$27,000/year, \$27,000-\$59,999/year, \$60,000-\$99,999/year, or ≥\$100,000/year.

2.2.2 Motivation

Motivation for PA was measured using the validated Behavioral Regulations in Exercise version 3 (BREQ-3)[27, 45]. The BREQ-3 uses five-point Likert scale responses, ranging from 0

To 4, to assess motivation for PA. Mean scores for each of the six subscales of motivation were calculated and also ranged from 0 to 4 [46].

2.2.3 Physical Activity- Frequency, Intensity, and Duration

PA was assessed using EMA. PA-bouts were recorded during the evening survey. Participants were asked: “Did you do PA at least one time today?” (CSU) – or – “Did you do PA for at least 10 minutes at least one time today?” (USC), with response options of “Yes”, “No”, and “Do not know/Prefer not to answer”. Participants could record up to three bouts of PA each day. Following bouts, the survey prompted users to select the type of PA that they completed from the following categories: walking, walking to get somewhere (only USC), gardening/yardwork, housework, jogging or running, cardio equipment (only USC), Hiking, cycling, swimming/ water aerobics, aerobics/aerobic dancing, yoga, weight lifting/ strength training, sports, playing with children (only USC), skiing and prefer not to answer (only USC). If their PA type was not included in the above categories, participants had the option of selecting “other” and were then prompted to explain their PA in a few words. Categories for High Intensity Interval Training (HIIT), manual labor, and snow shoveling were then added to the final data set. Metabolic equivalent (MET) values were then assigned to each type of PA in order to generate a value for PA intensity. MET values were derived predominately from the American College of Sports Medicine [47] and then multiplied by daily PA minutes, thus generating daily PA MET mins.

Participants in the USC sample were asked “During the first time you did PA today: How long did it last?” giving them the option to choose: 10-20 min, 20-30 min, 30-40 min, 40-50 min, 50-60 min, More than 60 min, Do not know/Prefer not to answer. CSU participants were prompted to enter minutes of PA. These values were later categorized into the same numeric ranges as the USC data for consistency across data sets

2.2.4 Time and Start Date

In order to assess the effect of the time in the context of the COVID-19 pandemic on PA min/day and MET min/day, we created a variable (time) in which day 0 represents March 13, 2020, or the date the United States declared a state of emergency. Subsequently, the first participants recruited and enrolled began their 28-day EMA period on day 20 (April 2, 2020) and ended on day 47 (April 29, 2020). We also created a variable (start date) to assess differences in daily PA mins and daily PA MET mins among participants who started data collection closer to March 13, 2020 and those who started later.

2.3 Statistical Analysis

2.3.1 Demographics

Data from CSU and USC were combined prior to analyses. Individuals without baseline data were removed from the final analysis. Descriptive data are reported as means and standard deviations (SD) for continuous variables, and frequencies and percentages for categorical variables.

2.3.2 Latent Profile Analysis

We used Latent Profile Analysis (LPA) to derive motivational profiles from participant BREQ-3 responses. LPA relies on a number of quantitative and qualitative fit statistics to determine the appropriate model and number of classes for adequate sample representation [31]. Log-likelihood measures a particular model's goodness of fit in which a higher value for log-likelihood indicates better model fit. Akaike information criteria (AIC) represents information lost by fitting a certain model and Bayesian information Criteria (BIC) helps to identify overfitting of a model [48]. The lowest AIC and BIC values are preferred when fitting a model for LPA [48]. Entropy represents the proportion of the sample included in each model. An entropy value closest to 1 is preferred as this would incorporate 100% of the sample [49]. Finally, the number of classes and number of participants within each class determines qualitative fit for the model [31]. Using these fit statistics, we tested a number of models to derive appropriate motivational profiles among this sample. Motivational regulation subtype scores were converted to Z-scores to assess motivational differences and similarities per each class in relation to the sample mean. Scores outside of 1 standard deviation from the mean were considered outside of the expected range [50]. We conducted one-way Analysis of Variance (ANOVA) to investigate differences in each motivational subtype among the resultant motivational profiles. When overall effects of profiles were detected, we used Tukey's HSD Post-Hoc tests to reveal specific between-group differences.

2.3.3 Multi-Level Regression Models

We used multi-level regression models, with days nested within participants, to examine the effect of motivational profiles on daily PA mins and daily PA MET mins. We began this analysis with an intercept only model, and then added control variables including age, sex, ethnicity, income, employment status, BMI, study site, and start date (the unique date each participant started their 28 days EMA survey protocol). Next, we tested the main effects of time (number of days) since the United Stated national emergency declaration (March 11, 2020) on daily PA mins and daily PA MET mins. Then we tested the effect of motivational profile on daily PA mins and daily PA MET mins. Finally, we examined the interaction effects of time by motivational profile and on daily PA mins and daily PA MET mins. All analyses were conducted in R version 4.0.0 with the packages "tidyLPA" and "nlm " (R: The R Project for Statistical Computing, 2019), and statistical significance was set at p<.05 [51]

CHAPTER 3: RESULTS

3.1 Demographics and characteristics

Table 1 shows participant demographics for our final sample which included 481 total participants recruited from CSU (286) and USC (195). Our sample included predominately non-Hispanic (85%), white (82.9%) females (77.9%), ages 18-77 years (mean=34.59±12.15). Additionally, the majority of participants held a college degree or higher (93.7%) and were employed (84.2%) during the early months of the COVID-19 Global Pandemic (see Table 1).Table 1. Whole Sample Demographic

Demographics	Total (N=481)
Site- Colorado State University	286 (59.5%)
Age in years (Mean ± SD)	34.59±12.15
Female	375 (77.9%)
Non-Hispanic	409 (85.0%)
White	399 (82.9%)
Black	11 (2.3%)
Asian American	51 (10.6%)
Indian/Alaska Native	10 (2.1%)
Native Hawaiian/ Pacific Islander	4 (.83%)
12th Grade or less	1 (.2%)
High School/ GED	7 (1.4)
Some College	15 (3.1%)
College Graduate or higher	451 (93.7%)
Working full-time	279 (58.0%)
Working part-time	108 (22.4%)
Unemployed	47 (9.7%)
Income less than $27,000/yr	70 (14.5%)
Income $27,000 - $59,999/yr	141 (29.3%)
Income $60,000 - $99,999/yr	96 (20.0%)
Income $100,000/yr or more	146 (30.4%)
Not a health care worker	427 (88.8%)
BMI (kg/m^2)	25.21±5.09

3.2 Motivational Profiles

Latent profile analysis identified the best-fit model to be either a 2, 3, or 4 class solution. Using log-likelihood, AIC, BIC, entropy and qualitative fit statistics we identified the 4-class option to best represent our sample (see Table 2).

Table 2. Quantitative fit statistics for model classes

Classes	2	3	4	5	6
Log-Likelihood	-3457.69	-3608.07	-3430.23	-3404.37	-34.27.86
AIC	6983.39	7268.13	6956.46	6918	6979
BIC	7126.00	7377.19	7157.80	7125	7239
Entropy	.95	.86	.75	.70	.54

Though the 2 class solution yielded the lowest BIC and highest entropy value, this model did not qualitatively align with other motivational profile research [33] and did not represent the full spectrum of motivational subscales by yielding only two profiles. The 4-class model, however, had a high log-likelihood value and the low AIC and qualitatively represented 4 distinct and diverse profiles aligning with the 6 motivational subscales (see Figure 2). Motivational subtype differences by class are depicted in Figure 2.

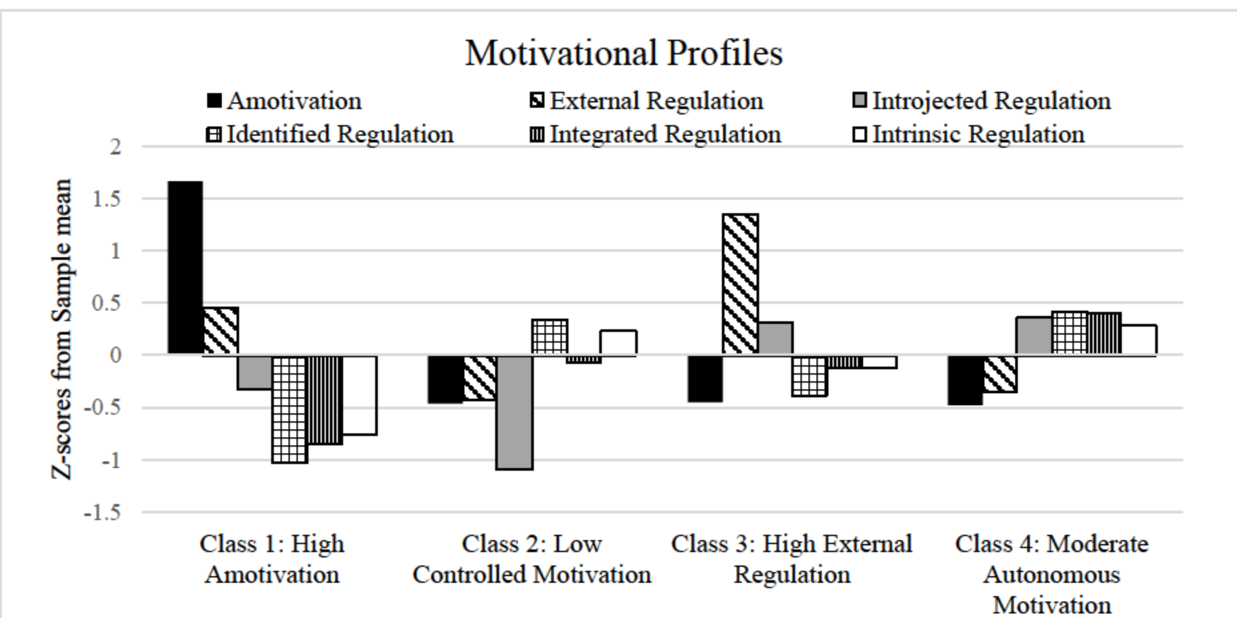

Figure 2 Motivational Profiles: Z-scores depicting distinct profile characteristics based on motivational subscale

Zero on the y-axis represents the sample mean. In this context, Z-scores indicate where the score for each subtype falls in relation to the sample mean. Class 1 is the “high amotivation” profile (n=104, 21.5%) which consists of higher than expected scores for amotivation and lower than expected scores for autonomous forms of motivation. Class 2, the “low controlled motivation” profile (n=54, 11.6%) indicates lower than expected scores on the controlled subscales of motivation, with specifically low introjected regulation. Class 3 is the “high external regulation” profile (n=47, 9.9%), which shows higher than expected scores on external regulation and introjected regulation and lower than expected scores on amotivation and autonomous motivational subscales. Finally, Class 4 is the “moderate autonomous motivation” profile (n=275, 57.1%), which indicates moderate autonomous motivation and lower than expected amotivation and external regulation sub-scores.

Table 3 contains demographic characteristics by class per the selected 4-class model. The mean BMI of our sample is 25.21±5.09. BMI is the only significantly different demographic variable among the classes. Class 1 (high amotivation) and Class 3 (high external) had significantly higher BMI ($p<.01$) than Class 2 (low controlled) and 4 (moderate autonomous). Classes 1 and 3 and Classes 2 and 4 were not statistically different from one another (see table 3).

Table 3. Demographics by Class

Demographics	Class 1[a] (N=104)	Class 2[b] (N=54)	Class 3[c] (N=47)	Class 4[d] (N=275)
Data Collection Site				
Colorado State University	61 (21.3%)	34 (11.9%)	27 (9.4%)	164 (57.3%)
University of Southern California	43 (22.1%)	20 (10.25%)	20 (10.25%)	111 (56.9%)
Age in years (Mean ± SD)	33.05±12.08	35.55±12.68	34.00±12.35	35.1±12.04
Sex (n (%))				
Male	19 (19.2%)	10 (10.1%)	9 (9.1%)	61 (61.6%)
Female	84 (22.4%)	42 (33.6%)	38 (10.1%)	211 (56.3%)
Ethnicity (n (%))				
Hispanic	18 (28.1%)	5 (7.8%)	7 (10.9%)	34 (53.1%)
Non-Hispanic	84 (20.5%)	47 (11.5%)	40 (9.7%)	238 (58.2%)
Race (n (%))				
White	78 (19.5%)	47 (11.8%)	36 (9.0%)	238 (59.6%)
Black	4 (36.4%)	0	1 (9.0%)	6 (54.5%)
Asian	20 (39.2%)	3 (5.8%)	8 (15.6%)	20 (39.2%)
American Indian/Alaska Native	2 (2.0%)	2 (2.0%)	1 (1.0%)	5 (5.0%)
Native Hawaiian/Pacific Islander	0	0	0	4 (100%)
Education (n (%))				
12th Grade or less	0	0	0	1 (100%)
High School/ GED	5 (71.4%)	1 (14.3%)	0	1 (14.3%)
Some College	5 (33.3%)	1 (6.7%)	2 (13.3%)	7 (46.7%)
College Graduate	52 (26.7%)	18 (9.2%)	23 (11.8%)	102 (52.3%)
Graduate Degree	40 (15.6%)	33 (12.9%)	22 (8.5%)	161 (62.9%)
Work Status (n (%))				
Working full time	65 (23.3%)	26 (9.3%)	27 (9.7%)	179 (64.2%)
Working part time	17 (20.2%)	11 (13.1%)	12 (14.2%)	44 (52.4%)
Working <20 hr/week	4 (9.5%)	10 (23.8%)	3 (7.1%)	25 (59.5%)
Not working not looking for work	6 (21.4%)	3 (10.7%)	4 (14.3%)	15 (53.6%)
Unemployed and looking for work	9 (47.3%)	2 (10.5%)	1 (5.3%)	7 (36.8%)
Disabled or retired	1 (33.3%)	1 (33.3%)	0	1 (33.3%)

Income (n (%))				
Less than $27,000	29 (41.4%)	8 (11.4%)	7 (1.0%)	36 (52.4%)
$27,000 - $59,999	35 (24.8%)	16 (11.3%)	12 (8.5%)	78 (55.3%)
$60,000 - $99,999	19 (19.8%)	9 (9.3%)	14 (14.5%)	54 (56.3%)
$100,000 or more	23 (15.8%)	16 (11.0%)	13 (8.9%)	94 (64.4%)
Health Care Worker in U.S.				
Not a health care worker	93 (21.8%)	48 (11.2%)	43 (10.1%)	243 (56.9%)
Health care worker	8 (18.2%)	5 (11.4%)	4 (9.0%)	27 (61.4%)
Anthropometrics (Mean ± SD)				
BMI (kg/m^2)	26.58±6.80	23.98±4.20	26.85±5.53	24.63±4.15

N includes all participants with baseline demographics data
Prefer not to answer options were available for each question but omitted from table
a: High Amotivation; b: Low Controlled Motivation; c: High External Regulation; d: Moderate Autonomous Motivation

Table 4 contains z-scores for each class in relation to the six subtypes of motivation assessed by the BREQ-3. We observed overall statistical difference among each subtype between the four motivational classes. The results of post hoc tests are shown in Table 4. Amotivation variable z-scores for Class 1 (high amotivation) were significantly higher than Class 2 (low controlled), Class 3 (high external), and Class 4 (moderate autonomous). External regulation z-scores for Class 1 (high amotivation) were significantly higher than Class 2 (low controlled) and Class 4 (moderate autonomous) and significantly lower than Class 3 (high external). External regulation z-scores for Class 3 (high external) were significantly higher than Class 2 (low controlled) and Class 4 (moderate autonomous). Introjected regulation z-scores for Class 1 (high amotivation) were significantly lower than Class 3 (high external) and Class 4 (moderate autonomous) and higher than Class 2 (low controlled). Identified regulation z-scores for Class 1 (high amotivation) were significantly lower than Class 2 (low controlled), Class 3 (high external) and Class 4 (moderate autonomous). Integrated regulation z-scores for Class 4 (moderate autonomous) were significantly higher than Class 2 (low controlled) and Class 3 (high external)

Table 4: Motivational Subscales by Class

	Class 1	Class 2	Class 3	Class 4	DF	F	P-Value[#]
Amotivation	1.03±0.34[,]	0.07± 0.16[a]	0.06±0.16[a]	0.06±00.15[a]	3, 476	594.74	<.001
External	1.46±0.91	0.6±0.59[a,c]	2.38±0.61[a,]	0.76±0.6[a,c]	3, 476	97.33	<.001
Introjected	2.26±0.88[,]	1.22±0.58[a,c,d]	2.74±0.7[a,c,]	2.87±0.6[a,b]	3, 476	89.34	<.001
Identified	2.83±0.55	3.40±0.38[a,c]	3.13±0.49[a,]	3.63±0.39[a,c]	3, 476	91.46	<0.001
Integrated	2.03±0.83	2.66±0.97[a,d]	2.98±0.82[a]	3.17±0.7[a,b,c]	3, 476	49.65	<0.001
Intrinsic	2.43±0.79[,]	3.24±0.8	2.95±0.7	3.25±0.7[c]	3, 476	33.6	<0.001

Class 1: High Amotivation; Class 2: Low Controlled Motivation; Class 3:High External Regulation; Class 4: Moderate Autonomous Motivation
#indicates the overall difference between classes based on one-way ANOVA, Tukey HSD
a=significantly different from Class 1; b=significantly different from Class 2; c=significantly different from Class 3;

Finally, z-scores for Intrinsic regulation for Class 1 (high amotivation) were significantly lower than all other classes. Class 3 (high external) Z-scores for intrinsic regulation were also significantly lower than Class 4 (moderate autonomous).

3.3 Main Effects and Class by Time interaction

Table 5 and Table 6 show the main effect of motivational profile class on PA engagement and the interaction effect of time and motivational profile class on daily PA mins and daily PA MET min day, respectively. There were significant main effects of both motivational profile and time on daily PA mins (see Table 5). Class 2 (low controlled) and Class 4 (moderate autonomous) reported significantly more daily PA mins (b=11.01, p<.01 and b =10.54, p<.01, respectively) and daily PA MET mins (b=61.08, p<.01, and b =61.46, p<.01, respectively) than Class 1 (high amotivation). In terms of time, we detected a decrease of 0.32 min of daily PA for the entire sample.

In regard to daily PA MET mins, Class 2 (low controlled) and Class 4 (moderate autonomous) also participated in significantly more daily PA MET mins (b=109.72, p<.01, and b =97.49, p<.01, respectively) than Class 3 (high external). We also detected a decrease of 1.40 daily PA MET mins for the whole sample.

Table 5: Adjusted multi-level models with motivational profile and time predicting daily PA mins

Models	Main Effects Model[a]		Moderation Model	
	b (SE)	*p*	*b (SE)*	*p*
Intercept	37.38 (7.91)	<.001	32.37 (8.30)	<.001
Motivation Class[a]				
Class 2 – Low Controlled	11.01 (3.66)	.003	24.30 (6.01)	<.001
Class 3 – High External	5.90 (3.66)	.11	2.18 (6.10)	.72

Class 4 – Moderate Autonomous	10.54 (2.53)	<.001	17.04 (4.12)	<.001
Time	-0.32 (0.3)	<.001	-0.21 (0.06)	.001
Intercept	-	-	32.37 (8.30)	<.001
Motivation Class*Time				
Time*Class 2 – Low Controlled	-	-	-.31 (0.11)	.01
Time*Class 3 – High External	-	-	.09 (0.11)	.44
Time *Class 4 – Moderate Autonomous	-	-	-.15 (.07)	.05

Class 1 as reference group; b = unstandardized beta; Se = standard error.
The models were adjusted for age, sex, ethnicity, race, income, employment status, body mass index, study site and start date

Table 6: Adjusted multi-level models with class and time predicting physical activity daily PA MET mins

Models	Main Effects Model[a]		Moderation Model	
	b (SE)	*p*	*b (SE)*	*p*
Intercept	208.25 (42.62)	<.001	198.42 (44.87)	<.001
Motivation Class[a]				
Class 2 – Low Controlled	61.08 (19.75)	.0021	93.37 (32.86)	.0047
Class 3 – High External	29.21 (19.71)	.14	-16.35 (33.38)	.62
Class 4 – Moderate Autonomous	62.46 (13.63)	<.001	81.14 (22.51)	<.001
Time	-1.40 (0.17)	<.001	-1.17 (0.36)	.001
Intercept			198.42 (44.88)	<.001
Motivation Class*Time				
Time*Class 2 – Low Controlled	-	-	-0.75 (0.61)	.22
Time*Class 3 – High External	-	-	1.06 (0.63)	.090
Time*Class 4 – Moderate Autonomous	-	-	-0.43 (0.41)	.30

Class 1 as reference group; b = unstandardized beta; Se = standard error.
The models were adjusted for age, sex, ethnicity, race, income, employment status, body mass index, study site and start date

We detected a significant interaction effect of class and time on daily PA mins. Class 2 (low controlled) showed a significantly greater decrease in daily PA mins (*b* =-0.31, p<.01) over time than Class 1 (high amotivation) (see Figure 3).

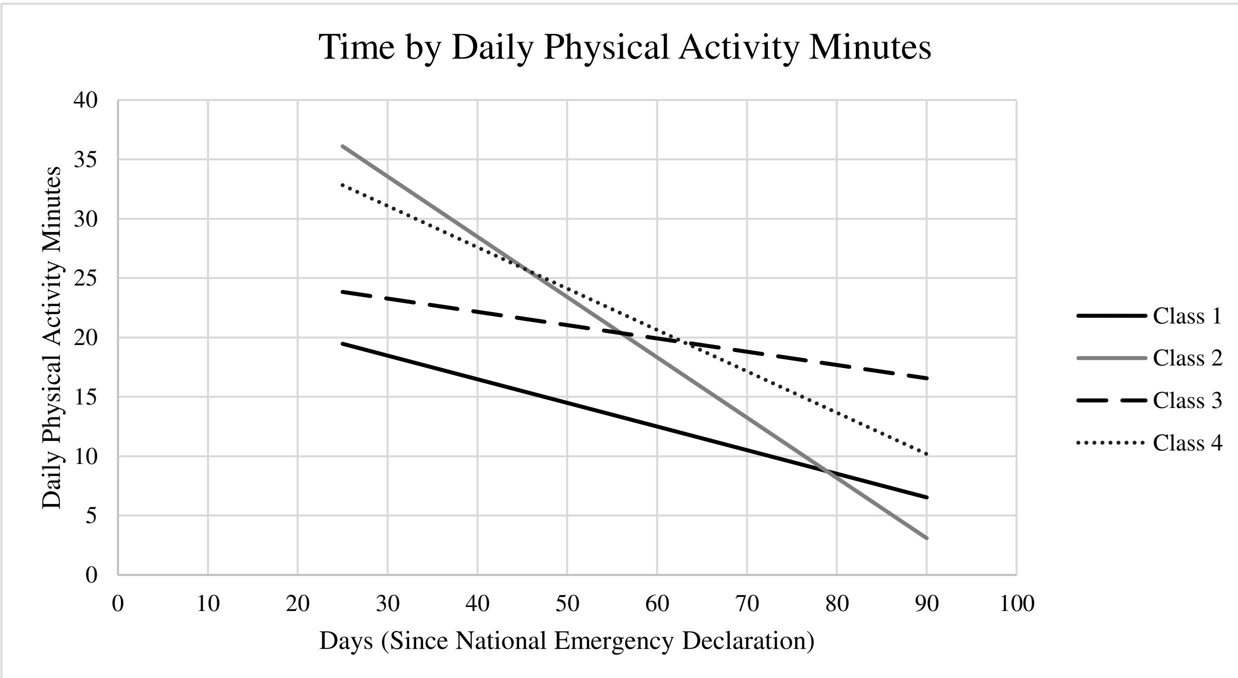

Figure 3: Effect of Motivational Class on Daily PA mins Across Time
Class 1: High Amotivation
Class 2: Low Controlled Motivation
Class 3: High External Regulation
Class 4: Moderate Autonomous Motivation

We also detected a significant interaction effect of class and time on daily PA MET mins. Class 2 (low controlled) and Class 4 (moderate autonomous) also showed significantly greater decreases in daily PA MET mins (*b*=-1.81, p<.05, and *b* =-1.49, p<.01, respectively) than Class 3 (high external) (see Figure 4).

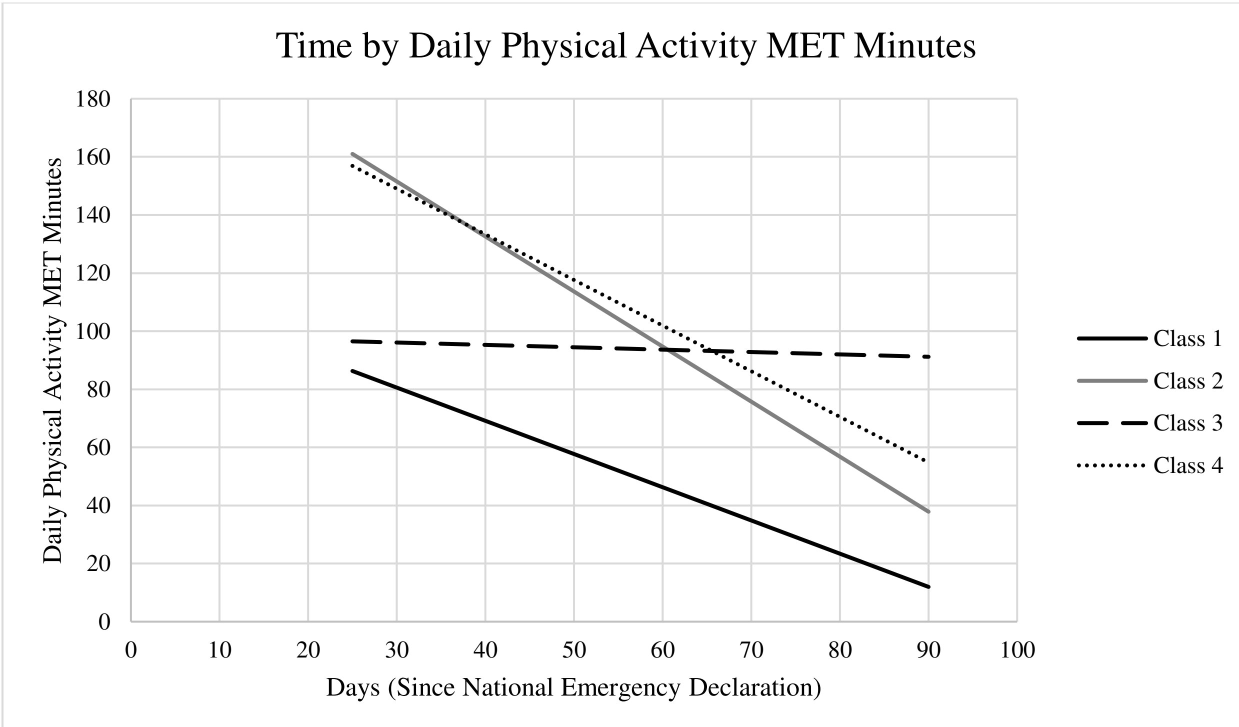

Figure 4: Effect of Motivational Class on Daily PA MET mins Across Time
Class 1: High Amotivation
Class 2: Low Controlled Motivation
Class 3: High External Regulation
Class 4: Moderate Autonomous Motivation

CHAPTER 4 DISCUSSION

4.1 Overview

In this study we examined the effect of motivational profiles on PA during early months of the COVID-19 global pandemic. Our participants with more autonomous motivational profiles participated in the most daily PA mins and daily PA MET mins at the beginning of the 28-day assessment period but unexpectedly, declined significantly more than the others over the course of the evaluation period. Our predominately externally controlled motivational profile, Class 3, sustained moderate amounts of daily PA mins and daily PA MET mins throughout the 28-day data collection. Our amotivated motivational profile, Class 1, was not statistically different from our controlled profile.

4.2 Autonomous Motivation

According to our results, Class 2 (low controlled) and Class 4 (moderate autonomous) recorded high mean daily PA and daily PA MET mins. A cross-sectional study conducted in Italy assessed motivation, intention, and PA behavior during early months of the COVID-19 Global Pandemic [52]. This study also found autonomous motivation predicted mean PA engagement. However, when we investigated the interaction between time and motivational profile, both Classes 2 and 4 saw a significant decline in both PA outcome variables across the 28-day evaluation period. A randomized control trial (RCT) conducted during early months of the COVID-19 global pandemic indicated that participants with high autonomous motivation at baseline also had higher steps per day at baseline (compared to those who had lower autonomous motivation), but lower steps per day after using a Fitbit for twelve weeks. No changes in motivation were detected, revealing that autonomous motivation alone is not sufficient to drive PA behavior (unpublished data, February 2021).

We speculate, then, that autonomous motivation may not directly predict behavior, but rather intention for behavior. Other researchers have demonstrated that intention does, in fact, mediate the relationship between autonomous motivation and PA engagement [53, 54]. In one such study, autonomous motivation predicted intention for PA, but intention for PA only predicted 11% of the variance in PA [54]. Similarly, Chirico et al. [42] found intention for PA to mediate the relationship between autonomous motivation and PA engagement.

Unfortunately, we did not measure intention for PA, therefore, the extent to which intention mediated this relationship among our participants is unknown. However, the intention-behavior gap suggests that intention may not always indicate follow-through of certain behaviors. Current evidence suggests that intentions only get translated into action approximately half of the time [55]. This weak relationship between intention and behavior has been widely observed among PA studies [56]. Therefore, we speculate that our autonomously motivated group may have intended to maintain high levels of PA throughout the pandemic but were ultimately unable to carry out this behavior through the entire 28-day collection period. Though SDT provides substantial insight into motivation for PA, this theory falls short in explaining how exactly motivation translates into PA behaviors. The Health Action Process Approach (HAPA) attempts to better explain health behaviors in two phases including the motivational phase and the volitional phase. This theory argues that once a behavioral intention to engage in regular exercise is formed, the motivation phase is completed and the person enters the volitional phase. The intended behavior must be planned, initiated, maintained and restarted when setbacks occur [55]. Various setbacks and barriers can arise between the completion of the motivational phase and the follow-through of that particular behavior. We speculate that COVID-19 likely served as a major barrier to PA among our autonomously motivated participants sometime after completion of the motivation phase.

4.3 Controlled Motivation

Our sample also revealed unexpected results by way of Class 3 (high external), as these participants' maintained consistent daily PA mins and daily PA MET mins throughout the 28-day data collection period. Experts in SDT often consider controlled forms of motivation to be low-quality while more autonomous forms are considered high-quality [57]. High-quality motivation persists for long periods of time and hinges upon more self-determined reasons for a behavior [57, 58]. Low-quality motivation, however, seeks to avoid punishment and relies heavily on external pressures to carry out a behavior [58]. Therefore, Class 3 (high external) would be considered a low-quality motivational group as this class indicated higher than expected values for external regulation. Our results suggest, then, that high quantities of low-quality, controlled motivation may provide some protective qualities for PA engagement in the short term [59]. More information is needed to understand the relationship between high quantities of low quality motivation as a predictor of PA engagement during stressful circumstances like that of COVID-19.

4.4 Application and Future Directions

Throughout the COVID-19 pandemic, state and local safety ordinances have varied but, mandates still persist one year later in an effort to mitigate the COVID-19 virus. COVID-19 vaccine administration in the United States signifies an end to the pandemic; however, many COVID-19 related changes are likely to persist for years to come. For instance, only 3.6% of Americans consistently worked from home prior to COVID-19, yet experts project that nearly 25-30% of Americans will be working from home by the end of 2021 [60]. We can only speculate which COVID-19 related policies will persist after the pandemic, but we can still draw parallels between the pandemic and other stressful life situations. Unemployment, divorce, death of loved ones, disease states, and many other common life experiences are likely to negatively influence PA among both controlled and autonomously motivated individuals [61]. Future studies involving motivational profiles and PA should focus on stressful stimuli such as these over long periods of time to better understand this relationship. Future studies should also focus on a larger and more diverse geographical range including states with differing climates, population density, and state-wide policies (i.e. Florida, Texas, New York, etc.).

4.5 Limitations

We acknowledge limitations of our study. Differences in data collection approaches between sites, such as the timing of EMA survey notifications, could have affected reporting of PA, particularly for individuals who engage in PA late in the evening. However, PA declines rapidly after about 5PM, which makes it unlikely that survey notification timing affected outcomes [62]. Other limitations exist in terms of generalizability. Participants in this study were predominately white, college educated, and of above average income. Finally, self-reported PA is subject to over/under reporting of PA engagement, though EMA minimizes this issue through the use of repeated, real-time data collection [36].

4.6 Conclusions

In this study we examined motivational profiles as a predictor for PA engagement during early months of the COVID-19 global pandemic. Using latent profile analysis we derived four distinct motivational profiles from our sample. These profiles included an amotivated class, a low controlled class, a high external class, and a moderate autonomous class. Our low controlled and moderate autonomous classes participated in the highest mean daily PA mins and daily PA

MET mins. However, after applying time as an interaction term for the association between motivational profile and PA, our low controlled and moderate autonomous classes reported the sharpest decline in daily PA mins and daily PA MET mins over the course of our collection period. Our high external group reported the most consistent daily PA mins and daily PA MET mins throughout the observation period. Findings from this study suggest that autonomous motivation may not be enough to maintain PA under certain circumstances. Perhaps external or more controlled forms of motivation may provide short term benefits for sustaining PA during unique and stressful circumstances, like that of the COVID-19 global pandemic.

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