Exploring the Link Between Travel Behavior and Mental Health

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Abstract

The mental health of young adults is an important social consideration, given increasing rates of isolation, depression, anxiety, suicide, and other ills. But the effect of daily travel on mental health — or the effect of mental health on daily travel — is not well understood. In this research, we explore the relationship between mental health and observed trip-making behavior in a longitudinal dataset of young adults. The participants in this study all expressed suicidal ideation in professional treatment setting and have an accompanying psychiatric diagnosis for social anxiety disorder, autism spectrum disorder, or are in a designated control group. Participants volunteered to use a mobile device application that surveyed them twice a day for several months on their reported mood while also tracking their physical location via location-based services. We find significant differences in activity engagement and motivation levels among the groups: The control group participated in more activities and reported higher motivation compared to the autism and social anxiety groups. Increased activity engagement did not consistently raise motivation levels; however, for those in the control group, more activities in parks lead to a statistically significant increase in motivation and for those in the autism group, more activities to grocery stores lead to a statistically significant decrease in motivation.
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1. Introduction

Mental health is a critical global issue that profoundly impacts individuals' emotional, psychological, and social well-being (Barry, 2009; Friman et al., 2017; Hoisington et al., 2019). It extends far beyond the mere absence of illness, influencing personal relationships, work efficiency, and lifestyle choices (Barry, 2009). Understanding the complexities of mental health is essential, particularly as it intersects with individual daily behaviors and choices. Among these behaviors, the allocation of time and individuals' travel patterns

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are particularly intriguing, as they are intricately linked to mental well-being (Friman et al., 2017; Mackett, 2021).

Previous research has explored many elements of the relationship between mental health and travel activity behavior patterns. This previous research has largely focused on the positive mental health effects of time in green space (Pelgrims et al., 2021; Pouso et al., 2021; Rautio et al., 2018; White et al., 2021), as well as the deleterious effect of isolation (Loades et al., 2020; Stanley et al., 2011). Other studies have considered the negative effects of travel satisfaction (Syahputri et al., 2022). Notably, (Lan et al., 2022) began to explore the relationship between travel behavior and mental health using mobile phone-based sensing to investigate daily activities, environmental exposures, and anxiety symptoms.

Despite the existing literature, significant gaps remain in our understanding of how different travel behaviors and patterns specifically affect mental health across various populations. While some studies have examined the well-being of individuals with autism and social anxiety, comprehensive analyses that consider the nuances of travel behavior in relation to mental health outcomes are still lacking. This gap underscores the necessity for further investigation into how travel patterns influence mental health, particularly among those with different neurological or psychological typology such as autism and social anxiety.

In this research, we investigate the longitudinal mental health of a sample of college students, incorporating trip-making behavior from their mobile device location data. This allows us to track how often and where participants travel, providing a clearer picture of their daily activities and social interactions. We pair this data with twice-daily survey responses concerning their mental health to identify patterns that link travel behavior to mental well-being. The longitudinal design also allows us to consider the order of effect: does increasing out-of-home activity frequency lead to an increase in mood, or vice-versa?

The following sections of the paper provide a literature review exploring the existing discussion around travel behavior and mental health. A methodology section describes our data assembly and curation process as well as the econometric framework we employ, followed by a results section presenting and discussing the econometric findings. A final concluding section emphasizes the contribution of this research in the context of its limitations and the need for future research.

2. Literature Review

In the United States, the prevalence of mental illnesses among adults, aged 18 or older, rose from 19.1% in 2018 to 22.8% in 2021 (Mackett, 2021; "Mental Health By the Numbers," 2023). Mental health and well-being are influenced by various factors, including social and environmental elements as well as travel behavior (Barry, 2009; Delbosc & Currie, 2011).

Social isolation and loneliness are critical determinants of mental health, with substantial evidence linking them to increased rates of anxiety, depression, and other mental health disorders [(Loades et al., 2020). The ability to travel and engage with others plays a vital role in mitigating these feelings. During significant periods of isolation, such as the COVID-19 lockdowns, the lack of social interactions highlighted the importance of mobility in maintaining mental well-being. Studies have indicated that social support networks and access to transportation are essential for fostering connections and enhancing overall mental health (Delbosc & Currie, 2011; Stanley et al., 2011).

The relationship between the built and natural environments and mental health is multifaceted, with various activity locations playing roles in influencing well-being. Green and blue spaces, for instance, have been shown to alleviate stress, anxiety, and depression, enhancing mood and bolstering cognitive function thus making them vital for enhancing mental health and overall well-being (Pelgrims et al., 2021; Pouso et al., 2021; Rautio et al., 2018; White et al., 2021). Similarly, libraries serve as essential community resources that not only provide access to information and educational materials but also foster a comforting atmosphere and therapeutic landscape that is welcoming, calming, empowering, and overall conducive to well-being (Brewster, 2014; Elia, 2019).

On the other hand, grocery stores and social recreation spaces, such as restaurants and theaters, present a more complex picture. Grocery shopping can induce stress due to factors like time pressure and crowd density, which can negatively impact shopping satisfaction as well as overall mental well-being (Aylott & Mitchell, 1998; Nilsson et al., 2017). In contrast, social recreation spaces offer opportunities for socialization and relaxation, which can enhance well-being by eliciting positive emotions and fostering long-term stress-coping mechanisms (Takiguchi et al., 2022) Researchers found a positive link between leisure satisfaction and well-being over time (Kuykendall et al., 2015)]. However, the quality of social interactions in these environments is crucial; supportive interactions can lead to higher quality of life, while negative interactions can diminish well-being (Yanos et al., 2001).

Moreover, the impact of social deprivation and loneliness on mental health remains a challenge, as individuals may experience loneliness even in crowded environments (Orben et al., 2020). This highlights the intricate interaction between activities in built and natural environments and mental well-being, suggesting that visits to these locations can either bolster or hinder overall mental health, depending on the nature of the interactions experienced.

Research indicates a connection between travel behavior and mental well-being, with studies showing that travel satisfaction significantly impacts social and mental health. For instance, a study by (Syahputri et al., 2022) found that individuals who reported higher travel satisfaction also experienced better mental health outcomes. However, while working or studying from home can enhance travel satisfaction, excessive time spent on obligatory activities may limit social interactions, negatively affecting mental health. Encouraging travel, even amidst significant commitments, can foster better social connections and mental well-being (Syahputri et al., 2022). Additionally, regular commuters often report lower life satisfaction compared to those who work from home, yet general travel experiences are associated with improved mood and overall life satisfaction. These insights underscore the importance of integrating travel into daily routines as a strategy to enhance mental health and well-being, emphasizing that positive travel experiences can lead to significant improvements in emotional health and quality of life (Friman et al., 2017).

Recent research by (Lan et al., 2022) used mobile phone-based sensing to explore the relationship between daily activities, environmental exposures, and anxiety symptoms. By tracking spatial movements through GPS and accelerometers, the study found that time spent in areas with high air pollution and noise was linked to increased anxiety, while exposure to green spaces correlated with lower anxiety levels. This research may have been been limited, however, by only including trips over a 7-day period. It also relied on a self-reported recollection of trips and trip location rather than an observation of where the trips or activities were located.

In spite of the numerous studies linking observed travel patterns to elements of mental health, numerous questions remain unanswered. Of particular importance are two that we hope to address in this research. First, existing studies often fail to control for preexisting or baseline mental health and its impacts on travel behavior; do people with neurotypologies or stressors predisposing them to heightened anxiety or depression **make fewer trips** than others, thus reversing the causality in the observed relationships? Second, regardless of neurotypology or mental health baseline, previous studies have failed to address the direction of causality in a compelling way. What is needed is a long-term observation of mental health indicators alongside travel and activity data on which baselines can be measured and the directionality evaluated.

3. Methodology

To evaluate longitudinal and bi-directional relationships between mental health and travel-activity while controlling for baseline conditions, we develop and analyze a unique dataset derived from a longitudinal study of mental health for a sample of university students, paired with mobile device location data for those students. This section describes the origin of the data, how we processed the data and prepared it for analysis, and the econometric tools we employ in the analysis.

3.1. Study Data

This research analyzed a unique dataset of 88 young adults who expressed suicidal ideation in therapy and subsequently enrolled in the study through the Brigham Young University (BYU) Counseling and Psychology Services (CAPS) program. The enrollment process identified age and sex at birth from medical records. The particpants self-reported their race, sex at birth and preferred gender identity. This final value did not affect our analysis for the limited number of students whose gender identity did not match their sex at birth, and we discarded it from further evaluation. A psychological evaluation measured each participant's intelligence quotient (IQ) and classified the participants into one of three neurotypology groups: those with autism spectrum disorder, those with social anxiety, or a final control group. Table 1 gives a statistical description of the sample organized by neurotypology; The study included 28 individuals in the social anxiety group, 29 in the autism group, and 31 in the control group.

Individuals with autism spectrum disorder (ASD) and those with social anxiety exhibit distinct travel behaviors that impact their daily lives and mental health. We use the term "autistic" as recommended by many self-advocates we know who prefer the identify-first label "autistic" over person-first terminology "individual with autism spectrum disorder (or condition)" (Kenny et al., 2016). Autistic individuals often face challenges in social communication and may rely on others for transportation, leading to missed opportunities and feelings of isolation. Research indicates that they engage in fewer activities, which correlates with lower well-being (Bailey et al., 2020; Deka et al., 2016; Lubin & Feeley, 2016; Ridgway et al., 2024). Similarly, individuals with social anxiety experience significant fear of judgment, resulting in increased social isolation and mobility limitations. They may avoid certain locations or travel only with familiar companions, which can further reduce their activity engagement and decrease their overall well-being (Leichsenring & Leweke, 2017; Öztürk & Mutlu, 2010; Ratering et al., 2024; Ye et al., 2021). Both groups demonstrate unique travel patterns that highlight the need for tailored support and inclusive transportation solutions to enhance their overall well-being.

Participants installed an app on their phones that collected cellular LBS data, with some providing data for one month and others up to a year. There was a one-month gap when no LBS data was collected. In addition to LBS data, the app prompted participants to complete mental health surveys in the mornings and evenings, asking questions like, "Have you felt stressed since your last survey?" "How would you gauge your motivation?" and "Have you thought about killing yourself in the past 12 hours?" Participants were monetarily incentivized to complete the surveys.

By integrating LBS data and survey responses, we can analyze the interaction between travel behavior and mental health, especially in relation to the three groups. Before proceeding with the analysis, we cleaned and processed the data.

3.2. Data Curation

The raw LBS data included each participant's ID (userID), timestamp (date and time), and location coordinates (latitude and longitude). The first step in data cleaning was to prepare the raw LBS data for further analysis by determining the activity day, applying a scoring algorithm, and refining the dataset.

Table 1: Descriptive Statistics by Group: Age, IQ Score, Sex, and Race

		Control (N=31)		Autism (N=29)		Social Anxiety (N=28)	
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Age		22.8	2.7	25.9	4.9	22.8	2.3
IQ		120.2	12.0	122.6	14.1	119.7	11.4
		N	Pct.	N	Pct.	N	Pct.
Sex	Female	23	74.2	20	69.0	22	78.6
	Male	8	25.8	9	31.0	6	21.4
Race	White	25	80.6	26	89.7	27	96.4
	Asian	0	0.0	2	6.9	0	0.0
	Hispanic or Latino	6	19.4	1	3.4	1	3.6

To capture daily travel patterns more accurately, we shifted the traditional 24-hour period (typically ending at 11:59 PM) to span from 3:00 AM to 2:59 AM. This adjustment ensured that any data points between 12:00 AM and 2:59 AM were classified as part of the previous day's travel activities. The data from this adjusted 24-hour window became the "activity day." Since the evening mental health survey closed at 3:00 AM, any surveys taken between 12:00 AM and 3:00 AM were linked to the preceding activity day, aligning travel and mental health data accordingly.

After establishing activity days and categorizing data points, we evaluated the quality and completeness of the LBS data for each combination of userID and activity day. In total, there were 12,051 userID-activity days with varying data quality. We implemented a scoring algorithm that categorized data by userID, activity day, and hour, allowing us to identify high-quality LBS data. The algorithm assigned scores based on the time of day and the number of LBS points recorded, with higher scores given to hours of significant activity and greater LBS point counts. By combining these scores, we calculated a total daily score for each userID-activity day, with a maximum possible score of 168 points. Days scoring 95 points or more were deemed "high scoring," ensuring that only data with sufficient completeness and accuracy was included for further analysis of participants' travel patterns.

The average total daily score was around 70 points, just below the midpoint of the possible score range of 84 points. Notably, 2,965 of the 12,051 userID-activity days had a total score of 0, indicating sporadic and incomplete data collection. The effectiveness of the scoring algorithm in identifying low-quality data highlights its value for data sorting and quality assessment. After applying the 95-point threshold, 4,405 out of 12,051 userID-activity days were retained, meaning approximately 37% had LBS data of sufficient quality for analysis.

After determining the activity days and identifying high-scoring userID-activity days, we streamlined the LBS data by reducing redundancy. The data collection application recorded an LBS data point every second, so we extracted a random sample of 6 LBS points per minute for each high-scoring userID-activity day. This sampling approach was consistent with the optimization used in the DBSCAN-TE algorithm, described in the following section (Macfarlane et al., 2024).

The data cleaning process involved essential steps to ensure dataset quality and integrity. We shifted the 24-hour period to 3:00 AM to 2:59 AM, capturing daily travel more accurately, particularly for activities occurring after midnight. This adjustment aligned with the evening mental health survey closing at 3:00 AM, ensuring consistency in activity day association. We then implemented a scoring algorithm to evaluate the quality and completeness of the LBS data for each userID-activity day combination. High-scoring days, defined as those with scores of 95 points or more, were retained for analysis, leading to a 63% reduction in userID-activity days. These measures refined the dataset, preparing it for subsequent analysis of individual travel behavior and its relationship with mental health outcomes.

3.3. Processing the Data

After preparing the data, we identified 4,405 userID-activity days with sufficient information to implement the DBSCAN-TE algorithm for determining activity locations. This algorithm classifies daily activities by grouping closely packed points into clusters and labeling those clusters as activity locations. The DBSCAN-TE algorithm uses four parameters, which were optimized and applied to the LBS data to identify activity locations for each userID-activity day (Macfarlane et al., 2024; Riches, 2022). Although it was only applied to high-scoring userID-activity days, results were produced for 3,845 out of the 4,405 days.

Once all activity locations were identified, we calculated the total number of activities for each userID-activity day. The average number of activities engaged in each day was 2.65 activities.

In addition to calculating the total number of activities for each userID-activity day, we identified activities that occurred at four specific location types: parks, grocery stores, libraries, and social recreation sites. Using OpenStreetMap data, we created GeoJSON shapefiles for these locations in Utah County and overlaid them with the spatial geometry of activities to determine the number of activities at each specific location type.

To enhance dataset completeness, we implemented an imputation procedure to address missing activity data on certain days, which could result from data collection gaps or quality issues. This process aimed to better align the activity data with completed mental health surveys. Using rolling averages, we estimated missing activity data over various time windows (seven, 14, and 30 days) to capture activity trends. This imputation was applied to total activities and separately for distinct activity types (e.g., parks, grocery stores, libraries, social recreation locations) to account for variations in activity patterns. After applying the rolling averages, we identified 5,673 userID-activity days for the seven-day rolling average, 6,252 for the 14-day rolling average, and 7,130 for the 30-day rolling average.

By calculating rolling averages and imputing missing activity data, the imputation algorithm enhanced the dataset's completeness and reliability, thereby facilitating more robust analyses of activity patterns and their associations with mental health outcomes.

3.4. Additional Travel Parameters

In addition to analyzing the number of activities and their locations, we analyzed other parameters to describe the travel patterns of individuals. These parameters were included because while the accuracy of the DBSCAN-TE algorithm in identifying activities is 91.5% accurate, it is not 100% accurate (Riches, 2022). We noticed some inaccuracy when we examined some of the raw LBS data. Instances appeared where activities seemed apparent but went undetected by the algorithm. These discrepancies prompted a deeper investigation into additional parameters that might shed light on daily travel patterns. However, after analyzing these parameters, we concluded that the DBSCAN-TE algorithm yielded sufficiently robust results, and the additional parameters did not provide any significant new insights.

3.5. Statistical Modeling

We combined semantic activities, travel pattern parameters, and survey responses to create statistical models that explore the relationship between mental health and travel behavior. Using motivation as an indicator of overall mental health and well-being, we analyzed how various factors influenced motivation, as represented in Equation 1

$$\text{Motivation}_{it} \tilde{} \beta(\vec{X}_{it}) \tag{1}$$

We examined a range of models using various variables related to the individuals and their travel behavior. These variables are outlined in Equation 2

$$X = \begin{cases} \text{individual descriptors}_i \\ \text{number of activities}_{it} \\ \text{avg. number of activities}_{i(t-t_7)} \\ \text{activity locations}_{it} \end{cases} \tag{2}$$

For our analysis, we analyzed an ordinary least squares (OLS) model, fixed effects (FE) model, and random effects (RE) model to determine which was the best fit for our data (Wooldridge, 2009). For all three models, the motivation, as reported in the evening surveys on a scale from 0-100, served as the dependent variable. Participants used a drag bar to indicate their motivation on the evening survey, with prompts provided: "0-19 None at all or little motivation", "20-39 Enough motivation to get by", "40-59 Typical motivation", "60-79 Plenty of motivation", and "80-100 Unusually high motivation feeling hyper or even agitated at times". The level of motivation was used as a measure for overall well-being. Additionally, the seven-day rolling average number of activities, as described previously, served as the independent variable for the models. In addition to the model analysis, we accounted for the potential for heteroskedasticity and autocorrelation in the selected models.

3.5.1. Ordinary Least Squares

Daily motivation levels were considered as a function of the seven-day rolling average number of activities described in the previous sections. Using these parameters, a linear regression model was estimated by OLS. Equation 3 shows the base OLS equation where α_i represents the fixed effects in the model, or the time invariant variables

$$\text{Motivation} = \alpha_i + \beta(\text{sev-day avg. no. of acts.}_{it}) + \mu_{it} \tag{3}$$

For linear regressions, it is assumed that the error terms are independently and identically distributed (IID) with a normal distribution of mean 0. The estimates resulting from this model may be inconsistent due to unobserved individual differences (violating the IID assumption). For example, all individuals have a different baseline or typical level of motivation. We want to account for changes in motivation by individual to see how their motivation deviates from its baseline. There are two common econometric techniques, known as FE and RE, that attempt to account for these baseline measures, which are discussed in the following sections.

3.5.2. Fixed Effects

The FE model, also called the within transformation, demeans the data by participant and looks at each participant's levels of motivation and seven-day rolling average number of activities individually. This results in having different intercepts for each participant. Equation 4 shows the base equation for the FE model

$$y_{it} - \bar{y}_i = \beta(x_{it} - \bar{x}_i) + \mu_{it} - \bar{\mu}_i \tag{4}$$

Since α_i from the OLS model is fixed overtime, these unobserved effects disappear in the FE model. In this case, the time constant characteristics are the demographic characteristics of each participant. These variables are absorbed by the intercept as they are unique to each participant.

The FE model is consistent but less efficient because it results in losing degrees of freedom to estimate individual intercepts for each participant. This results in larger standard errors for the estimates which can make it more difficult to recognize significance.

3.5.3. Random Effects

The RE model semi-demeans the data by participant. Based on a mean for the entire group, a mean is determined with a set standard deviation to represent the data of the entire group. The RE model assumes that α_i, the unobserved effect, is uncorrelated with the seven-day rolling average number of activities. λ represents a "transformation that eliminates serial correlation in the errors" (Wooldridge, 2009, pg. 490). Equation 5 shows the base equation for the RE model

$$y_{it} - \lambda\bar{y}_i = \beta_0(1-\lambda) + \beta_1(x_{it1} - \lambda\bar{x}_{i1}) + ... + \beta_k(x_{itk} - \lambda\bar{x}_{ik}) + (\nu_{it} - \lambda\bar{\nu}_i) \tag{5}$$

The RE model is appropriate to use if it is believed that the difference in motivation has an influence on the seven-day rolling average number of activities. It is possible that other variables that influence the seven-day rolling average number of activities are not included which can lead to bias in the model. Unlike the FE model, the RE model is more efficient because degrees of freedom are not lost to more estimates, but the results can be biased.

3.5.4. Autocorrelation and Heteroskedasticity

When analyzing how motivation changes over time for individual people, autocorrelation and heteroskedasticity can arise as statistical challenges. Autocorrelation occurs when observations in a time series are correlated with preceding or succeeding observations, violating the assumption of independence between observations. In the context of studying individual motivation over time, autocorrelation can manifest as a person's motivation level at one point in time being influenced by their motivation level at previous time points. This can lead to biased estimates and inflated significance levels in regression analyses. Heteroskedasticity refers to the unequal variance of errors across observations in a dataset. In the case of studying motivation over time, heteroskedasticity may arise if the variability in motivation levels differs between individuals or varies systematically over time. This violates the assumption of homoscedasticity, where the variance of the errors remains constant across observations.

Autocorrelation and heteroskedasticity can lead to biased parameter estimates or incorrect inference in statistical models. To address these issues, robust measures for standard errors are used. Specifically in our case, Heteroskedasticity and Autocorrelation Consistent (HAC) standard errors can be employed. HAC robust standard errors are particularly useful when dealing with time series or panel data where observations may be correlated across time periods. HAC estimators adjust for heteroskedasticity by allowing the variance of the errors to vary across observations. However, they also account for autocorrelation by incorporating a weighting scheme that considers the correlation structure of the data over time. This weighting scheme assigns higher weights to more recent observations and lower weights to distant observations, reflecting the

Table 2: Activity Descriptive Statistics by Group

	Control (N=1706)		Autism (N=804)		Social Anxiety (N=1893)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
No. of Activities	3.0	2.7	2.1	2.3	2.6	2.7
Sev-Day No. of Acts.	3.0	1.7	2.0	1.4	2.6	1.7

diminishing influence of past observations on current ones.

By adjusting for both heteroskedasticity and autocorrelation, HAC robust standard errors provide more accurate estimates of the standard errors of regression coefficients, ensuring valid statistical inference in the presence of correlated and heteroskedastic data.

4. Results and Discussions

Analyzing travel behavior and mental well-being requires a comprehensive examination of the individual's group. It is important to look at various factors related to how these groups travel and how their travel affects their well-being. Understanding the number and type of activities they engage in, motivational levels, and propensity towards suicidal ideation provides valuable insights for this analysis.

4.1. Activity Engagement by Group

This analysis examined the activity engagement patterns of the three groups: control, autism, and social anxiety. We analyzed the total number of activities and the seven-day rolling average number of activities for individuals in these groups. The descriptive statistics in Table 2 describe these results for each group.

Individuals in the control group engaged in an average of 3.0 activities, while the autism group averaged 2.1, and the social anxiety group averaged 2.6 activities. Standard deviations for the groups ranged from 2.3 to 2.7. A seven-day rolling average of activities showed similar trends but with slightly lower variability.

An ANOVA test revealed significant differences in the mean number of activities between the groups, with an F value of 32.97 and a p-value less than 0.001, indicating that the variation across groups was statistically significant.

After finding significant differences in activity levels among the three groups, a Tukey's Honest Significant Difference (HSD) test identified specific group differences. Individuals in the autism group participated in significantly fewer activities than the control group, with a mean difference of -0.896 ($p < 0.001$), and compared to the social anxiety group, with a mean difference of -0.375 ($p < 0.001$). Similarly, the social anxiety group engaged in fewer activities than the control group, with a mean difference of -0.521 ($p < 0.001$).

These results show significant differences in activity engagement across groups, with individuals with autism and social anxiety participating less than those in the control group. This underscores the importance of considering group differences when analyzing activity patterns and mental health outcomes.

4.2. Motivation by Group

We observed notable differences in well-being among the groups. Based on existing literature, we expected that individuals in the autism and social anxiety groups would report lower well-being compared to the control group. Using motivation as an indicator of well-being, we analyzed motivation levels from the evening survey, rated on a 1-100 scale.

The findings revealed differences in motivation across the groups. The control group had the highest mean motivation score of 47.7, with the lowest variability (standard deviation of 14.2), falling slightly below the middle range of the "typical motivation" category. The autism group had the lowest mean score of 34.0, with the highest variability (standard deviation of 19.4), falling in the "enough motivation to get by" category. The social anxiety group had a mean score of 40.3, falling between the other two groups and on the lowest end of the "typical motivation" category. An ANOVA test confirmed significant differences in motivation levels among the groups, with an F value of 362 and a p-value less than 0.001, indicating that these differences are statistically significant.

After confirming significant differences in motivation levels among the three groups, a Tukey's HSD test was conducted to identify specific group differences. The autism group had a significantly lower mean motivation level than the control group, with a difference of -9.99 points. The social anxiety group also had a significantly lower motivation level compared to the control group, with a difference of -7.74 points. When comparing the autism and social anxiety groups, the social anxiety group had a significantly higher motivation level by 2.25 points. All differences had p-values less than 0.001.

These results highlight significant differences in motivation levels, with the control group showing higher motivation than both the autism and social anxiety groups, and the social anxiety group showing higher motivation than the autism group. This pattern underscores the impact that the group has on an individual's motivation.

4.3. Suicidal Ideation by Group

The morning and evening surveys included different questions pertaining to suicidal ideation. The dataset presents an insightful glimpse into the prevalence of suicidal ideation within the groups, shedding light on

Table 3: OLS, FE, and RE Models

	OLS	FE	RE
Sev-Day No. of Acts.	1.420***	0.287+	0.362*
	(9.057)	(1.691)	(2.174)
No. of Obs.	4,211	4,211	4,211
AIC	35,969.8	34,519.76	34,596.1
R^2	0.021	0.001	0.047

Robust t-statistics in parentheses. + p $<$ 0.1, * p $<$ 0.05, ** p $<$ 0.01, *** p $<$ 0.001

potential differences in mental health concerns among them. We examined responses to the question "Have you thought about killing yourself in the past 12 hours or since you last took a survey?" across the three groups, where responses were "Yes," "No," or "No Response."

In the control group, participants reported no suicidal ideation on 66.4% of days and acknowledged suicidal thoughts on 2.1% of days. In the autism group, 51.6% of days were reported as ideation-free, while 4.9% of days involved suicidal ideation. The social anxiety group showed a different pattern, with no ideation reported on only 38.9% of days and ideation present on 15.6% of days. Some respondents across all groups chose not to answer, indicating the sensitive nature of the question.

A contingency table was constructed to organize the responses ("Yes," "No," or "No Response") by group, and a chi-square test of independence was performed. The test yielded a chi-square statistic of 388.06 with 4 degrees of freedom, and a p-value less than 0.001, indicating a significant association between group and suicidal ideation responses. This suggests that grouptypology influences the likelihood of reporting suicidal ideation, highlighting differences in how individuals from each group experience suicidal thoughts.

4.4. Model Comparison and Evaluation

As discussed previously, we ran three different models to analyze the effect of the seven-day rolling average number of activities on motivation levels. We ran the OLS, FE, and RE models with robust standard errors and t-statistics due to the potential for autocorrelation and heteroskedasticity. The results of these three models are shown in Table 3.

We used the Hausman test to compare the RE and FE models. The test checks whether the RE model estimates are consistent and efficient compared to the FE estimates. The null hypothesis assumes RE estimates are consistent and efficient, while the alternative supports the FE model. With a p-value of 0.0013 (less than 0.05), we reject the null hypothesis, indicating that the RE model is inconsistent. Therefore, the

Table 4: Fixed Effects and Demographics Regression

	Intercept Model
Female	-6.351 (-2.265)*
Age	0.089 (0.192)
IQ Score	-0.058 (-0.617)
Autism	-10.247 (-3.139)**
Social Anxiety	-8.544 (-3.164)**
No. of Obs.	62
Log. Liklihood	-222.022
AIC	458.044
R^2	0.264

t-statistics in parentheses. + p $<$ 0.1, * p $<$ 0.05, ** p $<$ 0.01, *** p $<$ 0.001

FE model is more appropriate and was used for the remainder of the analysis.

4.5. Effect of Demographic Factors on Motivation

Given the Hausman test results, we used the FE model for analyzing activity patterns and mental health data. A limitation of the FE model is its inability to account for time-constant variables. To address this, we performed a linear regression to assess how demographic factors (e.g., sex, age, IQ score, and group) are associated with the intercepts from the FE model. This linear regression is described generally in Equation 6

$$\bar{y}_i\,\tilde{}\,\beta(\vec{X}_{it}) \tag{6}$$

This allows us to understand how the baseline levels of motivation differ across groups. The sex, age, IQ score, and group were the independent variables, and the FE intercept values for each userID served as the dependent variable. The results from this model are shown in Table 4.

The analysis revealed significant findings regarding motivation levels. Being female was associated with a decrease of 6.351 points in motivation compared to males, with a statistically significant p-value less than 0.05. Age and IQ score did not show significant associations. In contrast, individuals with autism had a substantial decrease in motivation of 10.247 points compared to the control group, while those with social anxiety experienced an 8.544 point decrease, both with p-values less than 0.01. These results indicate that sex and group status significantly influence motivation levels, while age and IQ score have limited impact. The model explained approximately 26.4% of the variance in motivation, suggesting that other factors may also contribute. Overall, these findings highlight the importance of considering individual differences, particularly sex and group status, in examining motivation, with a focus on group typology for further exploration.

4.6. Models by Group

After identifying statistical differences in mean motivation, number of activities, and suicidal tendencies across the three groups, we opted to model each group separately. This approach aims to capture the unique characteristics and behaviors within each group, potentially revealing more nuanced relationships between variables and outcomes. Given the need for a FE model to account for individual differences, this method ensures that both observed and unobserved participant characteristics are considered in the analysis. Moving forward, we will employ FE models for each group, allowing us to explore factors influencing motivation while accounting for the distinct attributes of each subgroup.

4.6.1. Motivation and Number of Activities

To visualize the need to look at each group separately and each individually separately, we plotted the number of activities and levels of motivation for all individuals within each group. Figure 1 shows the relationship between motivation and the number of activities by group before taking into account the FE.

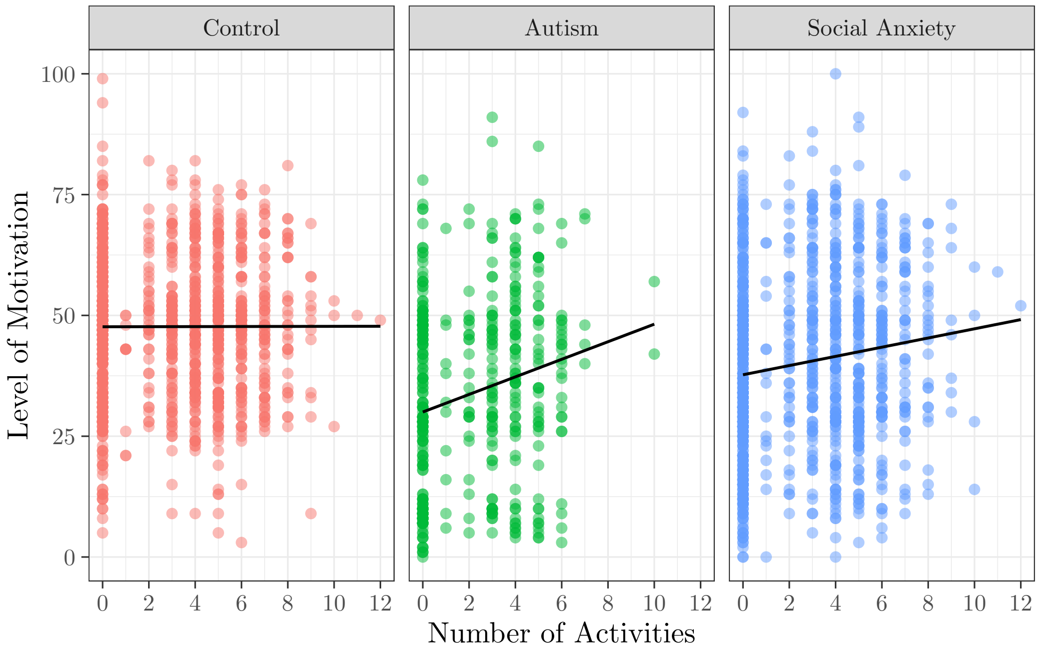

Figure 1: Motivation vs. number of activities for all three groups.

This analysis revealed that, without accounting for FE, there is no significant relationship between the number of activities and motivation in the control group. However, for the autism group, a steep slope indicates that as the number of activities increases, so does motivation. The social anxiety group also shows a positive slope, though less pronounced, suggesting a correlation between increased activities and higher motivation levels. These findings contradict existing literature, which support that motivation in the autism and social anxiety groups should not necessarily rise with more activities, underscoring the importance of using the FE model.

Figure 2 presents plots illustrating the influence of activities on motivation. The dashed pooling line represents the intercept and slope if all data were analyzed together, while the solid lines show individual lines of best fit for each participant. This means each individual has a different intercept, but all share the same slope.

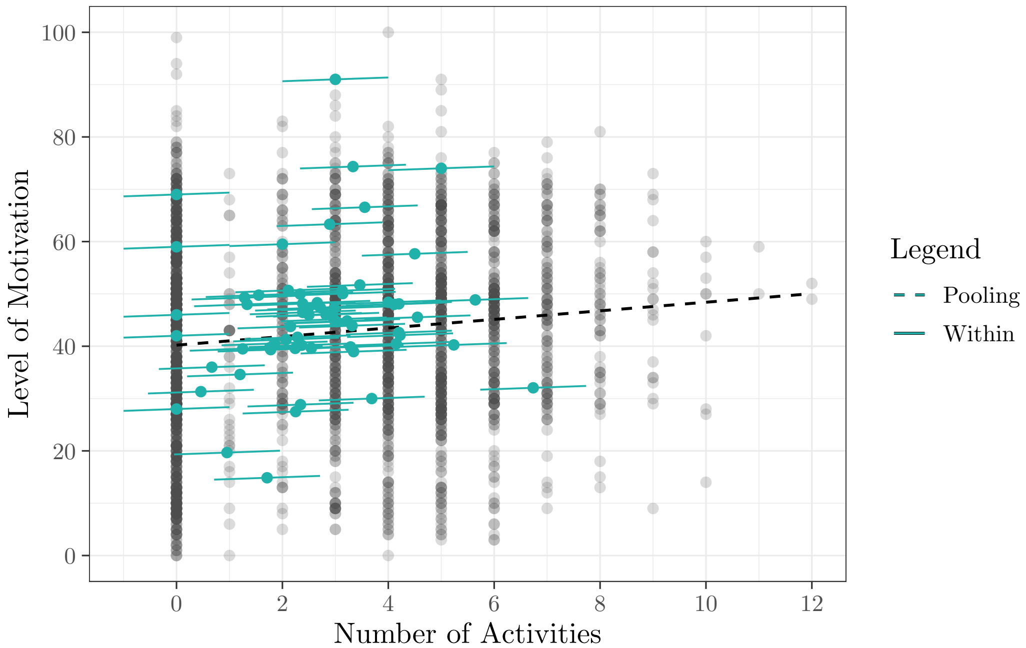

Figure 2: FE model for motivation vs. number of activities for all participants.

While modeling each participant individually is crucial for accounting for varying baseline levels of motivation, we found that applying a FE model to each group—control, autism, and social anxiety—was also important for understanding the true relationship between the number of activities and motivation, as each group may have different baseline levels.

Figure 3 presents the results of the FE models for all three groups. These models predict motivation based on the number of activities while considering both individual and group baseline differences. This approach allows for a more accurate assessment of the impact of activities on motivation within each distinct group. The plots illustrate unique patterns for each group, emphasizing the value of tailored analyses. Notably, the autism and social anxiety groups show steeper slopes when all data are pooled together; however, when individuals are analyzed separately, the slopes for each group are much less steep. These results align more closely with expectations from existing literature.

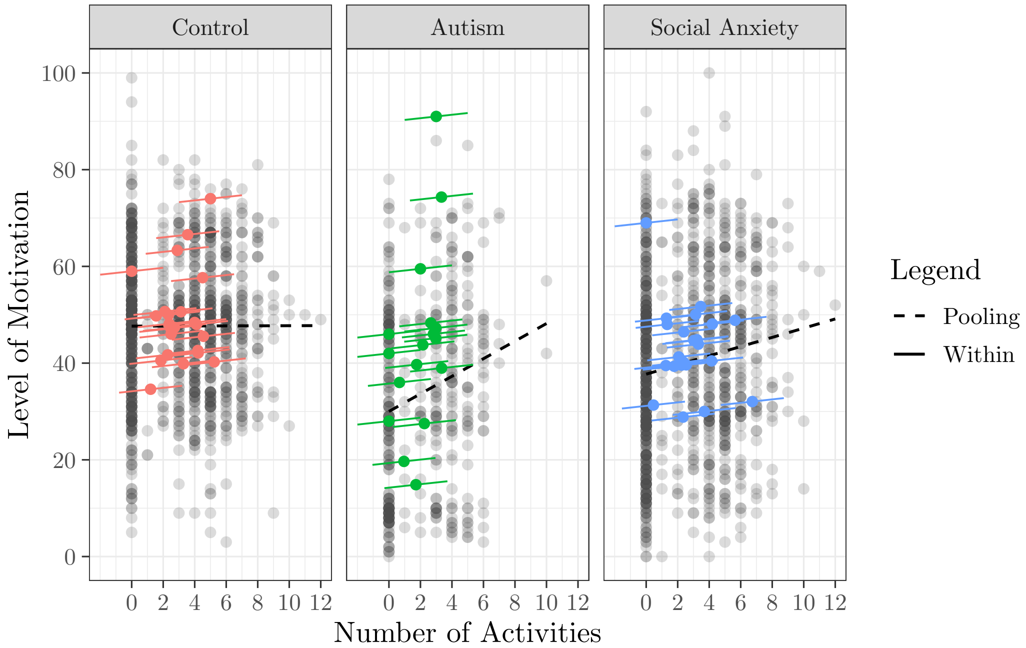

Figure 3: FE model for motivation vs. number of activities by group.

Since the FE models require both an evening survey response for motivation and the number of activities determined by the DBSCAN-TE algorithm, some data were lost. This reduced the sample size from 31 to 23 in the control group, from 29 to 17 in the autism group, and from 28 to 22 in the social anxiety group. The FE models need enough data points for each participant to ensure effective analysis, which explains the reduction in participants. After visualizing the relationships, we proceeded with running the FE models for each group. The results from these models are presented in Table 5.

The FE models for the control, autism, and social anxiety groups revealed different relationships between the number of activities and motivation. For the control group, the coefficient was 0.259, suggesting a marginally positive but not strongly significant relationship. In the autism group, the coefficient was 0.361, also indicating a positive but statistically insignificant relationship between activities and motivation. However, the social anxiety group had a coefficient of 0.483, showing a statistically significant positive relationship. This suggests that increasing activities is notably linked to higher motivation for individuals with social anxiety.

These findings underscore the importance of recognizing individual differences across groups. The significant positive relationship in the social anxiety group suggests that increasing activities could be particularly effective in enhancing motivation for this population. In contrast, the control and autism groups did not

Table 5: FE Models: Motivation and Number of Activities by Group

	Group: Control	Group: Autism	Group: Social Anxiety
No. of Activities	0.259+	0.361	0.483*
	(1.716)	(1.147)	(2.149)
No. of Obs.	1,167	451	1,033
AIC	9,177.454	3,597.049	8,797.231
R^2	0.003	0.003	0.004

Robust t-statistics in parentheses. + p $<$ 0.1, * p $<$ 0.05, ** p $<$ 0.01, *** p $<$ 0.001

Table 6: FE Models: Motivation and Suicidal Intensity by Group

	Group: Autism	Group: Social Anxiety	Group: Control
Suicidal Intesity	-0.095+	-0.160***	-0.361**
	(-1.927)	(-5.518)	(-3.293)
No. of Obs.	484	822	66
AIC	3,942.104	6,934.607	568.685
R^2	0.012	0.04	0.113

Robust t-statistics in parentheses. + p $<$ 0.1, * p $<$ 0.05, ** p $<$ 0.01, *** p $<$ 0.001

show strong evidence of this relationship, indicating that other factors might play a more critical role in influencing motivation for these groups.

4.6.2. Motivation and Suicidal Ideation

The prevalence of suicidal ideation across the groups underscores the complex interplay between mental health and activity engagement. The literature suggests that suicidal behavior is negatively associated with overall well-being (Fonseca-Pedrero et al., 2022; Fumero et al., 2021). Since we connected motivation to well-being, a similar association is drawn between suicidal tendency and motivation.

Based on similar conclusions from the motivation and number of activities analysis, we continued to perform the analysis by group. Table 6 shows the FE models for the impact of suicidal intensity, which was scored from 1-100, on level of motivation, which was also scored from 1-100, for individuals by group.

The FE models for the autism, social anxiety, and control groups show distinct relationships between suicidal intensity and motivation levels. In the autism group, the coefficient for suicidal intensity is -0.095, indicating a marginally significant negative relationship, suggesting that higher suicidal intensity may slightly

Table 7: FE Models: Motivation and Number of Activities at Parks by Group

	Group: Control	Group: Autism	Group: Social Anxiety
Seven-Day Park	3.017*	4.938	1.511
	(2.239)	(0.857)	(0.207)
No. of Obs.	1,840	774	1,597
AIC	14,509.34	6,215.856	13,615.11
R^2	0.002	0.001	0

Robust t-statistics in parentheses. + p $<$ 0.1, * p $<$ 0.05, ** p $<$ 0.01, *** p $<$ 0.001

reduce motivation, though the evidence is weak. In contrast, the social anxiety group shows a coefficient of -0.160, with a statistically significant negative relationship, meaning higher suicidal intensity is strongly linked to decreased motivation. Similarly, the control group's coefficient is -0.361, with a significant negative relationship, showing that increased suicidal intensity is associated with notably lower motivation levels.

These findings emphasize the need to consider the impact of suicidal intensity on motivation within each group. While the relationship is negative across all groups, the varying strength and significance highlight the necessity for tailored interventions to address motivational challenges in each population.

4.7. Activity Types

We examined how the number of activities at different locations—such as parks, grocery stores, libraries, and social recreation spaces—impacts motivation across each group. The analysis factored in activity counts determined by the DBSCAN-TE algorithm, along with seven-day and 14-day moving averages. While all activity locations and measurements were included, only a few yielded statistically significant results. Notably, significant findings emerged for the seven-day average park activities and daily grocery store activities, highlighting their potential influence on individual motivation levels.

4.7.1. Activities at Parks

Table 7 presents the FE models for the seven-day rolling average number of activities at parks for the three groups.

In examining park activities, statistically significant results were observed solely for the control group. A positive correlation emerged, indicating that each additional park activity within a seven-day period corresponded with a 3.017-point increase in motivation score. This suggests that frequent park visits over a week are linked to heightened motivation levels among individuals in the control group. Conversely, the analysis did not unveil any significant correlation between park visits and motivation levels for the autism

Table 8: FE Models: Motivation and Number of Activities at Grocery Stores by Group

	Group: Control	Group: Autism	Group: Social Anxiety
Grocery Store	-2.690+	-2.725***	0.519
	(-1.878)	(-3.721)	(0.614)
No. of Obs.	1,167	451	1,033
AIC	9,178.666	3,598.227	8,801.453
R^2	0.002	0.001	0

Robust t-statistics in parentheses. + p $<$ 0.1, * p $<$ 0.05, ** p $<$ 0.01, *** p $<$ 0.001

and social anxiety groups. This implies that park activities within the examined time frames do not notably affect motivation levels for these groups.

4.7.2. Activities at Grocery Stores

Table 8 presents the FE models for the number of activities at grocery stores for the three groups.

The examination of grocery store visits unveiled intriguing trends across the different groups. Notably, a statistically significant negative correlation was found for the autism group, indicating a decrease in motivation by 2.725 points with each additional grocery store activity ($p < 0.001$). Similarly, the control group exhibited a slight negative correlation ($p < 0.1$), with each additional daily extra grocery store visit reducing motivation by 2.690 points. Conversely, no statistical significance was observed for the social anxiety group. These findings underscore a nuanced connection between grocery store visits and motivation, with notable negative impacts identified in the autism group, while no significant associations were evident in the control and social anxiety groups.

4.7.3. Activity Impact on Motivation

These findings are important because they reveal how activities impact mental well-being differently for individuals with autism, social anxiety, and those without these conditions. For the control group, the positive correlation with seven-day average park visits suggests outdoor activities benefit overall well-being. Conversely, the negative correlation with grocery store visits for the autism group highlights the stress linked to routine tasks like grocery shopping. Understanding these differences is key to designing tailored interventions. For example, promoting park visits could boost well-being in the general population, while reducing stress in grocery environments could aid autistic individuals. The lack of significant results for specific locations in the social anxiety group suggests that overall activity levels, rather than specific locations, may be more crucial to their well-being.

5. Conclusions

This study has provided valuable insights into the complex relationship between travel behavior and mental health among young adults with suicidal ideation. By analyzing LBS data and conducting statistical modeling, we uncovered significant differences in activity engagement, motivation levels, and suicidal ideation across different neurological or physiological groups.

5.1. Overall Implications

In this study, we explored the distinct differences in activity engagement, motivation levels, and suicidal tendencies among individuals in autism, social anxiety, and control groups to better understand the unique challenges these populations face.

The study revealed that autistic individuals and individuals with social anxiety engage in fewer activities compared to the control group, indicating unique challenges in their daily routines and social interactions. It also showed that motivation levels are lower in both the autism and social anxiety groups compared to the control group, highlighting the significant impact these conditions have on personal drive. Specifically, the control group exhibited the highest motivation levels, followed by the autism group, with the social anxiety group having the lowest. Additionally, a correlation was found between increased suicidal intensity and decreased motivation across all groups, with the social anxiety group reporting the highest frequency of suicidal thoughts.

We also identified a minimal positive relationship between the number of activities and motivation, suggesting that simply increasing activity engagement is not enough to significantly enhance motivation. Moreover, a negative relationship between travel distance and motivation was observed, indicating that longer travel distances slightly decrease motivation, though the effect is relatively minor. Ultimately, adjusting either of these aspects of travel would not be a sufficient strategy for significantly boosting motivation for individuals.

Overall, these findings highlight significant differences in activity engagement, motivation levels, and suicidality among individuals with autism, social anxiety, and the control group. They underscore the need for tailored approaches to address the unique challenges faced by each group.

5.2. Group Specific Implications

Different types of activities had varying effects on motivation levels across the groups studied. For individuals with social anxiety, a positive relationship was observed between the number of activities engaged in and their motivation levels, indicating that increased activity participation could enhance their well-being. Conversely, for autistic individuals, there was a negative correlation between grocery store visits and motivation levels, suggesting that grocery store environments may present stressors that adversely affect their well-being. These findings are important as they provide insight into the distinct challenges faced by individuals with social anxiety and autism. Additionally, the strong positive correlation between seven-day average park visits and motivation levels in the control group highlights the beneficial impact of outdoor green-space activities on well-being.

In summary, each group benefits differently from various activities, underscoring the importance of personalized approaches to improving well-being tailored to the specific needs and preferences of individuals in each group.

5.3. Significance

In this research, we explored the critical link between travel behavior and mental health, focusing on young adults with suicidal ideation. By analyzing daily activities and movement patterns, the study highlights the importance of considering these factors in mental health interventions. The contributions of this work bridge the gap between travel behavior and mental health research, emphasizing the need for personalized approaches that take into account the unique challenges faced by individuals with autism and social anxiety.

The study reveals that individuals with autism and social anxiety engage in fewer activities and have lower motivation levels compared to the control group, underscoring the significant impact of these conditions on daily life. Additionally, the correlation between suicidal ideation and decreased motivation across all groups highlights critical areas for intervention and prevention.

The practical implications of these findings are significant. By understanding how travel behavior influences motivation levels and well-being, mental health practitioners can develop targeted strategies to support individuals struggling with mental health challenges. For example, interventions can be tailored to address specific needs related to travel patterns, such as mitigating stressors in grocery store environments for autistic individuals or encouraging activity engagement for those with social anxiety.

Overall, this research underscores the importance of considering travel behavior as a key factor in promoting mental well-being. It offers a roadmap for future studies to explore this intersection further, ultimately aiming to enhance the quality of life for individuals by informing more personalized and effective mental health strategies.

6. Limitations and Future Recommendations

There are some important limitations and future considerations following the analysis of the BYU CAPS data. These limitations are due to potential issues with data collection, lack of activities duration from the DBSCAN-TE algorithm, and the inability to confirm activity engagement for the participants.

6.1. Data Collection

The primary limitation of this study pertains to the quality of the data of the participants. Since participants participated for varying lengths of time and their phones were not always on to collect LBS data, the data was sometimes sparse. Even though a substantial amount of data had to be discarded due to poor quality, influenced by factors such as participants turning off their phones or the app failing to record data accurately, we did our best to accurately account for the well-being and activity patterns of the individuals. The inconsistency in data collection may have made it difficult for the DBSCAN-TE algorithm to perfectly identify activities. While it performed with 91.5% accuracy, some of the activity days that were manually checked appeared to be missing identified activities. Additionally, since the userID-activity days needed corresponding mental health data and activity data, we tried to account for the gaps by imputing the number of activities for a seven-day rolling average number of activities and by calculating the convex hull area and the distance traveled.

To address these limitations in future studies, improving data quality would be paramount. Strategies could include implementing measures to encourage consistent phone usage among participants or enhancing the app's reliability in recording data accurately. Additionally, incorporating redundancy measures within the data collection process, such as cross-referencing data from multiple sources or employing complementary data collection methods, could help mitigate the impact of sporadic data collection. Moreover, refining the DBSCAN-TE algorithm to improve accuracy in identifying activities, potentially through machine learning techniques or incorporating additional contextual information, could enhance the reliability of activity data. By prioritizing efforts to enhance data quality and implementing more robust data collection and processing procedures, future studies can better capture and analyze individuals' mental health and activity patterns, thereby yielding additional findings.

6.2. Activity Duration

The study also lacks detailed information on the duration of participants' activities. While the dataset indicates that certain activities occurred, it does not specify how long participants spent engaging in these activities. For example, we know whether participants visited parks, but not the duration of their stay at the park. This limitation means we cannot accurately assess the impact of time spent in specific environments on mental well-being. Additionally, since the algorithm determined activities based on relatively stationary LBS data, we did not account for instances where participants might have merely passed through green-spaces or parks without spending significant time there. This omission further complicates our understanding of the relationship between activities and mental health. These limitations highlight the challenges in using mobile-based data collection for mental health research.

Future studies could focus on improving the accuracy of location-tracking algorithms, ensuring consistent data collection, and capturing detailed activity duration to provide a more comprehensive understanding of the interaction between travel behavior and mental well-being.

6.3. Activity Diaries

One other potential limitation of our study is the inability to confirm which specific activities individuals participated in throughout the day. While we have identified activities using the DBSCAN-TE algorithm, there is a possibility that certain activities were not accurately identified by the algorithm, leading to their omission from our analysis. This lack of precision could potentially result in some activities going undetected, thereby limiting the comprehensiveness of our activity analysis.

To address this limitation in future research, integrating activity diaries into survey methodology could prove beneficial. By incorporating activity diaries, participants would have the opportunity to provide detailed accounts of their daily activities, including specific locations where these activities took place. This additional information could enhance the completeness and accuracy of our activity analysis, as it would provide valuable insights into the types and locations of activities individuals engage in throughout the day.

6.4. Overall Recommendations

To build on the findings of this study and address its limitations, future research should prioritize the following:

- Enhance Data Collection Methods: Consider using multiple data sources or complementary methods to ensure comprehensive data capture. Invest in refining activity identification algorithms and explore advanced machine learning techniques to improve accuracy and reduce gaps in activity data.

- Capture Detailed Activity Duration: Focus on capturing both activity types and durations by implementing time-tracking features to better understand the impact of activities on mental well-being.

- Implement Participant Activity Diaries: Integrate activity diaries to confirm activity engagement and duration. Enhance the completeness and accuracy of daily activity engagement.

By addressing these recommendations, future studies can improve the quality of data, enhance the accuracy of activity analysis, and provide a more comprehensive understanding of the interplay between activity patterns and mental health.

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