Exploring the Link Between Travel Behavior and Mental Health

Emily K. Youngs[a], Gregory S. Macfarlane[a], Jared A. Nielsen[b]

[a] *Civil and Construction Engineering Department, Brigham Young University, 430 EB, Provo, USA, 84602*

[b] *Psychology Department, Brigham Young University, 1070 KMBL, Provo, USA, 84602*

Abstract

This study explores the link between travel behavior and mental health, focusing on young adults with suicidal ideation. By examining daily activities and movement patterns, the research explores travel-related mental health strategies for individuals. The goal is to inform more personalized mental health strategies to improve quality of life.

Using location-based services (LBS) data collected over time, the study performs a longitudinal analysis of travel patterns and mental well-being across autism, social anxiety, and control groups. Statistical models were used to assess the relationship between suicidality, motivation levels, and travel behavior, as well as activity engagement at different location types. The study used the DBSCAN-TE (density-based spatial clustering of applications with noise, time, and entropy) algorithm to identify activities from LBS data, with additional efforts made to address issues with data quality and missing activity information.

The findings revealed 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. The research highlights the complex interplay between travel behavior, activity engagement, and mental health outcomes, emphasizing the need for tailored interventions based on individual needs.

Limitations include sparse data due to participants disabling phones or app malfunctions, and a lack of detailed activity duration information. All in all, this research sheds light on the complex relationship between travel behavior and mental health among young adults with suicidal ideation. By understanding how travel patterns impact motivation levels and mental well-being, tailored interventions can be developed to support individuals grappling with mental health challenges. Future research should enhance data collection methods to improve reliability and provide more robust insights into the relationship between travel behavior

and mental health.
Keywords: travel behavior, mental health, motivation, suicidality, activity types, DBSCAN-TE

1. Introduction

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). The essence of mental health extends far beyond the absence of illness, encompassing emotional, psychological, and social dimensions essential for holistic well-being. This holistic perspective highlights mental health's pervasive influence on personal relationships, work efficiency, and lifestyle choices, accentuating the need to examine its intersection with individual daily behaviors and choices. The allocation of time and its impact is particularly intriguing, as it closely ties to travel behavior, including both patterns and decisions, related to moving from place to place. These behaviors include trip frequency, destination choices, and daily travel decisions (Timmermans et al., 2003). Understanding the impact of these travel patterns on mental well-being is potentially crucial for empowering individuals to make informed decisions that promote positive mental health outcomes while avoiding behaviors detrimental to well-being.

In this thesis, through comprehensive data analysis and statistical modeling, we aim to uncover insights into how travel behavior impacts motivation levels and mental health across different neurological or psychological groups, exploring variations across autism, social anxiety, and control groups. Significant differences in activity engagement and motivation among individuals in the autism, social anxiety, and control groups underscore the complex interplay between these factors and mental health. Additionally, we investigate the relationship between suicidality, motivation levels, and travel behaviors within these groups. We also examine the impact of engagement in activities at different location types on motivation levels. By investigating this dataset, we aim to illuminate the relationship between various mental health parameters and individuals' daily activity engagement, thereby providing invaluable insights into overall mental wellness. Unraveling the connection between individual travel patterns and mental well-being holds potential in supporting those grappling with mental health challenges.

This thesis explores the connection between mental health and travel behavior patterns currently discussed in the literature. It outlines the methods used to analyze activities and integrate survey responses into a cohesive dataset. Models are then presented to analyze the relationship between mental health and travel behavior. Following this, the discussion focuses on the travel patterns and mental health outcomes across

*Corresponding author
Email addresses: emmykae@byu.edu (Emily K. Youngs), gregmacfarlane@byu.edu (Gregory S. Macfarlane), jarednielsen@byu.edu (Jared A. Nielsen)

the three different groups. Finally, the thesis concludes summarizing the key findings and by offering insights for future research.

2. Literature Review

Mental health and well-being are complex issues influenced by a multitude of factors, including social and environmental elements. Addressing these factors is essential for promoting individual well-being (Barry, 2009). Additionally, travel behavior has been recognized as a significant factor impacting social and mental health (Delbosc & Currie, 2011). In this review, we explore current research on the impacts of built and natural environments, social isolation, travel behavior, and activity types on mental health and well-being. We also examine the well-being and travel behavior of individuals with autism and social anxiety. Ultimately, we integrate these factors to highlight how our research aims to fill an existing gap related to the literature.

2.1. Impacts of Built and Natural Environments

Part of the increase in mental health problems come from factors that limit people's engagement with the world around them since positive mental health coincides with people's ability to access the natural environment. Recent researchers have underscored the therapeutic benefits on mental health of engaging with green and blue spaces, ranging from parks and forests to oceans and rivers, in alleviating stress and anxiety, enhancing mood, and bolstering cognitive function (Pouso et al., 2021; White et al., 2021). Green and blue spaces help support good mental health, but these spaces, the very thing that can help with mental health issues, are often inaccessible. Urbanization, for example, magnifies the predicament by reducing access to these spaces, thereby impeding efforts to foster mental well-being. In addition, the implementation of lockdowns and social distancing measures during COVID-19 further exacerbated this issue by limiting many individuals' interactions with nature, which was one observed major shift in travel patterns (Pouso et al., 2021).

In addition to facilitating access and engagement with the world, the built or urban environment significantly impacts well-being. Researchers in Brussels, Belgium, found that noise pollution, air pollution, and lack of green space were linked to higher levels of depressive symptoms and stress, whereas proximity to green spaces was associated with lower levels of stress and depressive symptoms (Pelgrims et al., 2021). A systematic review of the literature by (Rautio et al., 2018) confirmed these findings, underscoring the relationship between the living environment and depressive mood.

Overall, access to natural spaces within urban areas is crucial for mental well-being. Urban planning should prioritize green and blue spaces to mitigate stress and depressive symptoms associated with urbanization. Balancing development with the preservation of these natural spaces is essential for promoting public mental health.

2.2. Impacts of Social Isolation

Social isolation, or social exclusion, affects individuals' mental health. When looking specifically at the effects of the COVID-19 pandemic, (Loades et al., 2020) focused on the impact of social isolation and loneliness on the mental health of children and adolescents. The authors conducted a rapid systematic review of existing literature on the topic and found that social isolation and loneliness can have a negative impact on mental health, including increased symptoms of anxiety, depression, and post-traumatic stress disorder. (Barry, 2009) reviewed the determinants of positive mental health, emphasizing the importance of social support and social connectedness, a sense of control and autonomy, self-esteem, and meaning and purpose in life. She argues that mental health promotion should focus on building resilience, enhancing positive emotions, and developing skills and competencies to manage adversity. Many of these competencies are related to social interactions and avoiding social isolation (Barry, 2009).

While significant periods of isolation, like during the COVID-19 lockdowns, reduced social interactions, everyday sociality is influenced by one's ability to travel. Researchers in Melbourne, Australia, studied the link between mobility, social exclusion, and well-being. They found that increased mobility improved well-being and reduced social exclusion, positively impacting mental health (Stanley et al., 2011). Another study in Melbourne, Australia, explored how transport disadvantage and social exclusion affect well-being. Using survey data, researchers found that both factors negatively impact well-being, with social exclusion having a stronger effect (Delbosc & Currie, 2011). The ability and choice to make trips affects well-being and mental health of individuals.

Overall, these results suggest that social exclusion and isolation, transport disadvantage, and loneliness can negatively impact individual well-being and mental health. On the other hand, mobility and contact with others can have a positive impact on individual well-being. These findings highlight the importance of social support networks and access to transportation to facilitate social interactions.

2.3. Impacts of Travel Behavior

Research on travel patterns highlights the relationship between travel behavior and individuals' social and mental well-being. (Syahputri et al., 2022) conducted a study in the Bandung Metropolitan area to investigate the effect of travel satisfaction, linked to mental health, and activity travel patterns of household members. This study showed that travel satisfaction is positively correlated with social health and mental health. Individuals who spent more time working or studying at home had higher travel satisfaction, leading to better social and mental health. However, extended time on obligatory activities limited interactions with household members, which negatively affected mental health. Encouraging travel for those with significant commitments can enhance travel satisfaction, social health, and mental health. Additionally, regular daily activity travel patterns with breaks from obligations were linked to improved mental health.

Similarly, another study investigated how travel affects emotional well-being and life satisfaction. The researchers pointed out that those who regularly traveled to work experienced less life satisfaction than those who worked from home. However, the study revealed a positive association between general travel and emotional well-being, indicating that travel experiences contribute to improved mood and life satisfaction. Overall, these findings underscore the importance of integrating travel into daily routines to foster better mental health and overall well-being (Friman et al., 2017).

The reviewed studies highlight the significant influence of travel behavior on social and mental health outcomes. Factors such as travel satisfaction and activity travel patterns of household members play crucial roles in shaping these outcomes. Additionally, positive travel experiences are associated with improved emotional well-being and life satisfaction.

2.4. Impacts of Activity Types

People engage in various types of activities which can impact mental health and overall well-being. For instance, (Takiguchi et al., 2022) found that the types of activities people engage in can significantly affect the extent of positive emotions experienced. By analyzing various activity settings like green spaces, grocery stores, libraries, and social recreation spaces, we aim to uncover the potential benefits and implications of these activity locations on mental health and overall well-being.

2.4.1. Green Spaces

The role of green spaces in enhancing mental well-being has increasingly captured attention, with numerous studies attesting to their beneficial effects across diverse demographics and environments. This section explores the impact of spending time in green spaces on mental health.

Primarily, exposure to nature is consistently correlated with reduced stress, anxiety, and depression levels. For instance, participants who embarked on a 90-minute walk in natural settings exhibited decreased activity in the subgenual prefrontal cortex—a region linked to rumination and heightened mental health risks—compared to urban walkers (Bratman et al., 2015). Similarly, a meta-analysis of 25 studies indicated that natural environments positively influenced overall mental well-being, indicated predominantly through participants' self-reported emotional states (Bowler et al., 2010).

Long-term exposure to green spaces also yielded positive mental health outcomes. Research by (Gascon et al., 2018) revealed lower anxiety and depression levels in adults residing near green and blue spaces. Similarly, participants perceiving significant greenery in their neighborhoods exhibited notably better physical and mental health outcomes (Sugiyama et al., 2008). Furthermore, another study found that living in areas with increased green space concentration was correlated with lower salivary cortisol levels, indicative of reduced stress (Roe et al., 2013). Time spent in green spaces is associated with reduced levels of stress, anxiety, and depression.

While the relationship between green spaces and mental health is intricate, recent studies uniformly advocate for their positive influence. In sum, exposure to green spaces alleviates stress, anxiety, and depression, rendering them a promising avenue for enhancing mental health and overall well-being.

2.4.2. Grocery Stores

Supermarkets and grocery stores are integral to modern life, serving as essential hubs for purchasing food and household necessities. However, the experience of shopping in these environments can influence individuals' mental well-being. This section aims to investigate the effects of time spent in grocery stores on mental health.

A study surveyed 239 volunteers across 29 focus groups, exploring stress in the context of grocery shopping. Participants expressed stress related to time pressure, crowd density, employee attitudes, and store layout, as well as environmental factors such as music and lighting, and product availability (Aylott & Mitchell, 1998). No quantitative data were gathered and stress was not measured before or after spending time grocery shopping - these were just stresses that participants expressed experiencing while grocery shopping. While this study is from 1998, it sheds light on the stress experienced in the context of grocery shopping and shows that stress while grocery shopping is not a new issue.

As previously mentioned, time pressure experienced at grocery stores can induce stress. In one study, 1,023 participants responded to a questionnaire about grocery shopping and shopping satisfaction, specifically addressing how shopping satisfaction related to time pressure. Researchers found that time pressure had varying effects on satisfaction depending on whether it was a major shopping trip or a quick shopping trip for a few items. They found that overall, women were less satisfied with their shopping experience when under time pressure and men were satisfied with their shopping experience when under time pressure. Overall, time pressure had a negative impact on shopping satisfaction, although other factors also influenced customer experiences (Nilsson et al., 2017).

2.4.3. Libraries

Libraries serve as indispensable community resources, providing access to information, educational materials, and spaces for learning and social interaction. Beyond their traditional roles, libraries have increasingly been acknowledged for their potential to positively impact mental health and well-being. This section seeks to explore the diverse ways in which libraries can influence mental health outcomes.

Existing literature strongly supports the notion that libraries promote positive mental health and well-being. One literature review highlighted the mental health support offered by many libraries, noting the comforting atmosphere provided to patrons, often attributed to the supportive library staff (Elia, 2019). Similarly, another study described public libraries as offering a therapeutic landscape that is welcoming, comforting, calming, empowering, and overall conducive to well-being (Brewster, 2014).

Moreover, libraries often offer specialized programs and services aimed at promoting mental health and well-being. For instance, they may host mental health workshops, employ social workers, or introduce therapy dog programs to provide emotional support and coping strategies for patrons facing mental health challenges (Elia, 2019). Some libraries even have employees trained in bibliotherapy, a therapeutic approach that uses books and literature to support mental health outcomes. A systematic literature review synthesized evidence on bibliotherapy services at public libraries, revealing its effectiveness in aiding individuals with anxiety, stress, depression, and other issues (Zanal Abidin et al., 2023). This coupling of access to literature with trained bibliotherapy professionals enhances mental health outcomes for library patrons.

In sum, libraries play a multifaceted role in promoting mental health and well-being through resource accessibility, community engagement, and supportive environments. Their positive impact on individuals' mental health outcomes is evident in the literature.

2.4.4. Social Recreation

Social recreation spaces, such as restaurants, theaters, malls, and leisure spots, play a significant role in providing opportunities for socialization, relaxation, and entertainment. Despite their ubiquity, the impact of time spent in these environments on mental health is complex. This section explores the effects of social recreation spaces on mental health outcomes, drawing insights from recent research.

Leisure activities, which individuals choose to engage in when free from obligations, enhance well-being by eliciting positive emotions and fostering long-term stress-coping mechanisms (Takiguchi et al., 2022). Longitudinal studies support the positive link between leisure satisfaction and well-being over time (Kuykendall et al., 2015). However, the quality of social interactions within these spaces can significantly affect individuals' well-being. A study found that negative interactions were linked to lower quality of life, while supportive interactions corresponded with higher quality of life(Yanos et al., 2001). This highlights the importance of social interaction dynamics in shaping well-being.

Furthermore, limited research exists on the impact of social deprivation or isolation on adolescents and adults. Self-reported loneliness is linked to mental health issues, but disentangling the causal relationship between loneliness and mental well-being remains challenging. It is often unclear whether loneliness causes poor mental health or vice versa. Experimental studies on human loneliness face hurdles, as loneliness is not solely due to social deprivation as some individuals feel lonely even in crowded environments (Orben et al., 2020).

Social recreation spaces have a multifaceted influence on mental health outcomes, offering platforms for social interaction and stress alleviation while harboring potential risk factors contingent upon the nature of these interactions. The intricate interplay between activities in these environments and mental well-being suggests that visits to social recreation locations may either bolster or diminish overall well-being, contingent upon the nature of social interactions experienced therein.

2.5. Neurological and Psychological Typology

Navigating the intersection between mental health and travel behavior unveils a complex relationship that significantly influences individuals' daily lives. In this section, we look at the relationship between specific neurological and psychological conditions—autism spectrum disorder (ASD) and social anxiety—and their corresponding impacts on travel behaviors and overall well-being. Through recent research, we explore how autistic individuals and individuals with social anxiety navigate transportation challenges, revealing unique patterns that shape their mobility and mental health outcomes.

2.5.1. Autism

ASD, commonly referred to as autism, presents as a lifelong neurodevelopmental condition characterized by challenges in social communication and social interaction. In addition, autistic individuals tend to engage in restricted and repetitive behaviors. 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). Although typically diagnosed in early childhood, many autistic individuals may remain undiagnosed until later in life (Ridgway et al., 2024). Research comparing the well-being of autistic and non-autistic individuals highlighted significant disparities, with autistic individuals often exhibiting lower levels of well-being, particularly evident among college students who grapple with challenges in social connectivity and balancing academic demands (Bailey et al., 2020; Ridgway et al., 2024).

Despite its prevalence in many fields, autism remains relatively underexplored in transportation literature, with existing transportation surveys failing to neurologically categorize individuals. Recent studies have begun to address this gap, shedding light on the travel behaviors and experiences of autistic individuals. Surveys conducted among autistic adults in New Jersey underscored their reliance on others for transportation, often resulting in missed opportunities due to the unavailability of rides. Moreover, firsthand accounts from autistic individuals and their caregivers highlight feelings of isolation and depression stemming from transportation-related struggles (Deka et al., 2016; Lubin & Feeley, 2016).

These findings collectively suggest a potential link between lower well-being and less activity engagement illustrated by travel behaviors among autistic individuals, emphasizing the need for tailored support and inclusive transportation systems.

2.5.2. Social Anxiety

Social anxiety involves an overwhelming fear of embarrassment or rejection from others and refers to the anxiety stemming from anticipated or real interpersonal judgement in social situations. These fears and anxieties tend to lead socially anxious people to be more socially isolated than others (Leichsenring & Leweke, 2017; Öztürk & Mutlu, 2010; Ye et al., 2021). Frequently mistaken for shyness, social anxiety remains underrecognized, with a lifetime prevalence of 13% and a 12-month prevalence of 8% among adults and adolescents in the United States (Leichsenring & Leweke, 2017).

Two studies examining the relationship between social anxiety and well-being found a negative correlation between the two variables. These studies looked at social anxiety experienced by participants, and not necessarily at participants who have social anxiety disorder, which is a persistent state of social anxiety that can cause major impacts or changes in one's daily life (Leichsenring & Leweke, 2017). In one study, (Öztürk & Mutlu, 2010) investigated the correlation between social anxiety and well-being among university students. They observed that higher levels of social anxiety were associated with lower overall well-being. Similarly, (Ye et al., 2021) found a significant negative correlation between social anxiety and well-being among Chinese college students.

When considering the impact of anxiety disorders on travel patterns, (Ratering et al., 2024) studied the travel behavior of 40 Dutch adults diagnosed with anxiety disorders. They noted that individuals with anxiety disorders, including social anxiety, often faced mobility limitations due to anxiety-related concerns. Participants in the study used coping mechanisms such as traveling with familiar companions, avoiding certain locations, or staying at home altogether (Ratering et al., 2024).

Overall, heightened social anxiety is associated with reduced well-being and may prompt individuals to modify their travel behaviors, potentially resulting in fewer trips and less activity engagement.

2.6. Current State of the Research

Recently, a research group used mobile phone-based sensing to study daily activities and environmental exposures in relation to anxiety symptoms. (Lan et al., 2022) explored how individuals' activities in different environmental settings contributed to anxiety levels, using cross-sectional data from mobile phone sensors like global position services (GPS) and accelerometers to track spatial movements and activity patterns. Anxiety symptoms were measured with a standardized questionnaire, and environmental exposures such as air pollution, noise, and green space availability were assessed.

The study found that time spent in areas with higher air pollution and noise was associated with increased anxiety, while time in green spaces was linked to lower anxiety symptoms. Physical activity and social interactions in various environments also correlated with reduced anxiety. This study began to explore how individuals' travel can affect anxiety symptoms, but this study had limitations. GPS data were collected over a seven-day period, with anxiety levels assessed using a single questionnaire asking participants to reflect on the past two weeks. The study tracked exposure to various areas but did not pinpoint where specific activities occurred. Additionally, participants were not categorized into specific groups based on neurological or psychological conditions.

To address these gaps, this thesis takes a longitudinal approach, collecting location-based services (LBS) data from participants over one month to a year. Participants completed mental health surveys up to twice daily, allowing for more detailed and frequent assessments of mental health in relation to daily travel habits. Unlike the previous study, we identifed and analyzed specific activities rather than just GPS trajectories, ensuring accurate identification of where activities occurred. Furthermore, participants were categorized into groups—autism, social anxiety, and control—based on psychological evaluations. This approach enables a deeper analysis of travel behavior and mental health across different population segments, providing insights that can inform more targeted interventions.

2.7. Summary

Overall, this literature review examines various factors impacting mental health and well-being, focusing on the built and natural environments, social isolation, travel behavior, activity types, and the unique challenges faced by autistic individuals or those with social anxiety.

Access to green and blue spaces is crucial for mental health, as they help reduce stress and improve mood. However, urbanization and COVID-19 restrictions have limited access, worsening mental health issues. High pollution and lack of green spaces in urban areas are linked to increased stress and depression. Social isolation, exacerbated by the pandemic, has heightened anxiety and depression. Mobility and social support are key to mitigating these effects, making transportation access and social interactions essential. Positive travel experiences and regular travel are associated with better mental health. Green spaces significantly reduce stress, while grocery shopping can be stressful. Libraries and social recreation areas support well-being, whereas individuals with autism and social anxiety face unique travel challenges, leading to isolation and limited mobility.

Recent studies using mobile phone-based sensing have explored the relationship between environmental exposures, activities, and anxiety. This thesis addresses gaps by using longitudinal data to assess mental health impacts of travel behavior across three groups of individuals, aiming to understand the link between travel behavior and mental health.

3. Methodology

To explore the relationship between travel behavior and mental health, the data was cleaned, processed, and analyzed. This involved assessing data quality, ensuring integrity, and using the DBSCAN-TE algorithm to identify activities. Various statistical models were then applied to examine the connection between travel behavior and mental health. This section outlines the research methods used to study the correlation between travel behavior and mental health in young adults with suicidal ideation.

3.1. Study Data

This research analyzed a unique dataset of 88 young adults in Utah County who expressed suicidal ideation in therapy, as part of a study conducted by Brigham Young University's (BYU) Counseling and Psychology Services (CAPS). Participants were divided into four groups based on psychological evaluation: autism, social anxiety, control, or no group. The no-group participants initially believed they belonged to the autism or social anxiety groups, but after evaluation, they were reclassified and combined with the control group. The study included 28 individuals in the social anxiety group, 29 in the autism group, and 31 in the control group. Descriptive statistics such as age, IQ, sex, and race are provided in Table 1. The average participant was 23.8 years old, with an average IQ of 120.8, and the autism group had the highest average age and IQ. The sample included 65 individuals assigned female at birth and 23 assigned male at birth, with a similar gender distribution across the groups. Most participants were White, but Hispanic or Latino and Asian individuals were also represented.

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.

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

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. Cleaning the Data

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.

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. To assess this, the data was grouped by userID, activity day, and hour of the day, and a scoring algorithm was applied. This algorithm identified userID-activity days that have a high score, indicating a sufficient quantity and distribution of LBS data points. The scoring mechanism is based on two factors: the hour of the day and the number of LBS points recorded in that hour. For hours between 8:00 AM and 11:59 PM—when significant activity was more likely—a score of 3 was assigned, while for all other hours, a score of 1 was assigned. This aspect of the scoring algorithm is described in Equation 1 where H_t is the hourly score and t is the hour of the day

$$H_t = \begin{cases} 3 & \text{if } 8 \leq t \leq 23 \\ 1 & \text{otherwise} \end{cases} \tag{1}$$

The algorithm also adjusted the overall score based on the number of LBS points recorded within each hour, categorizing each hour into tiers and assigning corresponding scores. The tiers were defined as follows: hours with fewer than 500 points received a score of 0; hours with 500 to 1500 points received a score of 1; hours with 1500 to 2500 points received a score of 2; and hours with over 2500 points received a score of 3. This aspect of the scoring algorithm is described in Equation 2 where P_t is the hourly LBS score and where LBS_t is the number of LBS points in that hour

$$P_t = \begin{cases} 0 & \text{if } \mathrm{LBS}_t < 500 \\ 1 & \text{if } 500 \leq \mathrm{LBS}_t < 1500 \\ 2 & \text{if } 1500 \leq \mathrm{LBS}_t < 2500 \\ 3 & \text{if } \mathrm{LBS}_t \geq 2500 \end{cases} \tag{2}$$

To determine the combined score for each hour, the score based on the hour of the day and the score based on the number of LBS points were multiplied together. Equation 3 describes this step and S_t is the combined score for the given hour

$$S_t = H_t \times P_t \tag{3}$$

Then to determine the final score of the activity day, the scores for each hour of the day were summed to determine the total daily score for the activity day. Equation 4 shows this step in the calculation and S_{day} is the total daily score. The S_{day} is for the activity day which is from 3:00 AM to 2:59 AM, as previously described

$$S_{\text{day}} = \sum_{t=3}^{2} S_t \tag{4}$$

The scoring algorithm assigned a maximum possible score of 168 points for an activity day. By summing the daily scores and selecting high-scoring days, the algorithm provided a comprehensive assessment of the quality of LBS points for each userID-activity day combination. A “high scoring” day was defined as having a score of 95 points or more, ensuring that only sufficiently complete and accurate data was retained for further analysis of participants’ trip patterns.

Figure 1 shows the distribution of daily scores across all userID-activity days, with an average total daily score of 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.

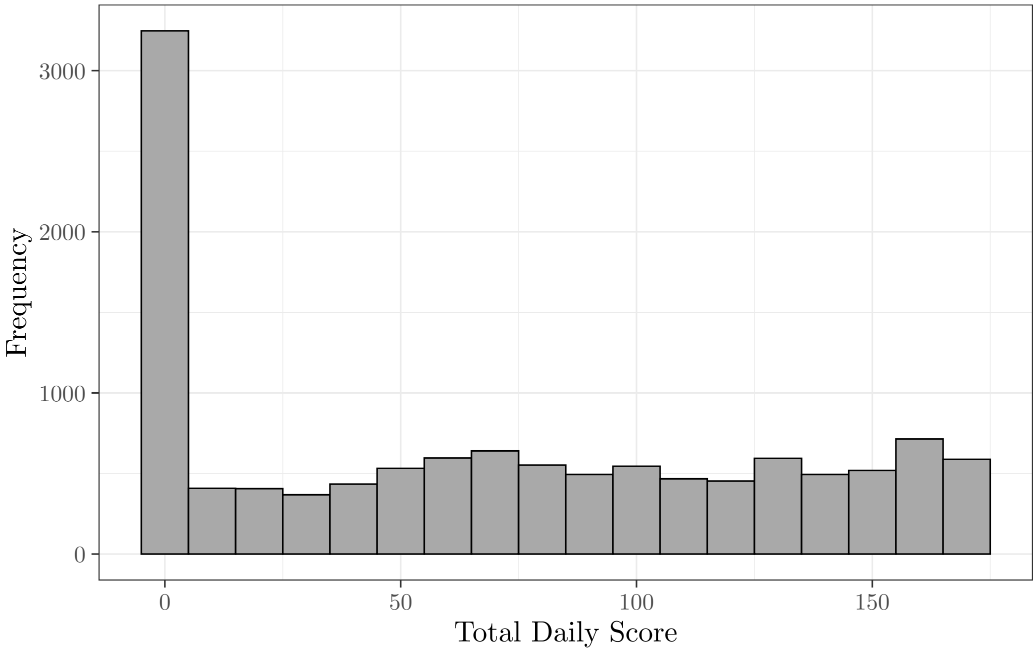

Figure 1: Distribution of scores for all userID-activity days.

To illustrate the quality of LBS data, we plotted the number of LBS points for four random userID-activity days by hour, as shown in Figure 2. This visualization, combined with the scores from the algorithm, provides valuable insights into data quality assessment. These randomly selected days showcase the spectrum of data quality within our LBS dataset.

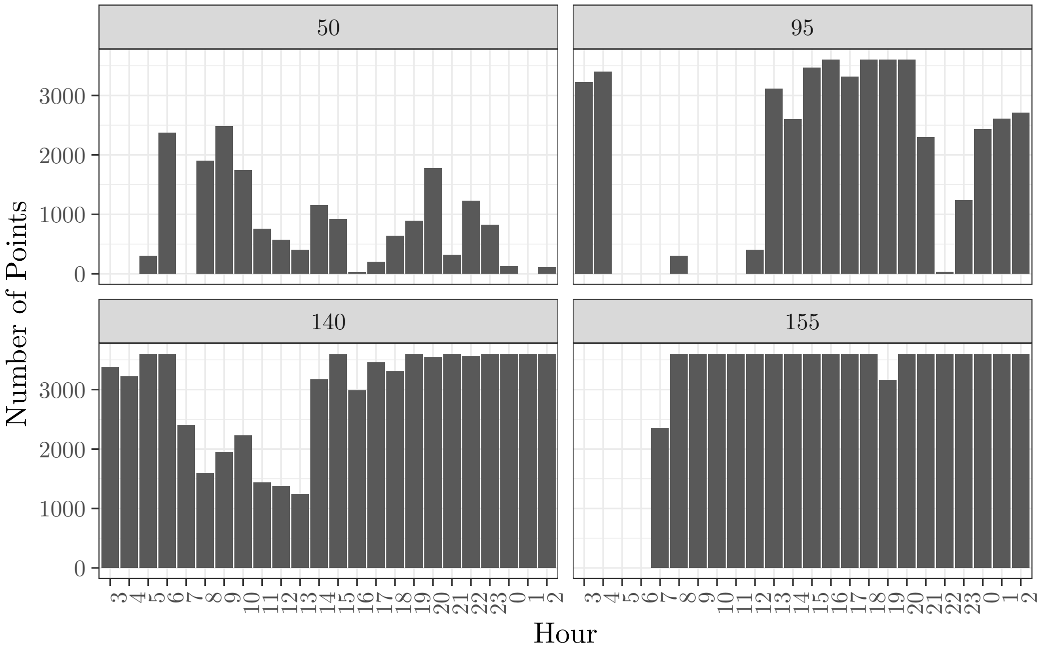

Figure 2: Examples of daily LBS data for differently scored userID-activity days.

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 distribution of the number of activities for the 3,845 userID-activity days is shown in Figure 3, with an average of 2.65 activities engaged in each day.

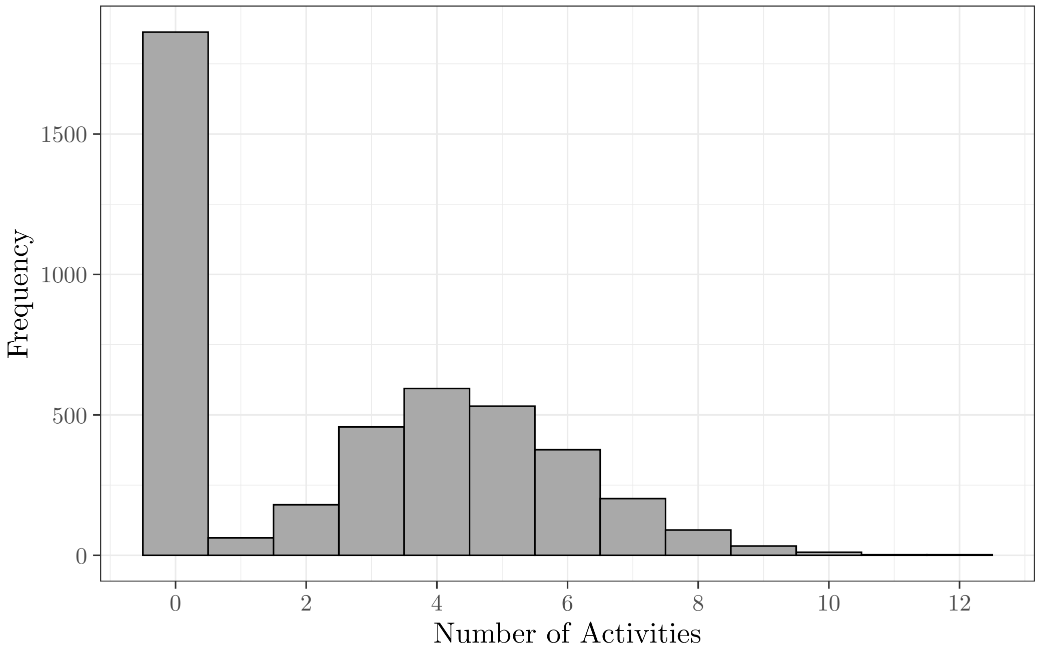

Figure 3: Distribution of activities per day for all userID-activity days.

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 executed 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.

Figure 4 show the distribution of activities for the seven-day rolling average, as an example.

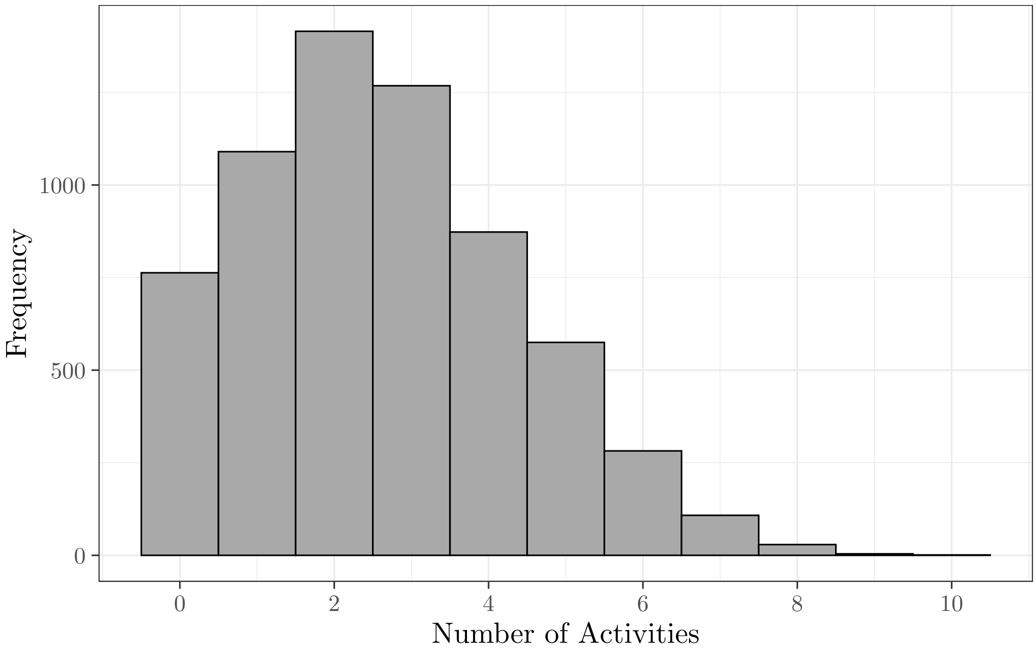

Figure 4: Distribution of seven-day rolling average number of activities for all userID-activity days.

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 5

$$\text{Motivation}_{it} \tilde{} \beta(\vec{X}_{it}) \tag{5}$$

We examined a range of models using various variables related to the individuals and their travel behavior. These variables are outlined in Equation 6

$$X = \begin{cases} \text{individual descriptors}_i \\ \text{number of activities}_{it} \\ \text{avg. number of activities}_{i(t-t_7)} \\ \text{activity locations}_{it} \end{cases} \tag{6}$$

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 7 shows the base OLS equation where α_i represents the fixed effects in the model, or the time invariant variables

$$\text{Motivation} = \alpha_i + \beta(\text{sev-day avg. no. of acts.}_{it}) + \mu_{it} \tag{7}$$

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 8 shows the base equation for the FE model

$$y_{it} - \bar{y}_i = \beta(x_{it} - \bar{x}_i) + \mu_{it} - \bar{\mu}_i \tag{8}$$

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 9 shows the base equation for the RE model

$$y_{it} - \lambda\bar{y}_i = \beta_0(1-\lambda) + \beta_1(x_{it1} - \lambda\bar{x}_{i1}) + ... + \beta_k(x_{itk} - \lambda\bar{x}_{ik}) + (\nu_{it} - \lambda\bar{\nu}_i) \tag{9}$$

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 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

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

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. Figure 5 displays the mean activities and 95% confidence intervals for group differences.

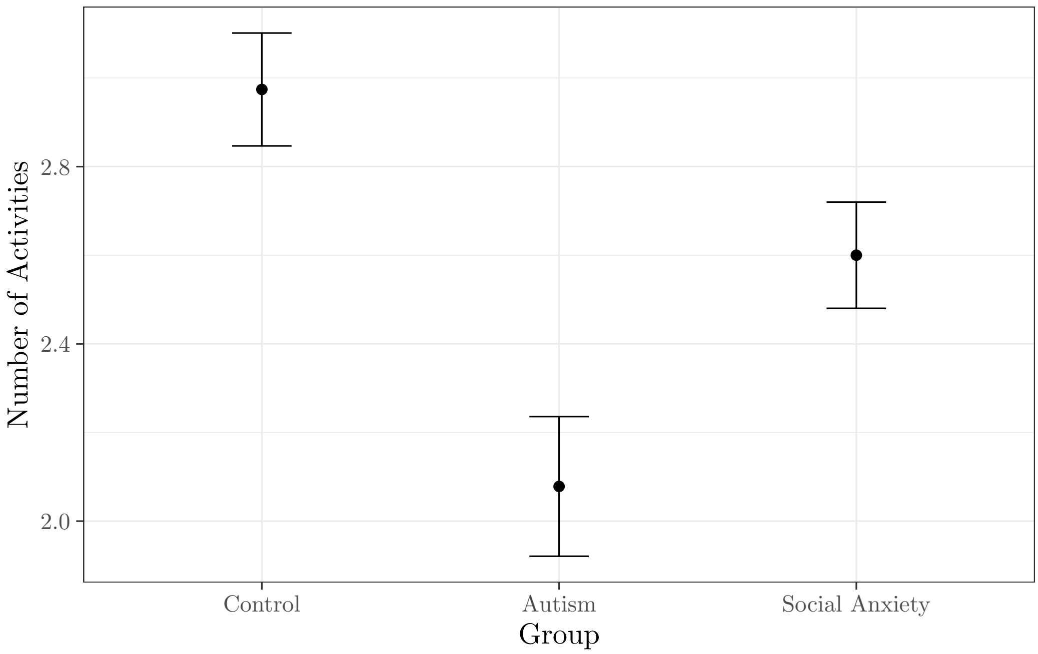

Figure 5: Mean number of activities by group.

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 <

Table 3: Motivation Levels by Group

	Control (N=1706)		Autism (N=804)		Social Anxiety (N=1893)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Motivation	47.7	14.2	34.0	19.4	40.3	18.5

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. Table 3 presents the mean and standard deviation of motivation for each group.

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

Table 4: Suicidal Ideation by Group

		Control (N=1706)		Autism (N=804)		Social Anxiety (N=1893)	
		N	Pct.	N	Pct.	N	Pct.
Suicidal Ideation	Yes	36	2.1	39	4.9	296	15.6
	No	1133	66.4	415	51.6	737	38.9
	No Response	537	31.5	350	43.5	860	45.4

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 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." The responses to this question are summarized by group in Table 4.

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 5.

Table 5: 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

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 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 10

$$\bar{y}_i \tilde{\ } \beta(\vec{X}_{it}) \tag{10}$$

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 6.

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.

Table 6: 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

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 6 shows the relationship between motivation and the number of activities by group before taking into account the FE.

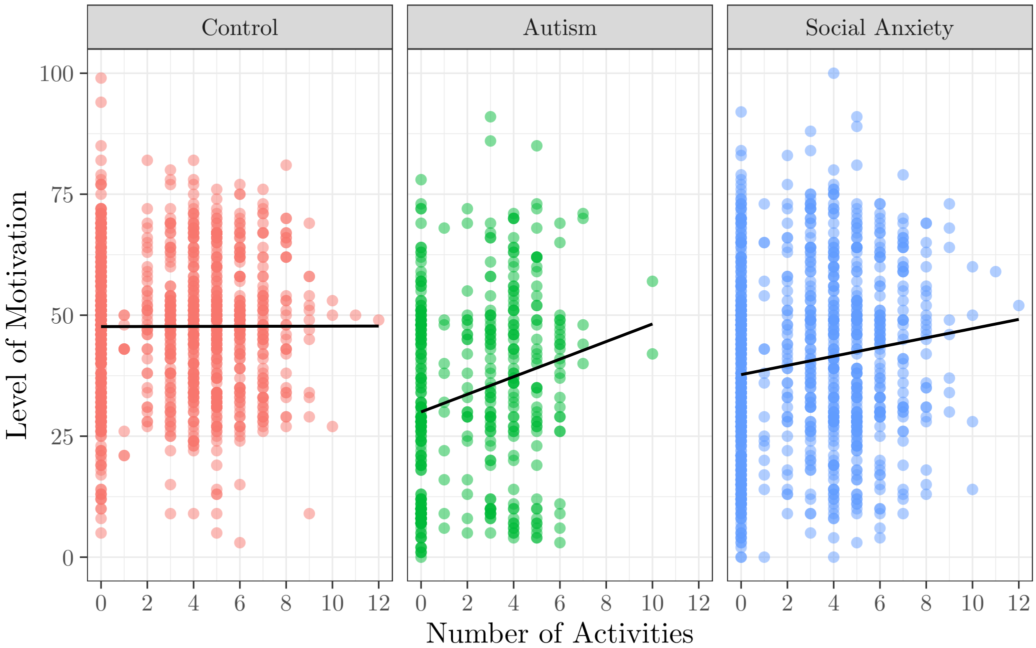

Figure 6: Motivation vs. number of activities for all three groups.

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 7 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.

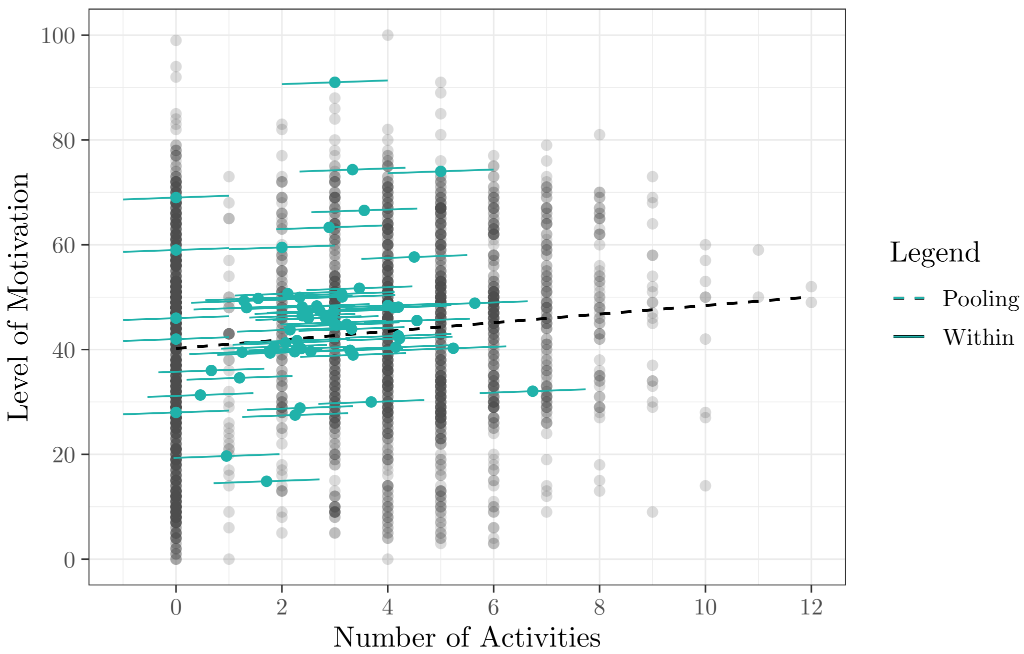

Figure 7: FE model for motivation vs. number of activities for all participants.

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 8 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.

Table 7: 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

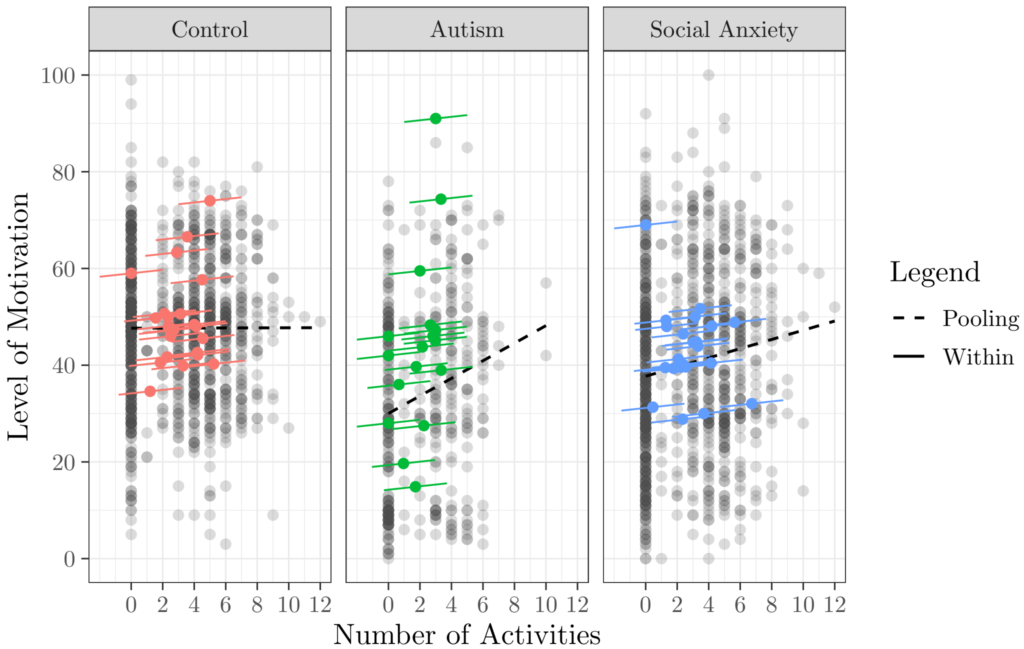

Figure 8: FE model for motivation vs. number of activities by group.

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 7.

The FE models for the control, autism, and social anxiety groups revealed different relationships be-

Table 8: 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

tween 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 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 8 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 9: 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 9 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 10: 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 10 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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