Introduction

This study was conducted within the context of a minor program titled *Sustainable Well-being in a Technological Society.* The program offers students a range of evidence-based practices aimed at enhancing well-being, resilience, and self-awareness. Students are also required to partake in research to evaluate the effectiveness of these practices, both for personal development and as a contribution to a broader understanding of well-being in academic settings.

The program includes lectures on well-being measurement, mindfulness sessions, and peer-to-peer (P2P) support groups. Generally, mindfulness practices have been shown to improve mental health, including reduced stress, increased focus, and greater emotional regulation (1; 2). Similarly, peer support through P2P groups has been associated with enhanced social connectedness and well-being (3). These components contribute to an approach to student well-being, grounded in both theoretical and practical applications.

This study uses a single-case experimental design (SCED) framework to capture the effects of these interventions on a single participant's well-being, namely me. SCED is often used in applied research to watch changes in individuals over time, especially in response to interventions (4). By repeatedly measuring an individual's response to interventions on a time-based manner, SCED allows for an analysis of changes (in metrics) within specific conditions (e.g., baseline, intervention). This method provides insights that may be obscured in group analyses, offering a nuanced understanding of how practices like mindfulness and P2P support can impact personal well-being. SCED's also has an emphasis on within-condition analysis, making it a valuable approach for this study.

This study applies an Experience Sampling Method (ESM), which is related to the SCED framework to capture real-time data on subjective well-being. The use of ESM allows for detailed and semi-frequent measurements, providing insights into how well-being changes in response to specific practices experienced during the study period. By participating in this minor program, students, like myself, gain firsthand experience with ESM as both a research method and a personal reflective tool, contributing data on the effect of mindfulness and P2P-group interventions in an academic setting.

Methodology

This study utilizes a single-case design with myself as the sole participant, spanning the period from September 19th to October 27th. Data collection occurred three times per week on pre-specified days (Tuesdays, Thursdays, and Sundays) at 21:00. During each of these sessions, I responded to a set of five questions targeting different aspects of well-being, specifically: Mood, Stress, Movement, Work-Life Balance, and Productivity.

The questions were presented in a Likert scale format (5), with responses converted into a standardized coding system designed to represent baseline values for easier comparison. A score of 0 indicates baseline, while -2 represents a decrease relative to baseline (e.g., increased stress or decreased productivity), and +2 indicates an improvement (e.g., reduced stress or enhanced productivity). This encoding standardizes results across categories, facilitating comparisons across dimensions of well-being.

Additionally, as part of the study, I attended two structured sessions: an 1.5-hour mindfulness session and an 1.5-hour P2P group meeting with fellow students participating in a similar study. The mindfulness session was aimed at increasing physical awareness and reducing stress, while the P2P meeting provided a social and targeted for sharing experiences and insights among participants. These sessions served as interventions to cause potential shifts in well-being metrics in the days following each meeting.

Furthermore, the data for this study was analyzed using a Jupyter Notebook, an interactive environment that allows for detailed data exploration, visualization, and documentation in a single platform (6). The notebook containing the full analysis is available on my GitHub repository (7), allowing for reproducibility and transparency in data handling and visualization techniques. Following a systematic approach similar to the SCED within-condition method as outlined by Lane and Gast (4), a structured, methodological assessment was employed to interpret the results. This method uses detailed trend analysis and an adaptation of the within-condition method, which is well-suited to single-case designs.

In this study, only one condition (continuous well-being tracking) was recorded, where the baseline would 0. To analyze trends and stability, we adapted within-condition analysis methods to focus changes within a single state, assessing stability, level changes, and trend consistency over time. This adaptation allows for a structured understanding of the natural variations in well-being metrics.

Results

In the study methodology, the baseline was set at 0, representing a pre-intervention state with count 1 across all metrics. Following the intervention, the B group had 17 measurements across five well-being metrics, allowing for a comprehensive descriptive analysis. Table 1 presents these descriptive statistics, including key information such as the mean, median, and range (minimum and maximum values) for each metric. Additionally, the stability envelope (covering the interquartile range from 25% to 75%) shows the concentration of values within typical limits for each metric. The change or delta, calculated as the difference between the first and last measurement, captures the overall trend across the observation period. Lastly, a percentage column shows the

Fig. 1: Descriptive Statistics for Well-being Metrics

heightMetric	Mean	Standard Deviation (std)	Min	25%	50%	75%	Max	Delta	% in Stability Envelope
Mood	0.94	0.83	-1	1	1	1	2	1	52.94
Stress	0.41	0.62	-1	0	0	1	1	0	94.12
Movement	1.06	0.56	0	1	1	1	2	0	70.59
Work-Life Balance	0.88	0.78	0	0	1	1	2	2	76.47
Productivity	0.82	0.88	-1	0	1	1	2	1	70.59

proportion of data points falling within the stability envelope, indicating the consistency of values for each metric over time.

When analyzing the results collectively, we observe that all metrics have positive means, indicating an improvement relative to the baseline. Movement has the highest mean, suggesting the greatest improvement, while stress has the lowest mean, showing only slight improvement. The standard deviations are relatively similar across metrics; however, mood and productivity exhibit the highest variability, implying more fluctuation in these areas. Additionally, all metrics have a positive delta, pointing to overall growth over time. Lastly, stress demonstrates the most stability, with the highest percentage of measurements within the stability envelope, while mood has the lowest, likely due to its higher standard deviation.

Continuing with a trend analysis, Figure 2 presents six graphs in total: five scatter plots for each individual well-being metric and a final graph displaying only the trend lines for comparison. Each scatter plot shows a visible upward trend, indicating overall growth relative to the baseline. When analyzing the combined trend lines graph, it becomes evident how the metrics differ in their progression. Productivity shows the most significant rise, with notable improvements also observed in work-life balance and mood. Meanwhile, movement and stress exhibit the least pronounced trends, indicating steadier, more gradual changes over time.

Although movement shows a higher average in the trend analysis, it is important to note that, theoretically, all metrics should start from a similar baseline. The previous descriptive statistics highlighted that movement has the highest mean, which initially suggested a greater improvement. However, this may not fully reflect true improvement relative to other metrics. Instead, the elevated average could indicate that movement was already at a higher level than other metrics at the baseline, thus perhaps suggesting a misinterpretation of its improvement over time.

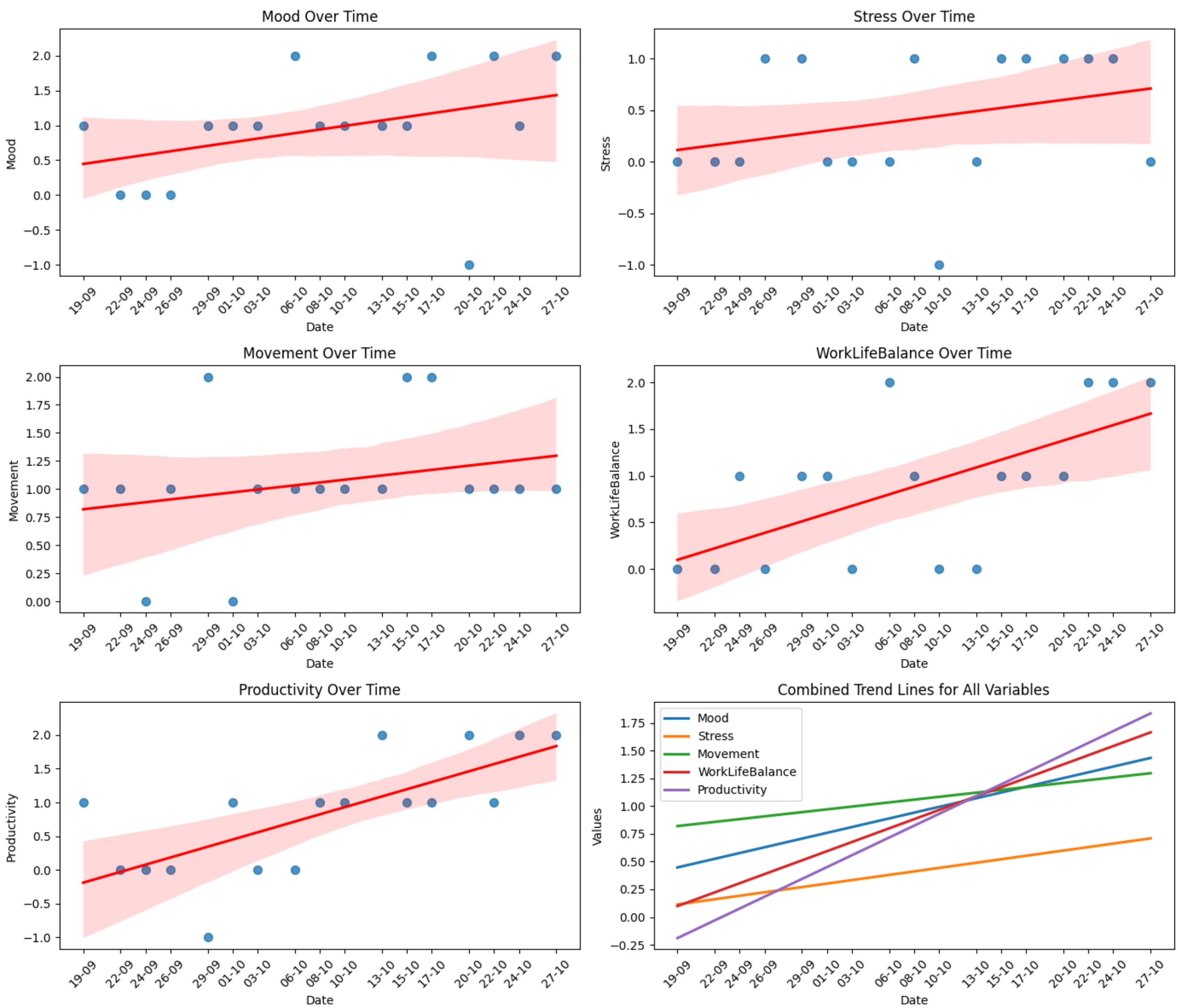

Fig. 2: Trendline analysis of all categories.

Discussion

Conclusion

This study aimed to examine the effects of well-being interventions—specifically mindfulness practices and P2P support groups—on personal well-being metrics within the framework of a single-case experimental design SCED. Using an ESM over a five-week period, we assessed the impact of these practices on various well-being metrics, including mood, stress, movement, work-life balance, and productivity. The results indicate positive shifts across all metrics, with consistent upward trends suggesting improvement relative to the baseline.

The descriptive statistics reveal that all metrics displayed positive means, with movement, work-life balance, and productivity showing the most notable improvements, while stress showed more moderate gains. The trend analysis further emphasizes this distinction, with productivity displaying the most significant growth, followed by noticeable upward trends in work-life balance and mood. Although movement had the highest mean value, further analysis indicated that this might reflect an already elevated baseline rather than pronounced improvement. Stress exhibited the least variability and had the highest percentage of values within the stability envelope, suggesting that it was relatively stable, with perhaps moderate improvements over the observation period.

These findings align with existing literature suggesting that mindfulness and peer support can enhance well-being and resilience. The interventions appeared to show improvements across mental metrics, with productivity and work-life balance being especially responsive. The upward trends support the effectiveness of structured well-being practices in contributing to personal growth and balance in a technologically-driven, academic environment.

Limitations

While the study provides insights into the impact of mindfulness and peer support on well-being, several limitations should be considered. First, as a single-case study, these findings are highly individualized and may not generalize to a broader audience without further replication. The self-reported nature of ESM data also introduces potential biases, such as mood or memory effects, which could affect the reported levels and trends. Additionally, the study's design did not include a proper baseline, limiting our ability to isolate the interventions' effects. Finally, with data collected only three times per week, certain fluctuations may have gone unobserved, potentially overlooking finer-grained shifts in well-being.

Disclaimer on the use of AI

Artificial Intelligence (AI), precisely Generative AI, has been incorporated to assist the author with formatting, specifically figures and tables in Latex and general latex (syntax) issues.

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