

User Adherence to Self-created Health Plans: MyYouthspan's 5 Week Adherence Study

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ABSTRACT

MyYouthspan is a personalized wellness site that can track and store one's daily health behaviors and help bring forth better lifestyles through user-defined goals. This study examines adherence to self-selected versus externally assigned health goals to determine whether user autonomy influences long-term engagement. Over a five week period, users tracked their daily life in four different categories: diet, lifestyle choices, amount and frequency of exercise, and supplemental intake. Adherence scores were collected and analyzed using K-Means clustering, which revealed three distinct clusters, or behavioral groups. Findings showed that participants who pursued rigorous, large changes and goals were at a higher risk to drop-off and quit, but this effect was reduced when the goals were self-chosen rather than assigned. In contrast, external, personal goals showed lower overall adherence than all other plans. These results suggest that through giving users the ability to define and create their own goals and motivations, the sustainability of a personalized approach to one's lifestyle is much greater than a one-size-fits-all approach. The implications show the importance of autonomy and personalized goals and catering in health-tracking platforms in order to promote meaningful, lifelong change.

Introduction

Unlike MyYouthspan (www.myyouthspan.com), other fitness platforms that encourage activity and a healthy lifestyle use a premade plan to set their clients on a path of success, or that they think is a path of success. When referring to the University of Texas at Dallas data that this research group conducted recently, it can be shown that when one honestly assesses his/her abilities and makes his/her own fitness plan, that person is more likely to stick to that plan because s/he knows him/herself much more personally and honestly than the fitness apps or fitness coaches do. Adherence to any plan is much more effective when it is tailor made for

oneself. One can only provide others with so much information, so being able to use everything one knows about themselves will allow for a much more accurate plan that one can use that is meant for their lifestyle, personal life, job, family, and any other niche commitment that may get in the way of a truly optimal plan.

Research shows that people are more likely to adhere to goals when they have the ability to set those goals themselves. According to the Self-Determination Theory (SDT), “when people are more autonomously motivated, they are more likely to achieve their health goals over time” (University of Rochester Medical Center [URMC], 2025). Motivation that is from one’s personal enjoyment or values of the specific behavior, rather than being pressured by external punishments or non-personal rewards, leads to more determination and satisfaction (URMC, 2025; APA, 2018). The APA dictionary defines SDT as the concept that “regulation of behavior varies along a continuum from externally controlled... to autonomous or intrinsically motivated... [and] negative outcomes ensue when people feel that they are driven mainly by external forces and extrinsic rewards” (APA, 2018).

One way to increase one’s likelihood of achieving goals is through planning that ensures situational cues link to specific actions. Implementation intentions, which can also be seen as if-then plans, are described as “if-then plans that link situational cues (i.e., good opportunities to act, critical moments) with responses that are effective in attaining goals or desired outcomes” (National Cancer Institute, n.d.). By specifying the when, where, and how of a specific behavior, such plans “enable people to deal effectively with self-regulatory problems that might otherwise undermine goal striving” and “make an important difference to whether or not people translate their goal intentions into action” (National Cancer Institute, n.d.).

In addition to proper motivation and planning, achieving goals can also depend on identifying the necessary conditions for success. Necessary Condition Analysis (NCA) is a method used to determine whether “a certain minimum level of X is necessary for a high level of Y” (Frontiers in Psychology, 2019). For example, studies using NCA have shown that “a certain level of intelligence is necessary for creativity” and that “a certain minimum level of safety consciousness is required to achieve top productivity results” (Frontiers in Psychology, 2019). While meeting these conditions does not guarantee success, failing to reach the conditions makes reaching the goal practically impossible. According to the article, “the significance of a necessity effect will, in some situations, tend to increase with increased degree of sufficiency... which is paradoxical for a method whose objective is to identify necessary but not sufficient conditions” (Frontiers in Psychology, 2019).

Together, SDT (the idea that people do best when they choose to do something that aligns with their interests, not when they are forced), implementation intentions (the “if-then plans” which

tell people exactly, when, where, and how a goal will be done), and the NCA (identification of necessary conditions which suggest autonomous motivation, structured planning, and awareness of important prerequisites) all collectively play a key role in helping individuals comfortably and efficiently reach their goals.

Methodology

Overview

The analysis was based on user log data from MyYouthspan, a personalized wellness site. There are four domains that goals are specified under: Diet, Lifestyle, Exercise, and Supplements. Adherence is defined as the proportion of logged behaviors that either met or exceeded the goals in the plan. In the cases where lower values indicated healthy behaviors, adherence was calculated directionally. Only the goals with valid entries were considered, as the raw logs were cleaned to remove any missing values.

Exploratory Analysis of Behaviors

To identify patterns in behavior, the Principal Component Analysis (PCA) is applied. This reduced the large-sized log data into a smaller set of principal components. These components were used to show variation in user engagement and provided a foundation for clustering.

Clustering of User Types

K-Means clustering was performed using adherence measures which were aggregated across four domains (diet, lifestyle, exercise, and supplements). Clustering was conducted with both domain adherence variables and frequency of logging. The validity of a cluster was evaluated through the silhouette score. This procedure exposed distinct groups of users for deeper analysis.

Modeling Adherence with XGBoost

XGBoost regression models were for predicting adherence. Adherence was defined as the proportions of goals achieved over goals set, with directional adjustments for behaviors where lower values returned healthier outcomes.

Three model configurations were evaluated:

1. A full predictor model which included all features (All Predictors)
2. A model pruned based on median feature importance (Median Importance Pruning)
3. A model pruned based on SHAP values (SHAP Pruning)

Performance was assessed using a 5-fold cross-validation, where model accuracy was measured by R^2 and RMSE metrics.

Sequential Analysis with Recurrent Neural Networks

Recurrent Neural Network (RNN) autoencoders were developed to display sequential adherence patterns. Each model included an encoder that converted log sequences into embeddings and a decoder that reconstructed the original sequences. Reconstruction performance was measured using mean square error.

Adherence at each time step was determined using four rule-based criteria: ratio range, greater-than-goal, less-than-goal, and exact goal. The values were assigned as followed:

- 1 = successful adherence
- -1 = unsuccessful adherence
- 0 = untracked goal
- 99 = padded values (padding for sequence lengths that are unequal)

Several architectures were tested, including single LSTM, stacked LSTM, and bidirectional LSTM models. A hyperparameter search was conducted to polish latent dimensions and dropout rates.

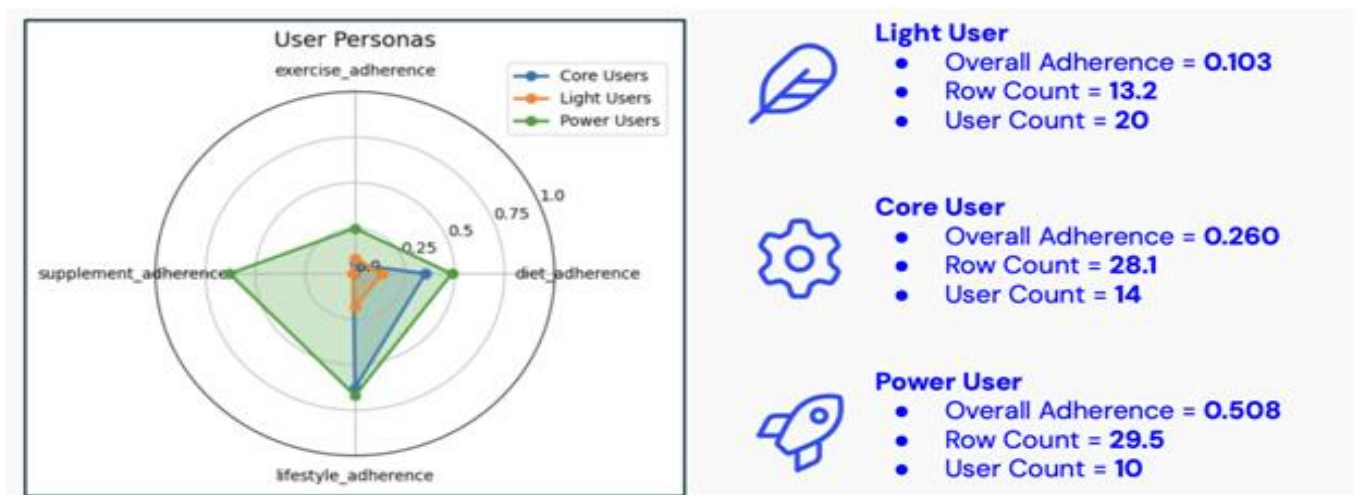
Results

Each participant was assigned an adherence score based on whether their logged behaviors support or contradicts the goals in their personalized plan. If a logged action moved a participant toward their target (e.g. increasing water intake), it was scored positively, while actions which moved the participant away (e.g. consuming an excess of alcohol) were scored negatively. Missing data, which is represented by days or behaviors that were not logged, were excluded from the averages.

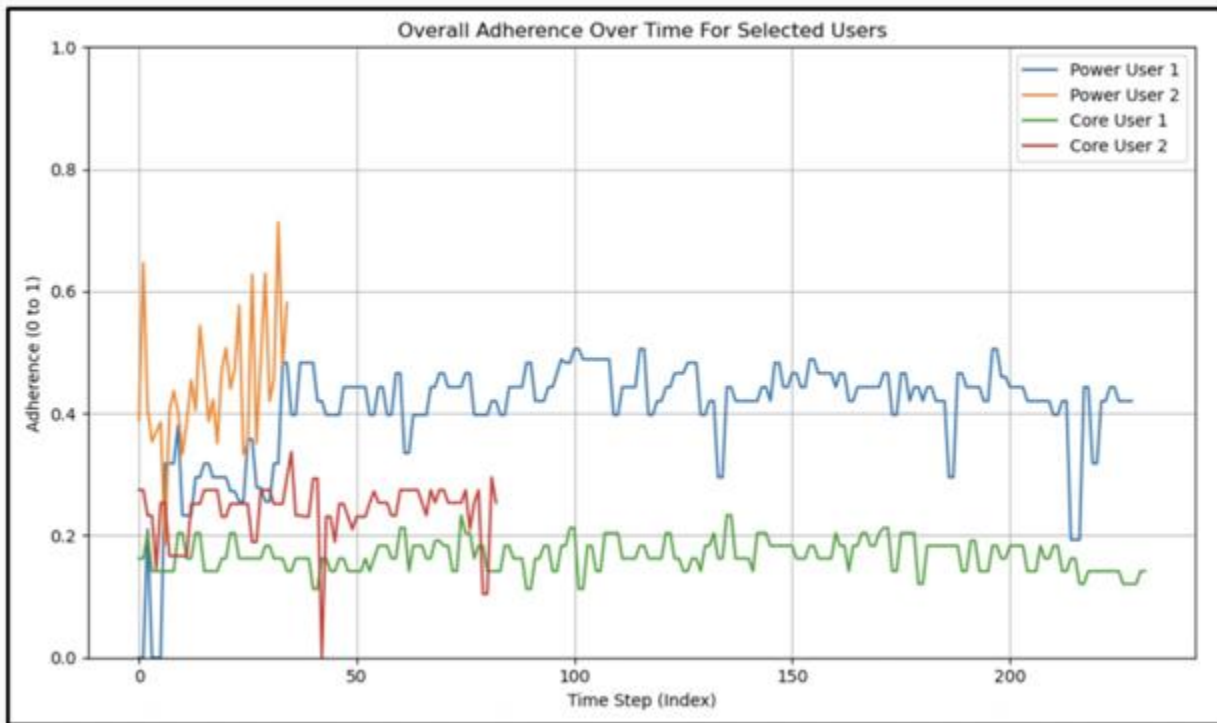
The first stage of analysis used to explore how different behaviors related to one another. Three strong components were identified. The first showed that participants who were highly engaged tended to do well in their fitness, nutrition, and social goals. The second highlighted that some participants were much more consistent in logging their actions than others. The third showed a split between those who met their goals and those who consistently exceeded them. These three components show that there were real differences between the types of users and set the stage for clustering participants into more specific groups.

PC1	High adherence to fitness, nutrition, and social goals; indicates general engagement with lifestyle plans
PC2	Variation in consistency of logging activity
PC3	Differentiates users who exceed goals from those who just meet them

When clustered, three types of users appeared. The light user had the weakest adherence. They averaged a score of 0.103 and only logged about thirteen days. They tracked very little and rarely followed through with their goals. The core users on the other hand showed moderate adherence, with a score of 0.260 and nearly thirty days logged. They were steady with their diet and exercise tracking but did not consistently log supplements, and their improvements were limited. The power users showed the strongest adherence. Their score was 0.508 with almost thirty days logged, and they tracked nearly every behavior with sustained effort. These three groups formed clear patterns of participation and results, with the power users standing out as the most committed and therefore more successful group.



When adherence was looked at over time, it became clear that the frequency of logging did not always mean better habits. Core users logged nearly as often as power users but could not match their adherence scores. Their tracking did not directly translate into meaningful improvement. Light users, who logged the least, also had the weakest outcomes, which confirms that without the engagement there was little chance of success. The power users, on the other hand, maintained both strong adherence and consistent logging across the study, proving that their habits were reinforced over time.



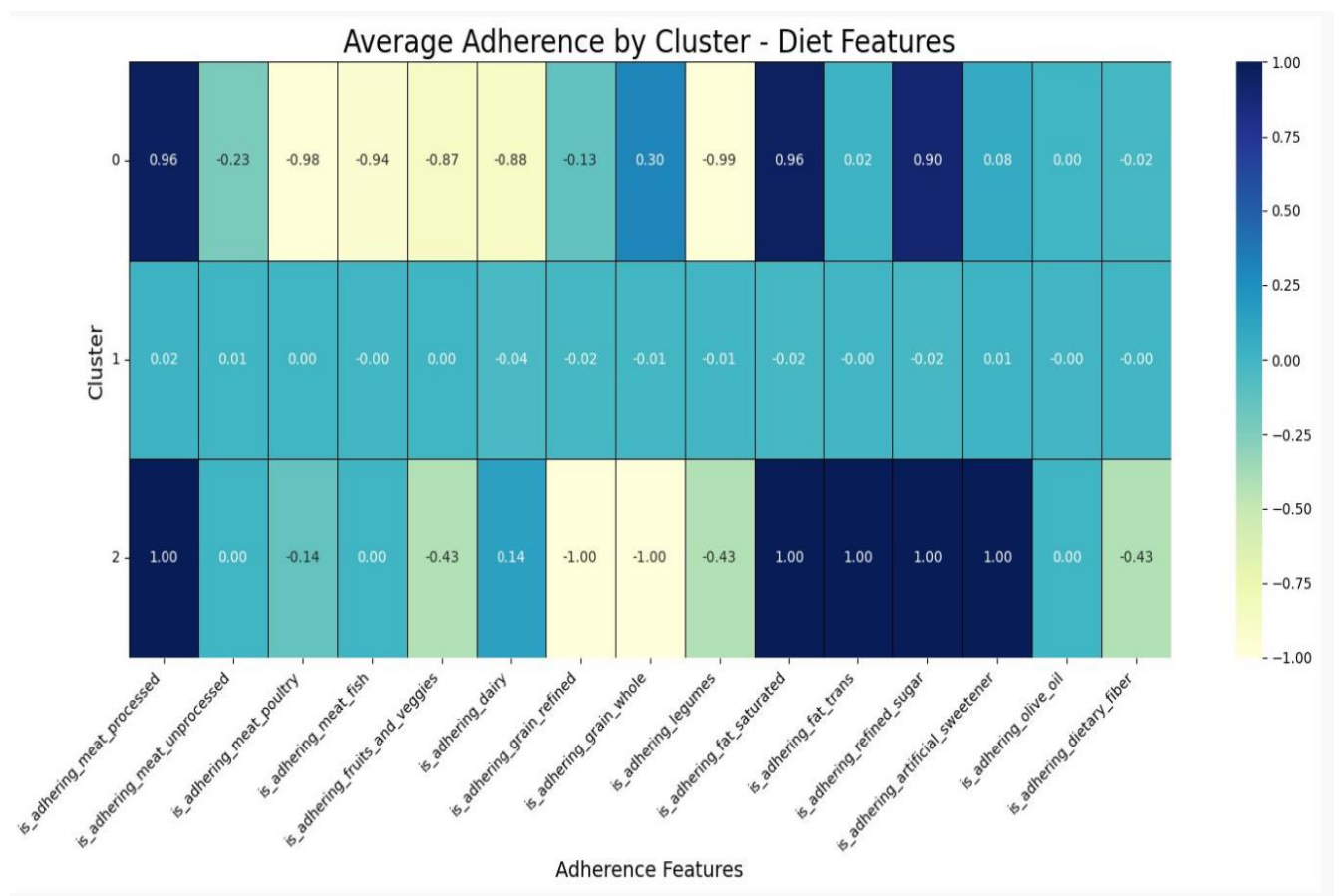
To see whether adherence could be predicted, this research team used an XGBoost model. The full model, which included all features, performed the best with an R^2 of 92.95% and no signs of overfitting. Even when predictors were redacted, the model remained accurate, though the R^2 fell to 89.08% with median importance pruning and dropped further to 67.32% with SHAP pruning. These results confirmed that adherence can be modeled reliably and that richer data does in fact lead to stronger predictions.

Model	RMSE	R^2
All Predictors	0.0322	92.95%
Median Importance Pruning	0.0401	89.09%
SHAP Pruning	0.0694	67.32%

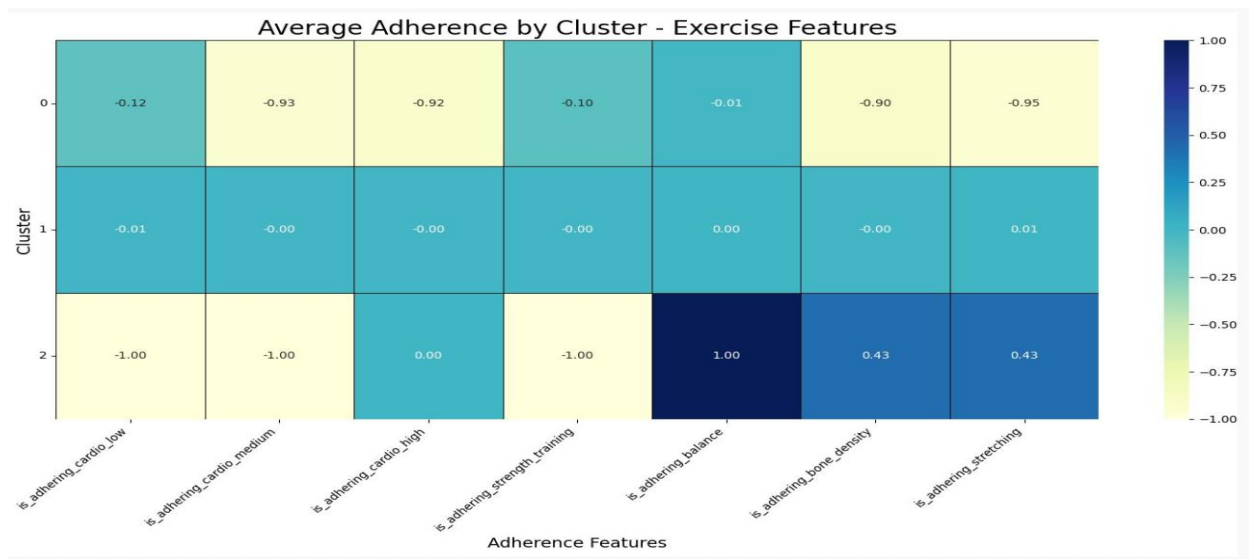
Recurrent neural networks gave a closer look at adherence for specific features. Cluster 0, which matched the core users, tracked many features but struggled to adhere to them, with weak

following despite high activity. Cluster 1, the light users, contributed very little data, so their adherence could not be measured with complete confidence, Cluster 2, the power users, tracker almost all features and maintained moderate adherence, showing broader success across categories than the other groups

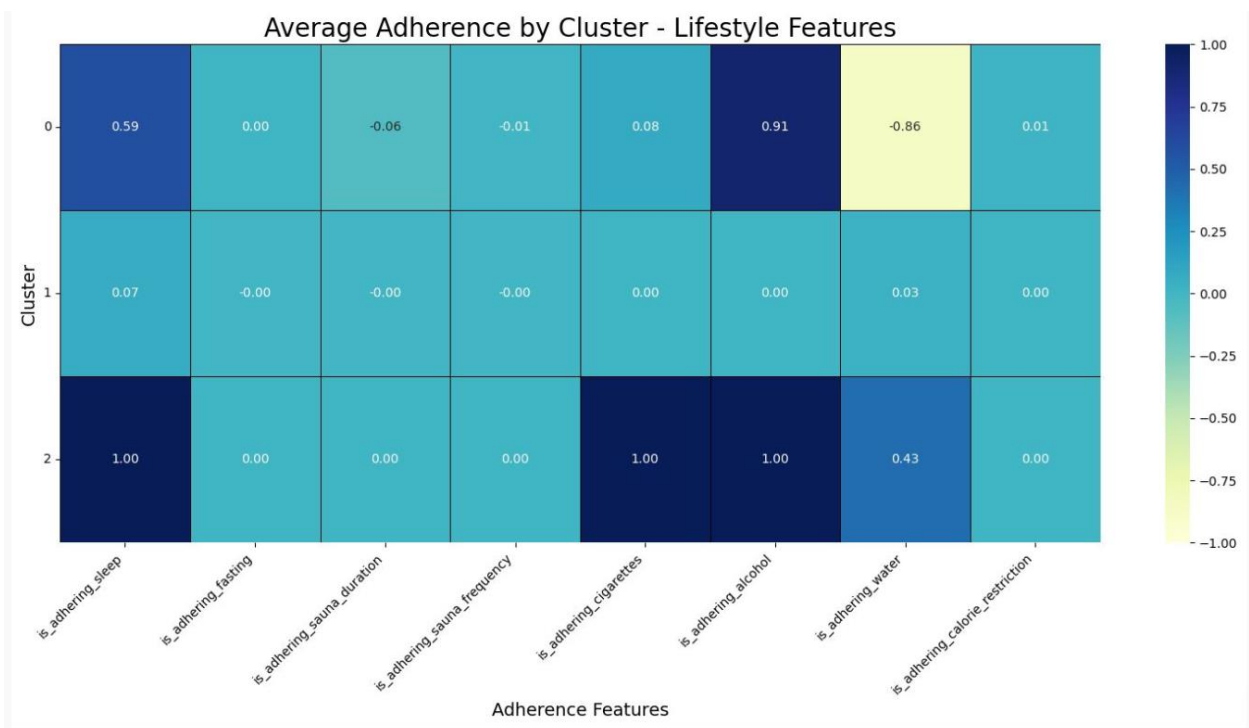
Looking at behavior related to diet, core users tried to track a wide range of features such as meat, dairy, fat, and sugar but often failed to stay on track, Light Users tracked almost nothing in thai category, leaving no actual evidence of adherence. Power users, however, tracked nearly all diet features and, while not perfect, showed consistent effort and moderate adherence



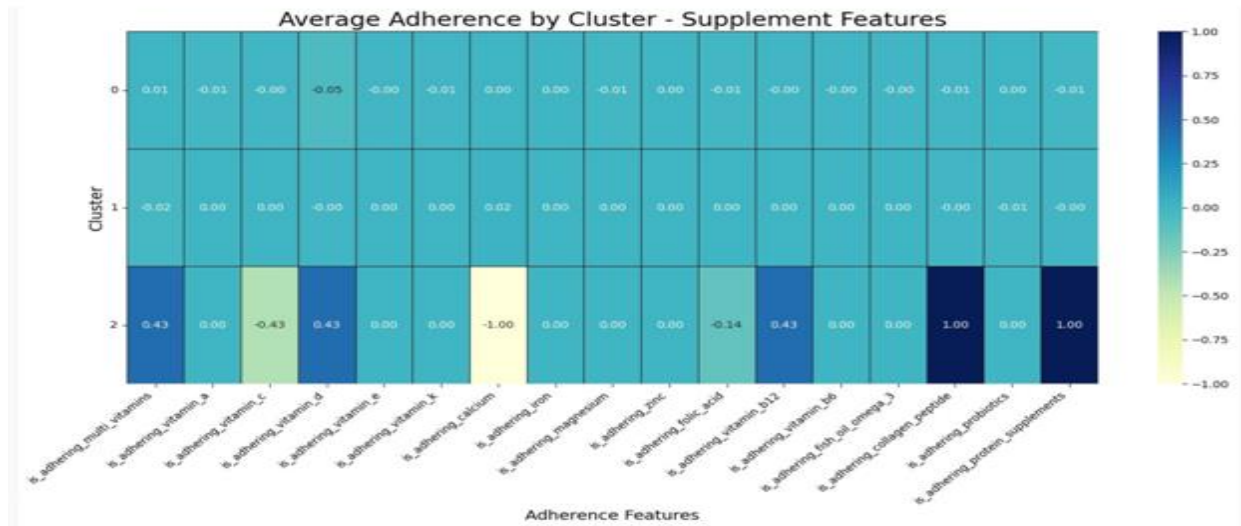
Exercise behaviors followed the same pattern. Core users tracked half of the available exercise variables, but rarely met their goals, showing that tracking alone did not lead to change. Light users again provided too little data for any meaningful evaluation. Power users again tracked almost every exercise behavior but, even with their effort, they still struggled with consistent adherence in the Thai category, which suggests that exercise goals were harder to meet than dietary goals.



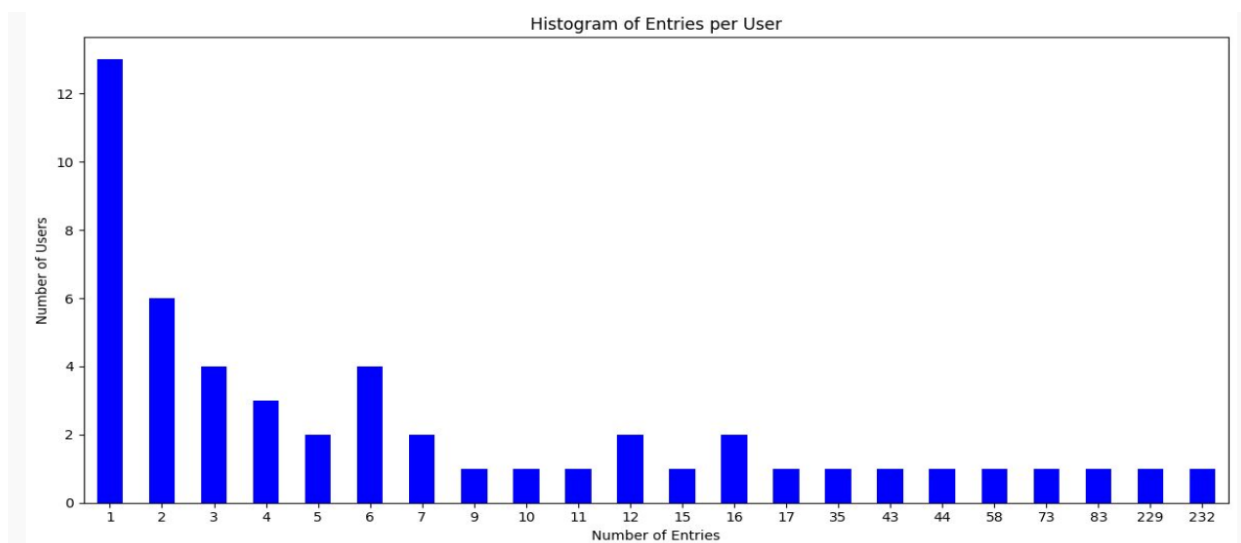
Lifestyle features showed stronger outcomes. Core users tracked a smaller set of behaviors such as sleep, alcohol, and water intake and met their goals about half the time. Light user tracker very little. Power sixers consistently logged lifestyle features and maintained moderate adherence, proving the behaviors like sleep and hydration were easier to sustain over time than other categories.



Supplements proved to be the weakest area for every group. Core users and light users tracked almost nothing, while power sixers logged a few supplements but only adhered inconsistently. This shows that even the most engaged participants struggled to keep up with supplement goals, suggesting that this was the hardest category to maintain.



Finally, the autoencoder model was used to test how well user behaviors could be captured and reconstructed. As the model ran, its error steadily decreased, showing that it was successfully learning the patterns in user data. The encoder was able to summarize user activity to compact embeddings that could be used to represent adherence at a deeper level, confirming that the platform can capture meaningful differences between participants.



From these results, several patterns were clear. The most consistent users, those who logged across many categories everyday, were also the ones who achieved the strongest adherence. Progress also built slowly, with the largest improvement showing up in the later weeks of logging. Some categories, such as supplements, were consistently weak across all groups and will require more attention to improve. While logging was important, it was not enough by itself. Core users proved that frequent logging without commitment skill led to weak outcomes, while power users showed that sustained engagement combined with consistent adherence could lead to lasting improvements.

Conclusion

This five-week adherence study offers important insights into how individuals engage with personalized health goals when given autonomy versus when goals are externally assigned. By tracking behaviors across diet, exercise, lifestyle, and supplement intake, the analysis revealed that autonomy plays a central role in sustaining motivation, consistency, and long-term adherence.

Scoring and Analysis

Adherence was defined as the proportion of behaviors logged that aligned with user goals. Positive actions (e.g., hydration, exercise, sufficient sleep) increased adherence scores, while negative behaviors (e.g., alcohol overuse, missed exercise) decreased them. Missing values were excluded to avoid skewing results. PCA, clustering, and advanced modeling—including XGBoost and RNN autoencoders—were then used to identify user types, predict adherence, and capture sequential behavioral patterns.

Key Takeaways

- **Autonomy Drives Sustainability:** Users who self-selected their goals were more consistent and resilient compared to those with externally assigned goals. Even when goals were ambitious, self-chosen goals reduced dropout risk compared to externally imposed ones.
- **Consistency and Logging Are Linked:** The most successful participants (power users) demonstrated that sustained daily logging directly correlated with stronger adherence and long-term improvements.
- **Tracking Alone Is Not Enough:** Core users showed that frequent tracking without committed adherence resulted in weaker outcomes, highlighting the need for both engagement and follow-through.

- **Certain Categories Are Harder to Maintain:** While lifestyle habits (e.g., sleep and hydration) were easier to sustain, supplement intake proved the most difficult for all user types, suggesting that some habits require additional support and interventions.
- **Progress Builds Over Time:** The largest improvements occurred later in the study, emphasizing the importance of patience and persistence in habit formation.

Optimization

These results show that individualized goal-setting, supported by predictive modeling, can create smarter, adaptive health plans. Future versions of platforms like *MyYouthspan* can use adherence data to refine recommendations, optimize goal difficulty, and provide timely nudges that balance motivation with achievability.

Future Directions

To further enhance and solidify the findings, future studies should aim to:

- Integrate tools such as wearable devices, notifications, and digital reminders to help increase the amount of logging.
- Conduct longer, more consistent studies to evaluate the adherence through a longer timeline.
- Explore personalized interventions, helping individuals individually with their hardest respective activities (e.g., exercise, caloric intake).
- Examine demographic and gender-based differences to uncover tailored strategies that reflect diverse user needs.

By addressing these areas, researchers and wellness platforms can better understand the mechanisms that sustain healthy behaviors. Ultimately, empowering individuals to define their own goals, supported by structured tools and data-driven adjustments, offers a more effective pathway toward lasting lifestyle change.

Acknowledgement

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