Are You Happy That You Snoozed Your Alarm Today?

By Rose Exeus and Chris Cargill

<u>Introduction:</u> How many of you snoozed your alarm multiple times today? This decision is a rather common occurrence. What about canceling plans day-of or making an impulsive, online purchase? There are many decisions scattered throughout the day, whether they're made alone or influenced by others. Have you ever chosen to do something in hopes that it would improve your Mood? Any decisions that led to Regret? The nuances of daily micro-decisions can have a great effect on people, and that's part of what the focus of this project wishes to investigate.

Micro-decisions alone may seem trivial, but analyzed together may reveal larger effects on emotional well-being, productivity, and overall life Outcome Satisfaction. This study employs machine learning techniques to understand the drivers of decisions made on a daily basis and potentially make a connection to healthier behavioral habits, improvement of decision-support systems, or digital wellness tools. Thus, our research questions are as follows: How do different motivational sources (e.g., Mood, Urgency, Social Pressure, cost implication) influence decision making? Can machine learning models predict Outcome Satisfaction or Regret associated with human micro-decisions?

<u>Literature Survey:</u> When researching for works about machine-learning surrounding daily micro-decisions, it was challenging to locate even one research paper that studied the impacts and relationships of using Machine Learning (ML) for micro-decisions; however, what was found in "AI micro-decisions in FinTechs" [3] details said scarcity and the rise in prevalence of people's reliance on AI for decisions. It's important to mention that [3] defines Artificial Intelligence (AI) as, "a system's capability to accurately analyze external data, to learn from such data, and to use this acquired knowledge to achieve specific aims and tasks through adaptation". This definition falls in line perfectly with what is discussed in [3] regarding the rise in reliance on AI's judgement: AI systems were not initially able to make their own decisions; however, now AI is being considered as an addition to HR for assistance with protocols, such as decision-making, which can be found in [6]. Through advancements on AI algorithms, some AI decisions are now unmonitored by or invisible to the user. Since Artificial Intelligence has not always had the capability to make decisions or aid in providing solutions, the uptick in dependence on AI for micro-decisions since its progressing of decision capabilities aligns with each other now that the decision-making process can be automated with the help of Artificial Intelligence [3].

There may be missing attributes that come with leaving out human intervention entirely, however. Within intuitive decision-making where pattern recognition and positive/negative feelings are associated with positive/negative outcomes, it is explained in [4] that people will have a "gut feeling" when making decisions; this intuition is said to aid in many decision types, but especially in critical decisions involving a prognosis of some terminal illness where the positive/negative association with judgement calls can be attributed to something similar of a fight-or-flight response, which would be lacking in an Artificial Intelligence or ML model. Despite this, there are publishings like [7] that have evidence of Artificial Intelligence transforming the care of its patients via involving AI in decision-making processes, including the decision to operate.

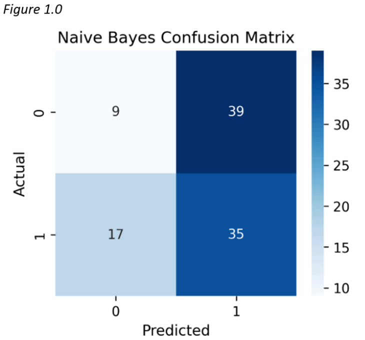
According to the National Institute of Health in [5], "to comprehensively understand how stress impacts decision making and other cognitive practices, numerous variables come into play." These variables include the diversity of the stressor, the context, the time between stress exposure and the decision, the specific task type, and individual differences, such as genetic background or life history. The role of these interacting variables is essential for developing a comprehensive understanding of the impact of stress on cognitive functions like decision making. Therefore, a robust analysis of the link between motivational sources and cognitive functions requires a multi-factoral approach that investigates all of these interactions.

Methods: This study utilized the Daily Micro-Decisions Tracker dataset found in [1] from Kaggle, containing approximately 500 synthetic but realistic decision records, from 20 simulated users. Each row corresponds to a micro-decision, with features describing Urgency Level, Cost Implication, Mood Before, Regret Label, Outcome Satisfaction, and Social Influence. The initial steps involve data selection and preprocessing, which included filtering irrelevant or redundant variables, addressing missing values, and handling categorical variables through binarizing: see [8]. For example, some variables had a wide range of both positive and negative numbers, which were transformed into either 0 for negative or 1 for positive, respectively. What's left are four independent variables: Urgency Level ({1,2,3,4,5}), Mood Before ({1,2,3,4,5}), Social Pressure ({0,1}), and Cost Implication ({0,1}). The target variables are Outcome Satisfaction ({1,2,3,4,5}), and Regret Label ({0,1}), which are treated as separate constructs.

The modeling phase involved training and evaluating multiple classification models to identify correlations between the motivational sources and decision outcomes. A Logistic Regression model, found in [2], will be employed to learn decision boundaries by modeling P(Y|X) (the probability of Y given X), and its interpretable coefficients will reveal each factor's influence on decisions. Additionally, the Naive Bayes model in [2], which assumes feature independence, will provide probabilistic predictions to reflect uncertainty in certain decision-making contexts. A final model, which was added during training, is the Random Forest model in [2]; the output from Naive Bayes gave insight into the structure of the data, showcasing that Naive Bayes may not be a good fit, which is where Random Forest comes into play. The Random Forest model will provide insight for how influential certain motivational sources are in predicting the chosen dependent variables.

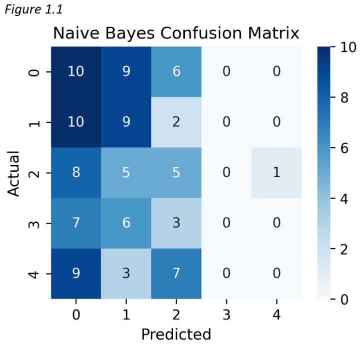
Model Training and Performance: Obtaining the results of this study involved using 3 main approaches. For the Naive Bayes model, the dataset was split 80/20 for training and testing. The specific predictor variables were defined for the model along with both outcome variables separately. The Naive Bayes model for Regret Label, when the Class = 0 and no Regret is present, the F1-score = 0.24, which means the overall performance is poor; however, when the Class = 1 and Regret is present, the F1-score = 0.56, which is still not great but is moderate and better than Class 0. The total model accuracy is 0.44, so only 44% of the predictions were correct, which is less accuracte than guessing. For Outcome Satisfaction, the Naive Bayes model has a total accuracy of 24%, severely underperforming because the F1-scores for Classes 1-5 all fall at or beneath 0.34. The confusion matrix for predicting Regret can be found in *Figure 1.0*. There are 17 false negatives and 39 false positives, which adds up to 56% of the total predictions made by the Naive Bayes Model as incorrect. This model underperforms severely for Regret Class = 0 specifically. The majority of predictions made by the model are Regret Class = 1, which points to a class imbalance; the majority of the training set included 1's for the Regret Label variable, so the test set's prediction performance reflected this preference heavily, resulting in a lack of predictive attention to the 0's for Regret. In *Figure 1.1*, the performance of the Naive Bayes confusion matrix for Outcome Satisfaction dips quite tremendously. Paying attention to the diagonal line for summing up the total amount of correct predictions made, the Naive Bayes model predicted only 24% correctly. Through the multi-level dependent variable's predictive performance, the dataset's class imbalance becomes more

Figure 1.0



Note: This confusion matrix represents the predictive accuracy of the Naïve Bayes model on the regret dependent variable.

Figure 1.1

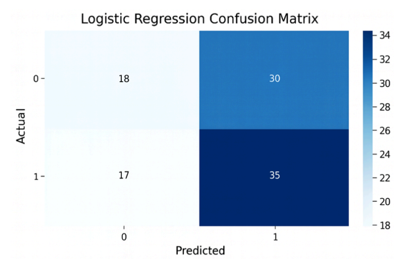


Note: This confusion matrix represents the predictive accuracy of the Naïve Bayes model on the outcome satisfaction dependent variable.

prevalent. Since the training set was more exposed to the lower levels of the dependent variable, the model was mostly unable to predict the upper two levels during the test as a result.

The Random Forest Regressor treated the outcomes as continuous variables, allowing the model to capture non-linear relationships and provide valuable feature importance rankings. The utilization of a tri-modeling approach offers complementary perspectives by employing both classification for discrete outcomes prediction and regression for understanding the magnitude of Outcome Satisfaction or Regret. A comprehensive evaluation was achieved through the use of multiple statistical metrics, including F1-score, R-squared, mean absolute error, root mean squared error, and confusion matrices These metrics provided a complete picture of model performance. Additionally, visual analysis consisting of over 12 subplots showcasing interaction effects and feature importance made patterns immediately interpretable. Finally, the 5-fold cross-validation ensured that the models were not overfitting and would generalize effectively to new decisions.

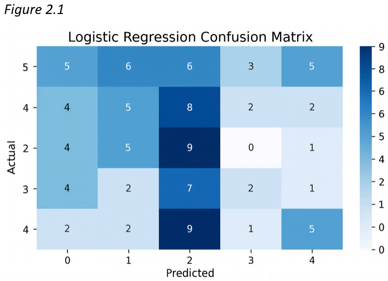
Figure 2.0



Note: This confusion matrix represents the predictive accuracy of the Logistic Regression model on the regret dependent variable.

When training the Logistic Regression model, the 1-5 scale of outcomes was treated as discrete classes. Since Outcome Satisfaction and Regret were treated as ordinal multi-class targets with five possible outcome levels, it was clear that the Multinomial Logistic Regression would be a better approach along with an 80/20 split of the data being used for training and testing. This allowed the model to estimate class ranking probabilities using a softmax activation function, rather than fitting multiple one-vs-all binary classifiers.

Figure 2.1



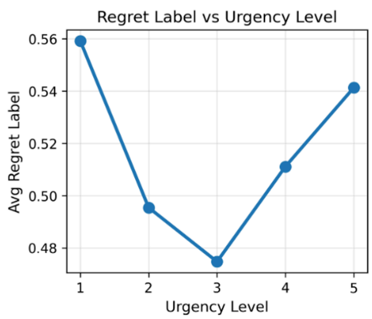
Note: This confusion matrix represents the predictive accuracy of the Logistic Regression model on the outcome satisfaction dependent variable.

Since this is a relatively small feature set, the Logistic Regression model reached convergence, showing that further training didn't have much of an impact on the model's parameters. During training, the model achieved 86% classification accuracy for the Outcome Satisfaction predictions, and 85% accuracy when predicting Regret Label. This indicated a strong learning of feature-outcome relationships. Cross validation results ranged from 83% to 88%, which proves that the model performance wasn't necessarily dependent on training specific subsets. The model's limitations revealed in the confusion matrices show that it struggles mainly with boundary cases between similar Outcome Satisfaction or Urgency Level.

Feature engineering was the biggest contributor to the training and test accuracy. This technique incorporated key two-way interaction terms including Urgency Level combined with Mood Before, Social Pressure, and Cost Implication, as well as interactions amongst the other features. These interactions were essential for capturing the complex real-world decision making dynamic that was missed by using single features. The feature importance hierarchy revealed that Mood Before was the strongest predictor, as emotional state fundamentally shapes outcomes. This is followed by Urgency Level, which often correlates with lower Outcome Satisfaction and higher Regret, then Cost Implication and Social Pressure in hierarchical order. Overall, the Logistic Regression model demonstrated stronger predictive accuracy and computational efficiency, outperforming the Naive Bayes model and providing results that were more consistent with the Random Forest model.

<u>Results:</u> The Naive Bayes model produced line graph comparisons between each dependent variable and the four motivational sources individually. The charts were a first sneak peak into concretely determining that the Naive Bayes model is not a good fit for the dataset due to the complex relationships represented between both Regret and Outcome Satisfaction with Urgency Level and Mood Before. *Figure 3.0*, which measures the relationship between Regret and Urgency Level, produced a parabolic shape, creating a picture of the medium Urgency Level (Urgency Level = 3) being most likely to result in a decision without Regret. *Figure 3.1* represents the graph between Regret and Mood, which achieved a shape similar to a cubic line graph, drawing up a more complex relationship in that a slightly poor Mood (Mood Before = 2) is the Mood rank that is most likely to produce a decision without Regret.

Figure 3.0



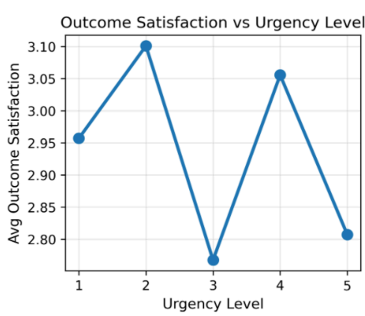
Note: This line graph represents the relationship between the dependent variable, Regret, and the independent variable, Urgency Level, one of the four motivational sources. The result is a parabolic-like-shaped relationship.

Figure 3.1

Note: This line graph represents the relationship between the dependent variable, Regret, and the independent variable, Mood Before, one of the four motivational sources. The result is a cubic-like-shaped relationship.

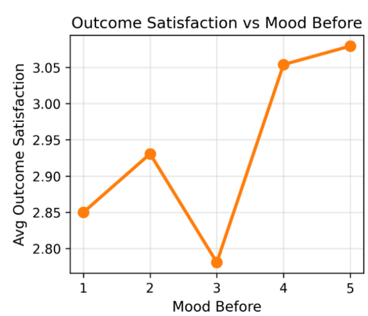
Figure 3.2 and *Figure 3.3* measure the relationships between Outcome Satisfaction and Urgency and Outcome Satisfaction and Mood, both graphs produced curved relationships, loosely in the shape of an "M". These nonlinear relationships that Urgency and Mood hold with both Regret and Outcome Satisfaction exemplify the complexity in decision-making factors.

Figure 3.2



Note: This line graph represents the relationship between the dependent variable, Outcome Satisfaction, and the independent variable, Urgency Level, one of the four motivational sources. The result is a curved, nonlinear relationship.

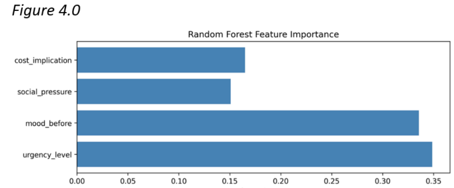
Figure 3.3



Note: This line graph represents the relationship between the dependent variable, Outcome Satisfaction, and the independent variable, Mood Before, one of the four motivational sources. The result is a curved, nonlinear relationship.

The Random Forest model is now introduced to check the predictive power across the four motivational sources. This model addition was important because the other two motivational sources, when each compared to the dependent variables in the same manner, produced simple, linear relationships. Since there was a noticeable difference in the results when testing the relationships of both dependent variables and the four independent variables, checking the predictive power of the motivational sources for both Regret and Outcome Satisfaction gave way to the observation of a clear imbalance of effect in the independent variables' involvement in decision-making. The nonlinear, complex relationships that Urgency

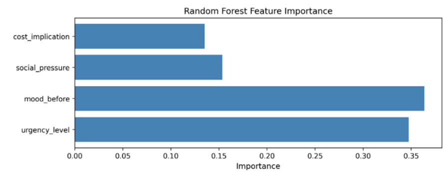
Figure 4.0



Note: This Random Forest Feature Importance graph represents the predictive power of each of the four independent variables, or motivational sources, on the dependent variable, regret.

and Mood have with both dependent variables proved more explanative of the nuances of the dataset; the output of the Random Forest Feature Importance graph in *Figure 4.0* presents Urgency Level and Mood Before being responsible for 35% and 33% of the total predictive power for Regret respectively. *Figure 4.1* presents similar results—Urgency Level and Mood Before account for the majority of predictive power: for Outcome Satisfaction, Urgency Level and Mood Before account for 37% and 34%; these two predictors are responsible for slightly more of the predictive power for Outcome Satisfaction. Both *Figure 4.0* and *Figure 4.1* show that Cost Implication and Social Pressure are responsible for only approximately 25% of the predictive power combined, so these motivational sources have an unequal influence on the dependent variables, suggesting that a model suited for nonlinearity would complement better. The main output to focus on for judging the model's overall predicting performance is through the confusion matrices. Overall, the mean values of Urgency Level and Mood Before are relatively the same (3.03 for Class = 0, no Regret, and 3.02 for Class = 1, Regret; 3.00 for Class = 0 and 2.96 for Class = 1), which creates an issue for the Naive Bayes model regarding predicting accurately. The mean values for Social Pressure have a slightly higher rate for Regret Class = 1, but, again, Cost Implication's means for the two Regret Classes have virtually no difference. This can be said for Outcome Satisfaction as well as all five rank classes have relatively the same mean values. The Standard Deviations (SD's) for the binary variables (Cost Implication and Social Pressure) are approximately 0.5 and the SD's for the scaled variables (Urgency Level and Mood Before) are roughly 1.4 pointing to a nice variability within each variable; however, the between variability is marginably obsolete, providing a challenging set of features to differentiate from for the Naive Bayes model when predicting for Regret and Outcome Satisfaction.

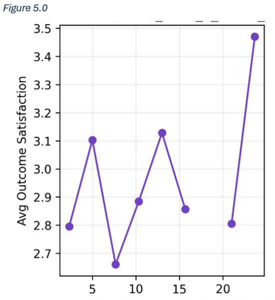
Figure 4.1



Note: This Random Forest Feature Importance graph represents the predictive power of each of the four independent variables, or motivational sources, on the dependent variable, outcome satisfaction.

Similarly to the Naive Bayes and Random Forest models, the Logistic Regression model revealed that Outcome Satisfaction is positively correlated with good Mood and positive Cost Implication, but negatively correlated with high Urgency. Conversely, the Regret Label has the expected inverse relationship with Satisfaction and is higher when individuals experience Social Pressure and poor Mood. As seen in *Figures 5.0 and 5.1,* Outcome Satisfaction peaked at moderate Urgency Level = 2, with a 3.10 mean of Outcome Satisfaction, and dropped sharply at Level 3, with a 2.78 Outcome Satisfaction. This revealed complex, non-monotonic relationships between predictor variables and decision outcomes, with Mood Before emerging as the dominant predictor (average absolute coefficient = 0.87), substantially exceeding the influence of Urgency, Cost, and Social Pressure. Feature-specific analysis showed Urgency tracing an inverted-U curve for Outcome Satisfaction (peaking at moderate Urgency) but a U-shaped trajectory for Regret (minimized at moderate Urgency), suggesting an optimal Urgency window for positive outcomes. Mood effects differed greatly, showing an approximately linear positive relationship with Outcome Satisfaction, but leads to an inverted-U pattern for Regret (minimum Regret at moderate Mood Level 2), indicating that moderate emotional states may optimize decision-making. Social Pressure consistently reduced Outcome Satisfaction and increased Regret, while Cost Implication showed the expected positive correlation with Outcome Satisfaction and inverse correlation with Regret, though these effects were smaller than those for Mood and Social Pressure.

Figure 5.0



Note: This graph shows the relationship between outcome satisfaction and UrgencyxMood as a feature interaction. The mood before line is binned to ensure that both feature impacts are visible.

Figure 5.1

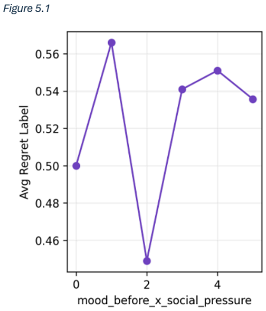


Figure 4.2: This line graph displays the relationship between Mood_BeforexSocial_Pressure, and its impact on the regret label.

Despite this improved performance compared to the previous models, the standard deviations of the

Logistic Regression model show that the performance still was not ideal, as seen in *Figures 6.0 and 6.1*. For example, with Urgency Level, the means for Regret vs. no Regret are nearly identical with values of 3.02 and 3.03, while the standard deviation is around 1.4. The same pattern appears for Mood, where the mean values are similar, and the standard deviation remains high (~1.4-1.42). Overall, many of the features have similar means and standard deviations across each class, affecting the model's ability to accurately classify features and their corresponding predictions.

Figure 6.0

mood_before:

outcome_satisfaction	mean	std
1	2.950495	1.336983
2	2.819048	1.492165
3	3.043860	1.372230
4	2.964706	1.459346
5	3.168421	1.419114

Note: This figure displays the mean and standard deviations when mood before is used as an independent variable, with outcome_satisfaction as the dependent variable

Figure 6.1

mood_before:

regret_label	mean	std
0	3.008264	1.408309
1	2.968992	1.422104

Note: This figure displays the mean and standard deviations when mood before is used as an independent variable, with regret as the dependent variable, using 0 and 1 as the 2 regret classes.

Key Findings: Across all models, Mood Before and Urgency emerged as the strongest predictor, accounting for approximately 35% of model predictive power based on the Random Forest's feature importance scores. These two features demonstrated a consistent effect on outcome ratings, averaging a 0.22-point increase in outcome ratings as Mood increases by a full point. The dominance of these 2 features aligns with many psychological assumptions because they are fundamental to behavioral economics theories concerning how decisions are made. Mood and Urgency function as a perceptual filter, shaping how an individual evaluates options, assesses risks, and interprets outcomes. These current findings suggest that decision-making is fundamentally emotional, but with further research, other factors may have a heavier influence. Our second, and final, key finding revolves around the relationship between the two chosen, dependent variables—Outcome Satisfaction and Regret. The predictive accuracy for each variable whether in the Naive Bayes or Logistic Regression models were not working in tandem; that is to say, the variables were not the inverse of one another. When a decision resulted in high Outcome Satisfaction, that did not also provide information on the status of the Regret in said decision. In fact, decisions with high Outcome Satisfaction could also have Regret. Similarly, when decisions did not contain Regret, there was no accurate judgement to be made about the rank of the Outcome Satisfaction: decisions could include both Regret and low Outcome Satisfaction. This observation is another reminder of the complexity of predicting decision outcomes.

Limitations: While providing valuable insights on the predictive relationships within our dataset, the analysis on micro-decision outcomes faced some critical limitations, primarily stemming from its reliance on a synthetic dataset rather than real-world behavior. While this approach gives us an idea of how certain features may impact decision-making, it fails to capture the true messiness and complexity of real-world human decisions-making. Human choices are often influenced by irrational tendencies, cognitive bias, and contextual factors that are difficult to replicate in a simulated environment. This analysis was restricted to a narrow feature set with a small sample size of approximately 20 participants. The omitted variables may reveal more about an individual's habits or established routine, which greatly impacts the decisions made on a day-to-day basis. While the sample size was a good starting point for initial model development and feature selection, a model that truly captures the diversity of decision-making would require a larger sample size. The limited scope of the research conducted for this project led to an oversimplified and incomplete understanding of a cognitive process that is typically more complex.

Conclusion: The outcome of this study produced ML models capable of predicting the positive or negative outcomes of micro-decisions. Beyond predictive performance, the project generated insights into how psychological and contextual variables—such as Mood, Social Pressure, and Urgency—jointly influence human decision-making. These insights hold potential applications in behavioral economics, consumer behavior modeling, and digital wellness tracking. In expanding this research further, the usefulness of an ML model of predictive outcomes associated with decision-making would be applying this to certain companies, such as a law firm, where high-level pattern recognition can facilitate whether to accept or deny certain cases.

Future Research: It would be beneficial to collect authentic decision-making data; particularly, a longitudinal study where a select group of participants are observed for short periods across a long period of time in order to gain different angles on the influential factors and motivational sources involved in human decision-making. This choice in study will expand the bank of known motivational sources that contribute and potentially sway decisions as well as increase the number of options for decision outcomes. A final takeaway for a more niche aspect to study for human decision-making would be the personality differences and their role in micro-decisions. Focusing on particularly impatient individuals, for example, could produce heavier emphasis in the Urgency and Mood motivational sources.

To summarize, investigating personality-driven micro-decisions to understand their influence on broader, long-term behavioral patterns; and exploring the specific mechanisms by which personality traits affect the perception and execution of small choices are two ways researchers can fully complete the understanding of the trait-behavior link. The findings could then support several practical applications, including enhancing app features by integrating personal experience and data, creating highly accurate personalized predictions by tracking individuals' historical decision data and unique personal patterns over time, incorporating specific personality traits into prediction models and feature design, and developing interventions that provide real-time support and guidance during the decision-making process.

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