Predicting mood changes: the role of daily activities, social context, and location

Grotto Tommaso

1. Introduction

Mood plays a pivotal role in shaping human experiences and well-being, influencing daily interactions, decision-making, and overall quality of life. Understanding the factors that contribute to mood changes throughout the day has significant implications for mental health interventions, context-aware applications, and personalized well-being strategies. This study investigates the intricate relationships between daily activities, social contexts, and locations in predicting mood changes, leveraging advanced data collection and analytical techniques to address this critical area of research.

Recent advancements in mobile sensing technologies have revolutionized the study of mood dynamics, enabling the unobtrusive collection of behavioral, social, and environmental data. Prior research has demonstrated the potential of these technologies to predict mood by analyzing diverse variables, including personality traits, activity patterns, and contextual factors. For instance, studies such as Meegahapola et al. (2023) and LiKamWa et al. (2013) highlighted the importance of personalized and context-aware models in improving mood prediction accuracy. These findings underscore the need to account for individual differences and contextual nuances when modeling mood dynamics.

This study builds on the existing literature by focusing on mood change, a less explored yet highly relevant aspect of mood dynamics. Unlike static mood inference, mood change captures the transitions in emotional states, offering a more dynamic perspective on mood regulation. By integrating data on personality traits, human values, demographic characteristics, temporal variables, and daily activities, this research aims to provide a comprehensive understanding of the determinants of mood changes throughout the day.

The data for this study were collected as part of the WeNet project, using the ILog app to track daily activities, locations, social contexts, and mood among 241 university students over a month. The analysis focuses on the first two weeks of data, during which participants provided detailed responses every 30 minutes. After rigorous data cleaning, the final dataset comprised 98 participants and 43,380 records, enabling robust modeling and analysis.

To predict mood changes, we employed a combination of regression and machine learning techniques, including Logistic Regression, Random Forest Classifier, and Gradient Boosting Classifier. These methods were applied across five variable groupings, personality traits, demographic characteristics, temporal variables, daily activities, and all variables combined, to systematically evaluate the relative importance of each factor. Additionally, regularization techniques such as Ridge and Lasso, along with dimensionality reduction via Principal Component Analysis (PCA), were used to address challenges like multicollinearity and feature selection.

This study contributes to the growing body of research on mood prediction by emphasizing the dynamic nature of mood changes and exploring the interplay of daily activities, social contexts, and locations. By employing diverse analytical methods and addressing key challenges in predictive modeling, this work offers valuable insights into the factors shaping daily mood dynamics.

2. Literature Review

The prediction of mood status has emerged as a critical area of research, leveraging advancements in mobile sensing technologies to capture nuanced insights into human behavior, emotions, and interactions.

Mobile sensing has been widely used to infer mood by analyzing smartphone data. Meegahapola et al. (2023) highlighted the importance of geographical and cultural contexts in mood inference, showing that country-specific models outperformed generic multi-country approaches. These findings emphasize the role of context in understanding mood, suggesting that models tailored to specific populations are more effective. Similarly, LiKamWa et al. (2013) developed MoodScope, a system that uses app usage and communication patterns to predict mood, achieving a personalized accuracy of up to 93% after two months of training. These studies demonstrate the potential of mobile sensing to provide personalized and context-aware insights into mood dynamics.

The role of daily activities in shaping mood has been a focus of recent research. Assi et al. (2023) explored the detection of complex daily activities using multimodal smartphone sensors, finding that activity recognition models perform better when tailored to specific contexts. Their work highlights the importance of considering the diversity of activities in mood prediction. Rachuri et al. (2010) contributed to this research field by integrating emotion sensing with activity and interaction tracking, showing how social contexts influence emotional states. These findings suggest that mood prediction models should account for both individual activities and the broader social and environmental contexts in which they occur.

Longitudinal studies have provided valuable insights into mood dynamics over time. Servia-Rodríguez et al. (2017) conducted a large-scale study using smartphone data, demonstrating that mood is strongly correlated with daily routines and psychological variables. Their findings underscore the potential of mobile sensing to capture mood patterns over extended periods. Similarly, Wang et al. (2014) examined the impact of academic workload on students' mood, revealing significant fluctuations in mood and stress levels throughout the term. These studies highlight the importance of temporal factors in mood prediction and the value of longitudinal data for understanding mood changes.

Behavioral markers derived from mobile sensing data have been shown to predict mood changes effectively. Sano and Picard (2013) identified correlations between stress and features such as mobility and screen usage, demonstrating that these markers can serve as proxies for emotional states. Canzian and Musolesi (2015) further explored this relationship by analyzing mobility patterns to predict depressive mood changes, emphasizing the role of physical location in mood dynamics. These findings suggest that integrating behavioral markers with contextual data can enhance the accuracy of mood prediction models.

The existing literature highlights the importance of integrating data on daily activities, social contexts, and locations for mood prediction. While much research has focused on mood inference and general mood patterns, this study addresses a gap by investigating how these factors specifically predict mood changes throughout the day. By combining data on personality traits, human values, and contextual variables, this research builds on prior studies to offer a comprehensive understanding of the determinants of mood dynamics. By employing advanced machine learning techniques and addressing challenges such as class imbalance and multicollinearity, this work contributes to the growing field of mood prediction.

3. Research Question and Data Description

The research question of this study is: how do daily activities, social context, and location predict mood changes throughout the day?

The data comes from the WeNet project, which used the ILog app to collect daily data from 241 Unitn students for a month, starting the 14 of November 2020. The app collects smartphone information and asks the user every half hour what they are doing, where they are, with who, and their mood.

In this study, the data that is being used is the one from the first two weeks of the research because past this period the push notifications arrive every hour and not every 30 minutes. The subjects also filled out a pre-study questionnaire, where their demographic characteristics were collected and their personality traits and human values scores were assessed.

The days were codified so that the day would start at 5 a.m. and end at 4:30 a.m. of the next day to represent the actual way in which people live the day. After cleaning the data the subjects remaining were 98 and there were 43380 records in total. For the data visualization, we used the standardized version for each participant's mood, for the regression and machine learning models we used the numeric version for a better performance.

The dependent variable is the mood change, a categorical variable that was created by measuring when there is a change in the mood of the person, which is measured on a scale from 1 to 5. The categories of mood change are increase, decrease, and no change. The independent variables encompass multiple dimensions, including personality traits, human values, demographic information, temporal patterns, and daily activities. These variables are:

Personality traits (BFI):
extraversion: tendency toward sociability, energy, and positive emotions; agreeableness: propensity for cooperation, trust, and altruism; conscientiousness: tendency for self-discipline, organization, and goal-directed behavior; neuroticism: susceptibility to negative emotions like anxiety, depression, and emotional instability; openness: inclination toward creativity, curiosity, and openness to new experiences.

Human values (BVS):
conformity, tradition, benov, univers, self, stim, hedon, achieve, power, security, open, selfenh, selftran, conserv, excitements, suprapersonal, interactive, promotion, existence, normative, linguistic, logicmath, spatial, bodykines, musical, interpersonal, intrapersonal, environmental, spiritual

Demographic characteristics:
gender, department, age, residence in relation to the university, degree, nationality

Temporal variables:
day of the week, hour of the day

Activities, location and social context:
what they are doing, where they are, and with who

For a better analysis, we aggregated some categories together: Restaurant/pub and Canteen/Other uni place were added to another indoor category, In the street was added to another outdoor category, all the movement categories were aggregated into a travel category, free time culture, personal care, rest/nap/anything, and break coffee were aggregated into leisure category, Inchat/e-mail/seeking internet and phone/video calling were united into distant communication/ seeking internet category.

4. Methodology

We employed a combination of regression and machine learning techniques to analyze the determinants of mood change. Specifically, we utilized Logistic Regression, Random Forest Classifier, and Gradient Boosting Classifier to identify the most influential variables and assess predictive accuracy. Each method was applied with varying sets of variables to explore their relative importance and predictive power and weights were used to balance the classes of mood change.

To systematically assess the impact of different factors, we created five variable groupings: personality traits, demographic characteristics, temporal variables, daily activities variables, and all variables combined.

For the logistic regression method, we built four initial models trained on the first four variable groups and, to address specific modeling challenges, we implemented three additional models, trained on the all variables set, with distinct regularization techniques. Ridge regression (L2 regularization), to address multicollinearity by penalizing large coefficients. Lasso regression (L1 regularization), to both address multicollinearity and perform feature selection by shrinking irrelevant coefficients to zero. Principal Component Analysis (PCA), which reduced dimensionality by transforming the predictor space into uncorrelated components while retaining 95% of the variance, followed by regression on the principal components.

The Random Forest classifier, an ensemble method, was employed to capture non-linear relationships and interactions among predictors. Averaging predictions from multiple decision trees provides robust predictions and calculates feature importance scores to identify the most influential variables.

The Gradient Boosting Classifier, another ensemble method, iteratively improves predictions by focusing on correcting errors from previous iterations. This approach is particularly effective in capturing complex, non-linear patterns within the data.

For each model, we evaluated performance on the test set using these metrics: accuracy, which measures the proportion of correctly classified instances out of the total number of instances, and F1 score for each class, which is the harmonic mean of precision, the proportion of true positives out of all predicted positives, and recall, the proportion of true positives out of all actual positives.

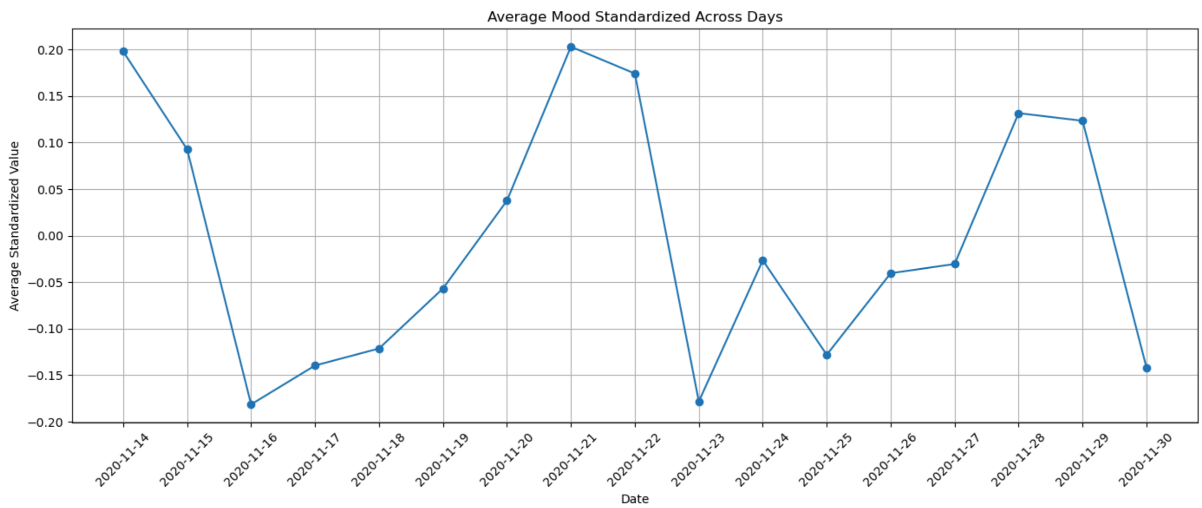
Weights were used to solve the imbalance in the number of observations in the mood change variable, since the no change class had more obsevations that the increase and decrease classes. The models were trained on a set comprising 70% of the observations and tested on a set comprising 30% of the observations to assess generalizability.

By employing a diverse set of methods and variable groupings, we systematically evaluated the determinants of mood change, addressing key challenges such as multicollinearity, non-linearity, and feature selection, while providing a comprehensive understanding of the factors influencing daily mood dynamics.

5. Results

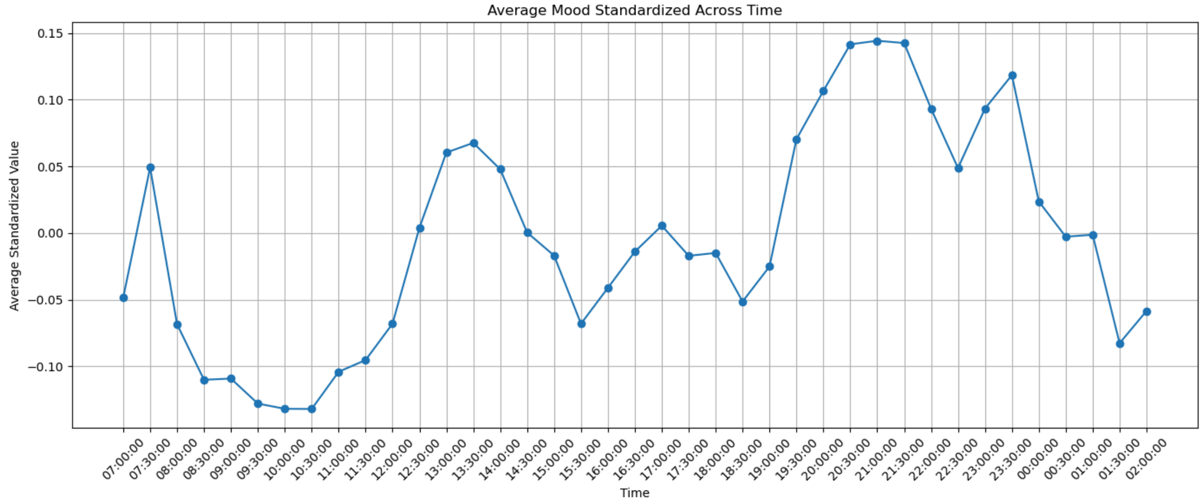
We begin by displaying the distributions of the mood across different days and through the hours.

Graph 1: Average standardized mood trend across days



Looking at the distribution of the mood we can see that the highest scores are registered on the weekend days and the lowest are on Monday. The trend shows that the average mood constantly increases from Monday to Sunday for the first week and increases with some ups and downs in the second week.

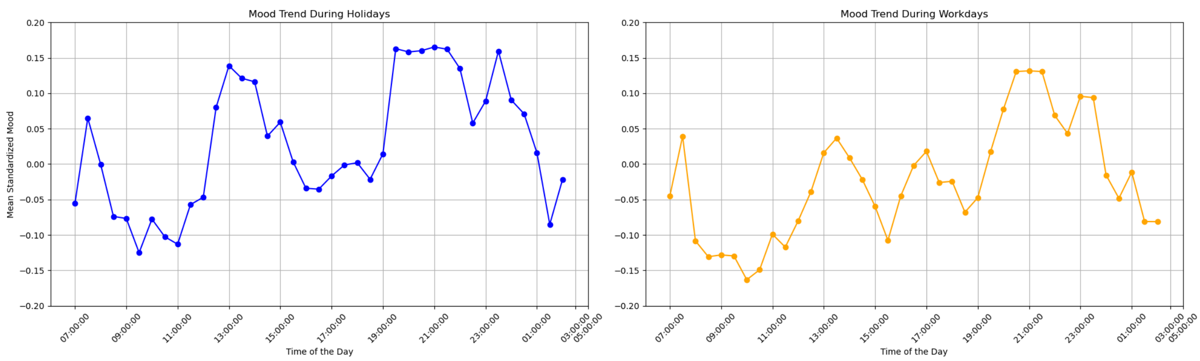
Graph 2: Average standardized mood trend across the hours of the day



We can see that the distribution of the mood during the day has some fluctuations. The morning is the period of the day with the lowest average mood, there is an increase in the lunch hours, then the mood slightly decreases in the afternoon, and finally, in the evening it gets to the highest point, for then to lower in the late night hours.

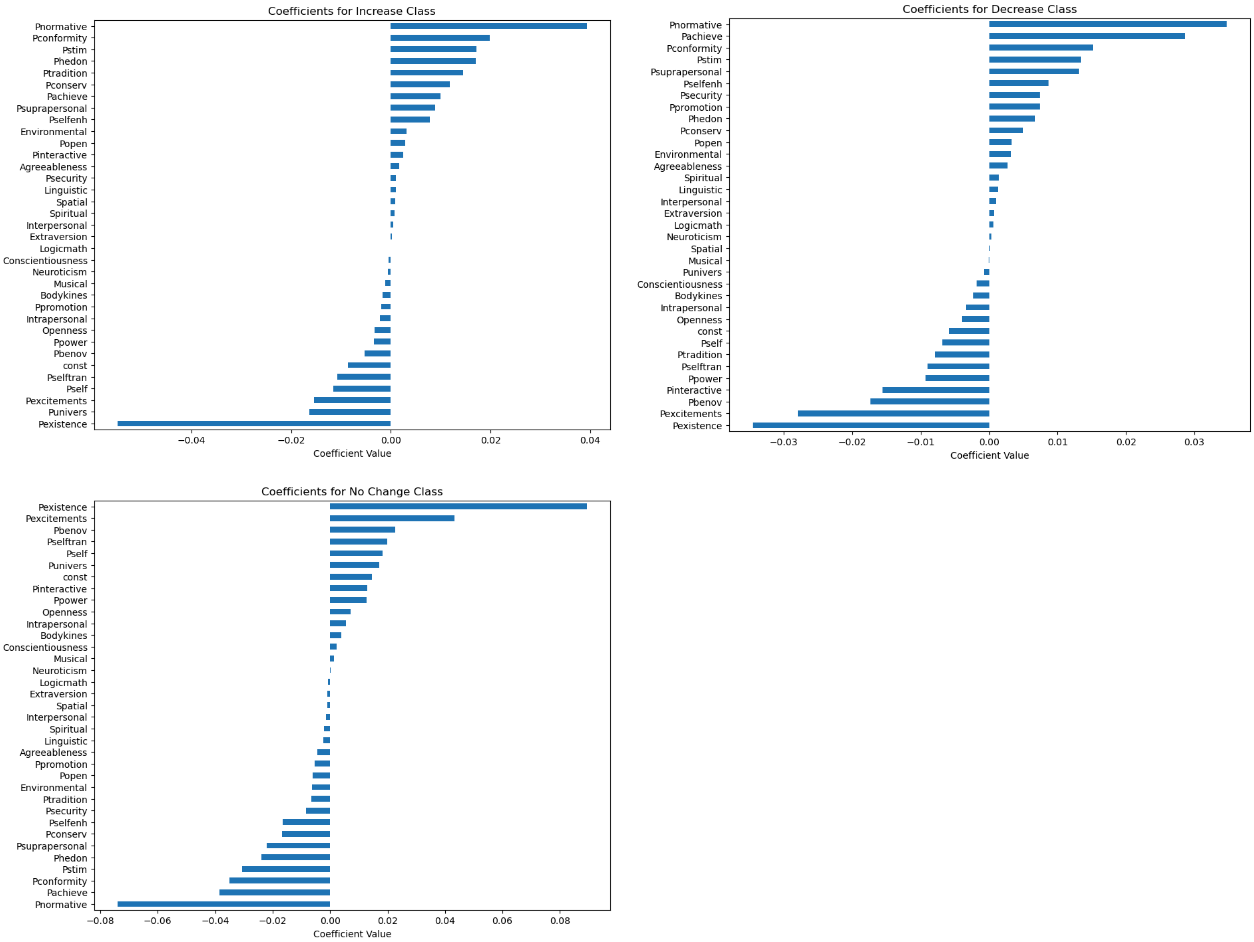
The plot does not display the mood from 2:30 to 6:30 because there are too few observations during those hours.

Graph 3: Average standardized mood trend across the hours of the workdays and holidays



We can see that the trends of mood in the holidays and workdays are similar to the general one, having the lowest point in the morning and the highest in the evening. In the holidays the increase in the lunch hours is more prominent and the whole distribution is higher than the workdays.

Graph 4: Log odds for the personality traits logistic regression model



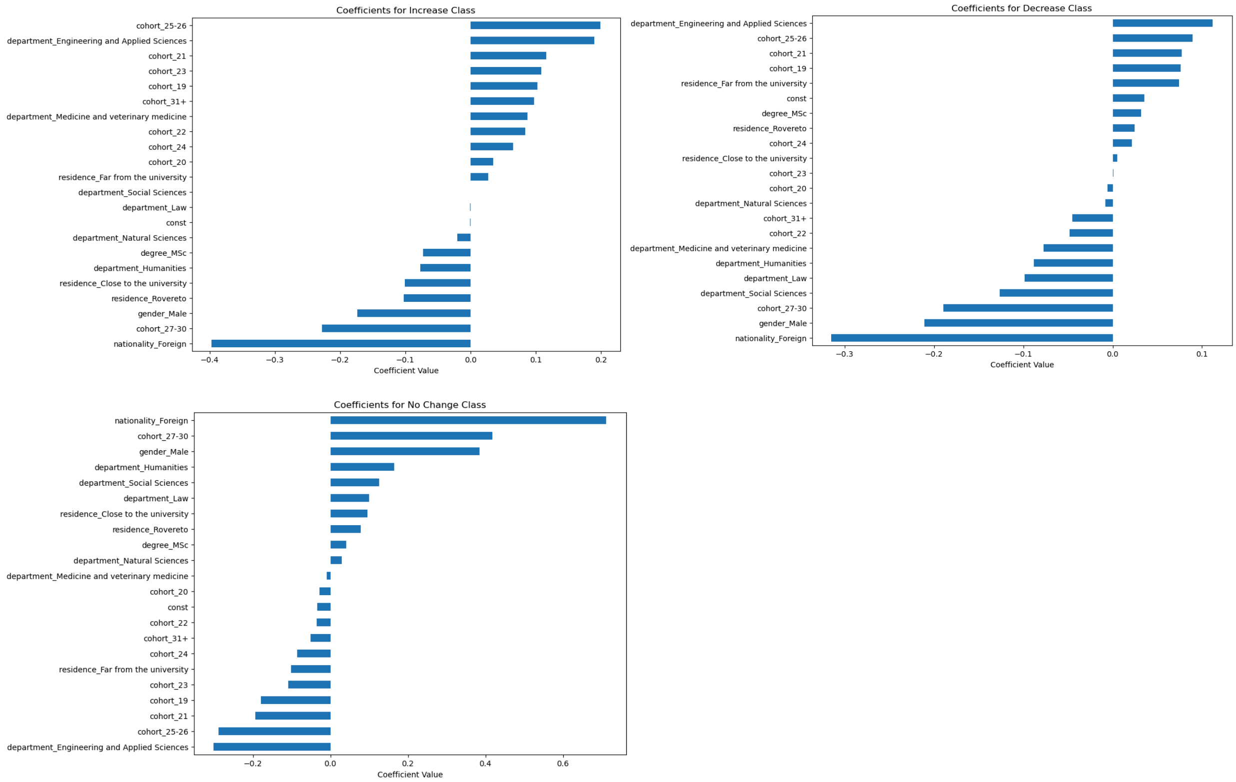
We can see that the variables that have positive log-odds for increase class usually have also positive log-odds for decrease class and negative for no change class. This is due to the fact that features that are predictive of mood changes, either increase or decrease, often act in a similar way because both categories represent a departure from stability (no change). The same features that predict movement away from stability will have negative coefficients for no change, reflecting the decreased likelihood of stability.

Pnormative is the variable that increases the most the likelihood of a mood change, with a slightly higher value for increase than decrease. Pexistence is the variable with the highest positive value for no change and the highest negative for increase and decrease classes.

Pachieve has high positive log odds for the decrease, slightly lower log odds for the increase class and high negative log odds for the no change class. Pconformity has high positive log odds for the increase, slightly lower log odds for the decrease class and high negative log odds for the no change class.

Pstim, Phedom, Ptradition, Pconserv, and Psuprapersonal are variables with positive log odds for increase and decrease classes and negative log odds for no change class. Pexcitement, Punivers, Pself, Pselftran, and Pbenov have positive log odds for no change class and negative for increase and decrease classes.

Graph 5: Log odds for the demographic characteristics logistic regression model



The references for the variables are cohort 17-18, Department of Business/Economics, gender female, bachelor's degree, residence in Trento, and nationality Italian.

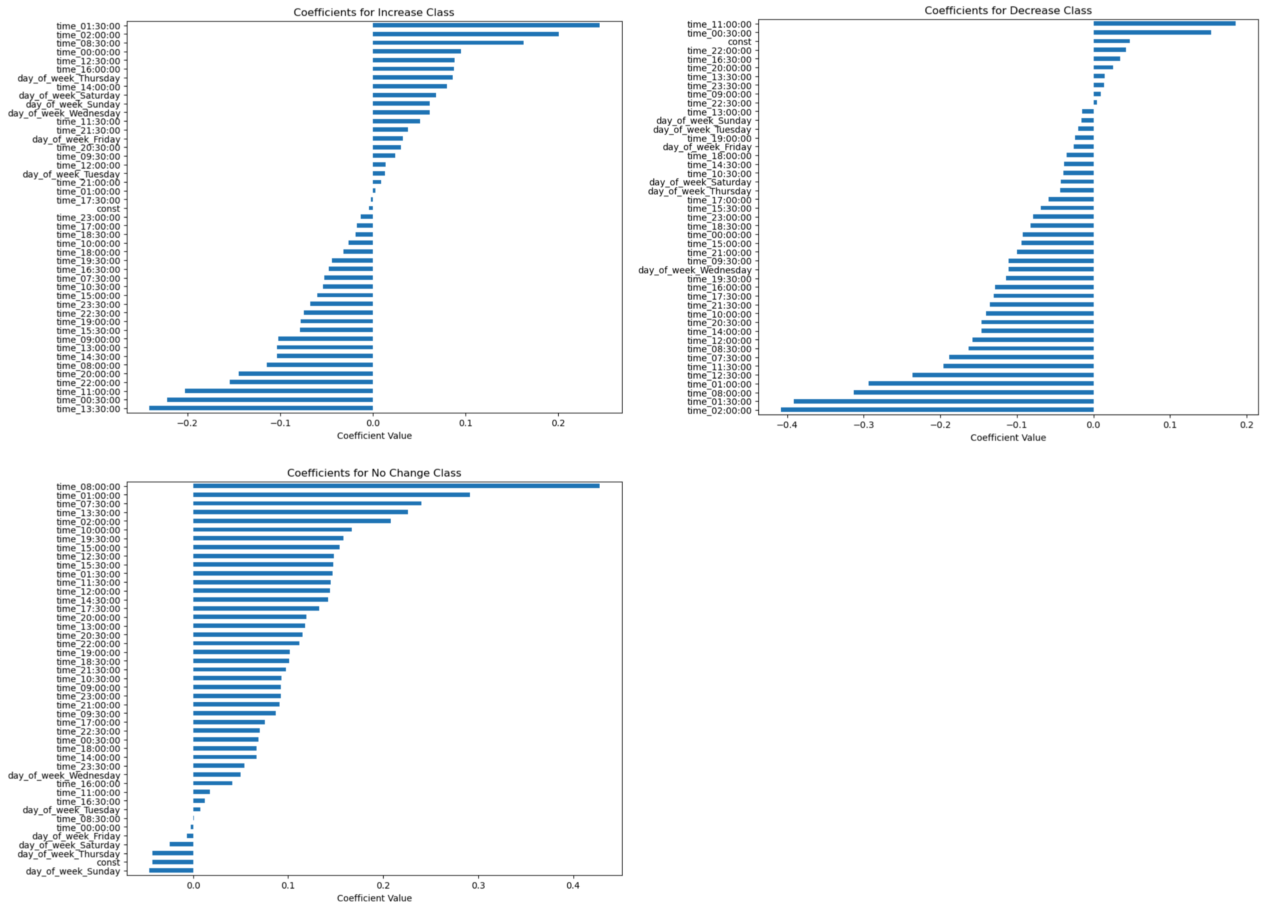
On the cohort variable, we can see that 25-26, 21, 24, and 19 cohorts have positive log odds for increase and decrease classes and negative log odds for no change class, 27-30 cohort has positive log odds for no change class and negative log odds for increase and decrease classes.

On the department variable, we can see that the Department of Engineering and Applied Science has positive log odds for increase and decrease classes and negative log odds for no change class. The Humanities Department has positive log odds for no change class and negative log odds for increase and decrease classes. The law and social sciences departments have neutral log odds for increase class, negative for decrease, and positive for no change.

The male gender has positive log odds for no change class and negative log odds for increase and decrease classes. The master's degree has almost neutral log odds for the three classes, it is slightly negative for increase class and positive for decrease and no change classes. Foreign nationality has positive log odds for no change class and negative log odds for increase and decrease classes.

The residence in Rovereto has positive log odds for decrease and no change classes and negative for increase class. Residence close to the university has positive log odds for no change class, negative for increase class, and neutral for decrease. Residence far from the university has positive log odds for decrease class, negative for no change class, and neutral for increase.

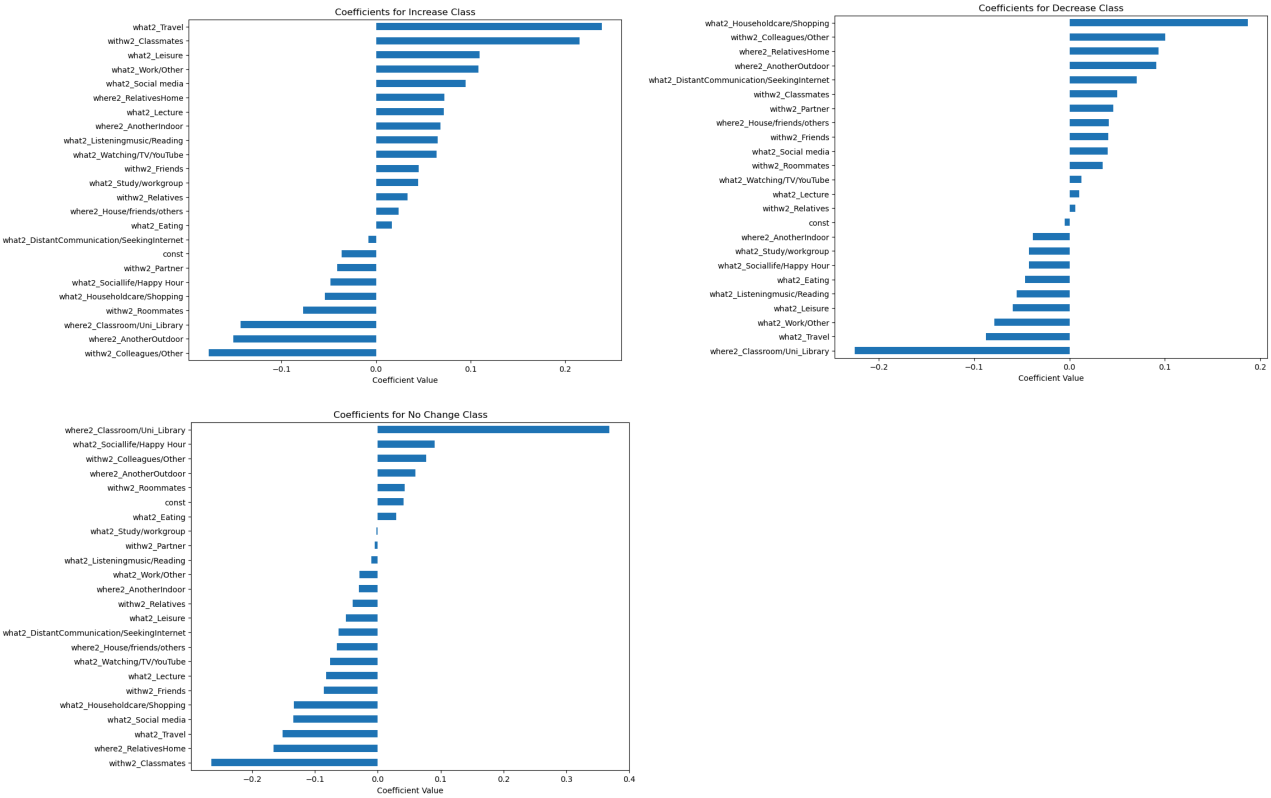
Graph 6: Log odds for the temporal variables logistic regression model



The references for the variables are 7:00 and Monday. For the day of the week variable, we can see that Thursday, Friday, Saturday, and Sunday have positive log odds for increase class and negative for decrease and no change classes. Tuesday has negative log odds for the decrease class and neutral for the increase and no change classes. Wednesday has negative log odds for decrease class and positive for increase and no change classes.

Almost all hours of the day have positive log odds for no change class, a majority have negative log odds for the decrease class and they are split into positive and negative log odds for the increase class. The hours that have positive log odds for increase class do not seem to have something in common.

Graph 7: Log odds for the activities, location, and social context logistic regression model



The references for the variables are cooking for what doing, house/apartment for location and alone for social context. Traveling, leisure, and work/other have positive log odds for increase class and negative for decrease and no change classes. Social media has positive log odds for increase and decrease classes and negative for no change class. Lecture and watching tv/youtube have positive log odds for increase, negative for no change and neutral for decrease.

Classmates and friends have positive log odds for increase and decrease classes and negative fo no change class. Roommates and collegues/others have positive log odds for decrease and no change and negative for increase.

Relatives' home and another indoor have positive log odds for increase and decrease classes and negative for no change. Classroom/uni library and another outdoor have negative log odds for increase and decrease classes and positive for no change.

Table 1: Performance on the test set for logistic regression models

	Accuracy	F1 No Change	F1 Increase	F1 Decrease
Personality traits model	0.48	0.65	0.15	0.14
Demographic model	0.46	0.62	0.16	0.15
Temporal variables model	0.30	0.43	0.15	0.15
Activities, location, social context model	0.52	0.69	0.14	0.13
Ridge model	0.48	0.64	0.17	0.17
Lasso model	0.80	0.89	0.07	0.06
PCA model	0.45	0.61	0.17	0.15

This table evaluates the performance of logistic regression models across different groupings of predictors for predicting mood change. The metrics reported include accuracy and F1 scores for the three mood change classes: no change, increase, and decrease.

The personality traits model's accuracy is 48%, moderately better than random guessing in a balanced dataset. The F1 no change is 0.65, indicating decent performance for the dominant class. The F1 increase and decrease are low (0.15 and 0.14), showing difficulty in distinguishing these minority classes. Personality traits moderately predict mood stability (no change) but fail to capture the nuances of mood increases or decreases.

The demographic variables model's accuracy is 46%, similar to the personality traits model. The F1 performance for no change (0.62) is comparable to the personality traits model, but increase (0.16) and decrease (0.15) show marginal improvements. Demographic characteristics like gender, age, and residence provide limited predictive power for mood changes, likely because they are static and do not account for situational or behavioral variability.

The temporal variables model's accuracy is 30%, significantly lower than other models. The F1 no change is 0.43, showing poor performance even for the dominant class. The F1 increase and decrease are stagnant at 0.15. Temporal variables (e.g., time of day, day of the week) alone are insufficient for predicting mood changes, likely because they lack contextual or individual-specific information.

The activities, location, and social context model's accuracy is 52%, the highest among all models. The F1 no change is 0.69, the best performance for the dominant class. The F1 increase and decrease are low (0.14 and 0.13). Daily activities, location, and social context are strong predictors of mood stability but fail to capture the dynamics of mood changes. This suggests that these variables reflect routine behaviors more than emotional shifts.

The Ridge regression model's accuracy is 48%, comparable to the personality traits model. The F1 scores are slightly better balanced between increase (0.17) and decrease (0.17) classes. Ridge regression's ability to handle multicollinearity improves predictions for minority classes, though the improvement is modest.

The Lasso regression model's accuracy is 80%, significantly higher than all other models. The F1 no change is 0.89, indicating excellent performance for the dominant class. The F1 increase and decrease are extremely low (0.07 and 0.06). Lasso regression likely overfits to the dominance of no change class by shrinking coefficients for features associated with minority classes to zero. While this boosts overall accuracy, it fails to capture meaningful patterns for increase and decrease.

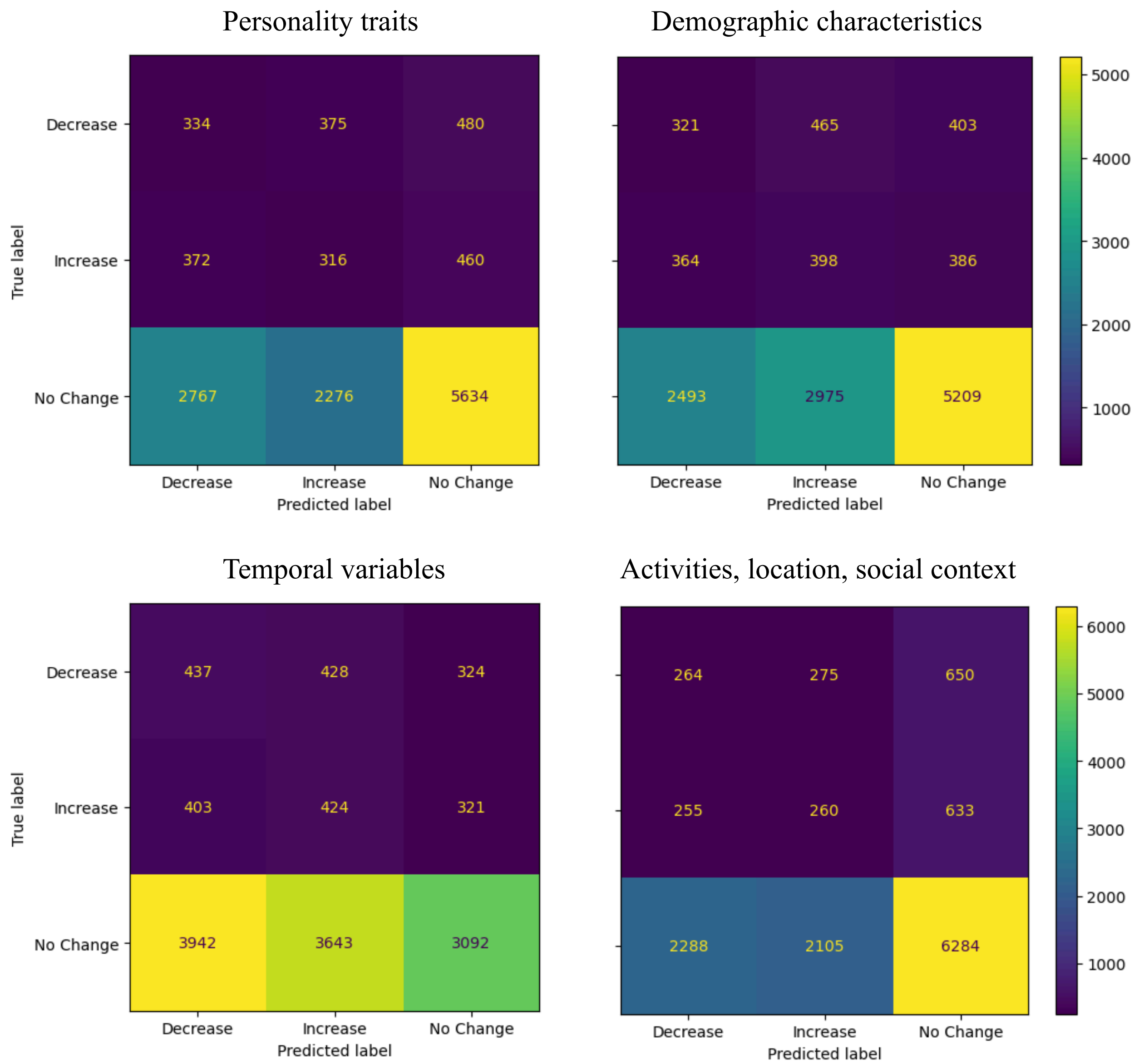
The PCA model's accuracy is 45%, slightly lower than Ridge and personality traits models. The F1 no change is 0.61, slightly lower than Ridge but comparable to demographic and personality models. The F1 for increase and decrease show marginal improvement (0.17 and 0.15). PCA reduces dimensionality effectively but sacrifices predictive power for the dominant class (no change) in exchange for marginally better performance on minority classes.

Across all models, no change is predicted with significantly higher accuracy and F1 scores, reflecting its dominance in the dataset. Minority classes (increase and decrease) remain challenging to predict due to their smaller representation.

The activities, location, and social context model achieves the highest accuracy among non-regularized models, highlighting the importance of behavioral and situational factors in mood prediction.

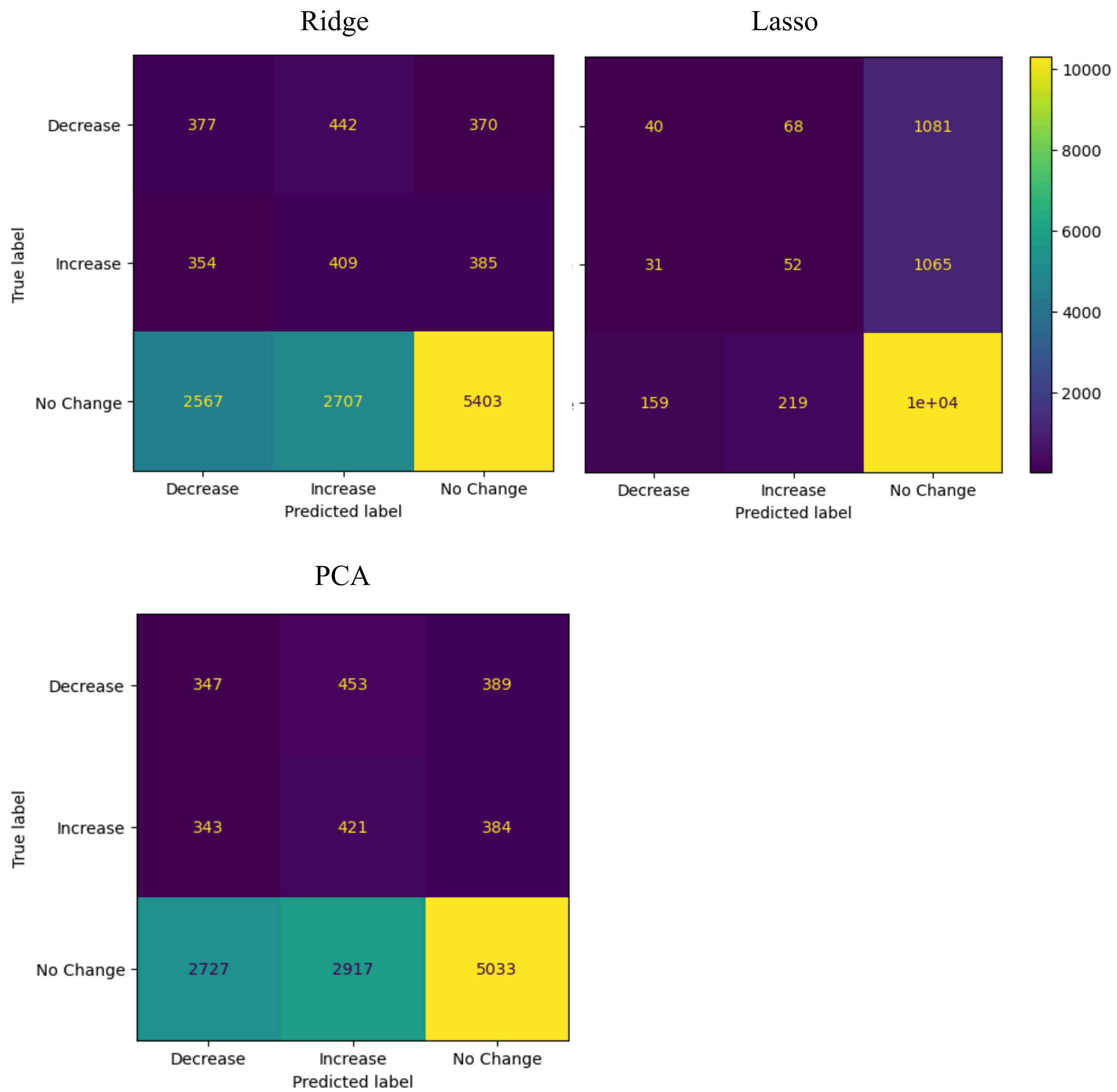
Ridge regression balances predictions across all classes better than other regression models. Lasso Regression focuses too heavily on the dominant class, leading to overfitting and poor performance for minority classes. PCA offers slight improvements for minority classes but reduces overall accuracy, suggesting it may not capture the most relevant features for mood change prediction.

Graph 8: Confusion matrix for the logistic regression model



We can see that the models correctly predict the no change class most of the time but incorrectly predicts the increase and decrease classes more times than they actually are, due to the use of the weight balanced on the frequency of each class.

Graph 9: Confusion matrix for the logistic regression(ridge, lasso, pca) models



We can see that the Ridge and PCA models predict the decrease and increase classes more times than they actually are. The Lasso model predicts the no change class more ofter than the other logistic regression models.

Table 2: Performance on the test set for Random Forest models

	Accuracy	F1 No Change	F1 Increase	F1 Decrease
Personality traits model	0.50	0.67	0.20	0.17
Demographic model	0.47	0.64	0.17	0.16
Temporal variables model	0.35	0.49	0.13	0.15
Activities, location, social context model	0.37	0.53	0.14	0.13
All variables model	0.80	0.89	0.05	0.05

This table evaluates the performance of Random Forest models in predicting mood change using different sets of predictors. The metrics include Accuracy and F1 scores for the three mood change classes: no change, increase, and decrease.

The personality traits model's accuracy is 50%, slightly better than chance for a balanced dataset. The F1 no change is 0.67, indicating moderate success in predicting the dominant class. The F1 increase and decrease are 0.20 and 0.17, reflecting reasonable improvements for minority classes compared to logistic regression models. Personality traits capture some aspects of mood stability (no change) and provide moderate insight into mood dynamics (increase and decrease). However, their predictive power remains limited for short-term emotional changes.

The demographic variables model's accuracy is 47%, slightly lower than the personality traits model. The F1 no change is 0.64, showing a slight drop in performance for the dominant class. The F1 increase and decrease are 0.17 and 0.16, indicating similar performance to the personality traits model. Demographic characteristics, being static and broad, provide limited predictive power for dynamic phenomena like mood changes.

The temporal variables model's accuracy is 35%, the lowest among all models. The F1 no change is 0.49, indicating poor performance even for the dominant class. The F1 increase and decrease scores are low (0.13 and 0.15). Temporal variables alone are insufficient to predict mood changes, as they lack individualized or contextual information.

The activities, location, and social context model's accuracy is 37%, slightly higher than the temporal variables model but still low. The F1 no change is 0.53, showing moderate performance for the dominant class. The F1 increase and decrease are 0.14 and 0.13, indicating poor predictive power for minority classes. While daily activities, location, and social context are relevant, their predictive utility may require interaction with other variables to improve performance.

The all variables model's accuracy is 80%, significantly higher than all other models. The F1 no change is 0.89, indicating excellent performance for the dominant class. The F1 increase and decrease are extremely low (0.05 each), reflecting poor performance for minority classes. Including all variables leads to overfitting to the dominant class (no change) at the expense of minority classes. This highlights the limitations of Random Forest in handling imbalanced datasets without proper weighting or resampling.

Across all models, the no change class is predicted with much higher accuracy and F1 scores, reflecting its dominance in the dataset. minority classes (increase and decrease) remain challenging to predict.

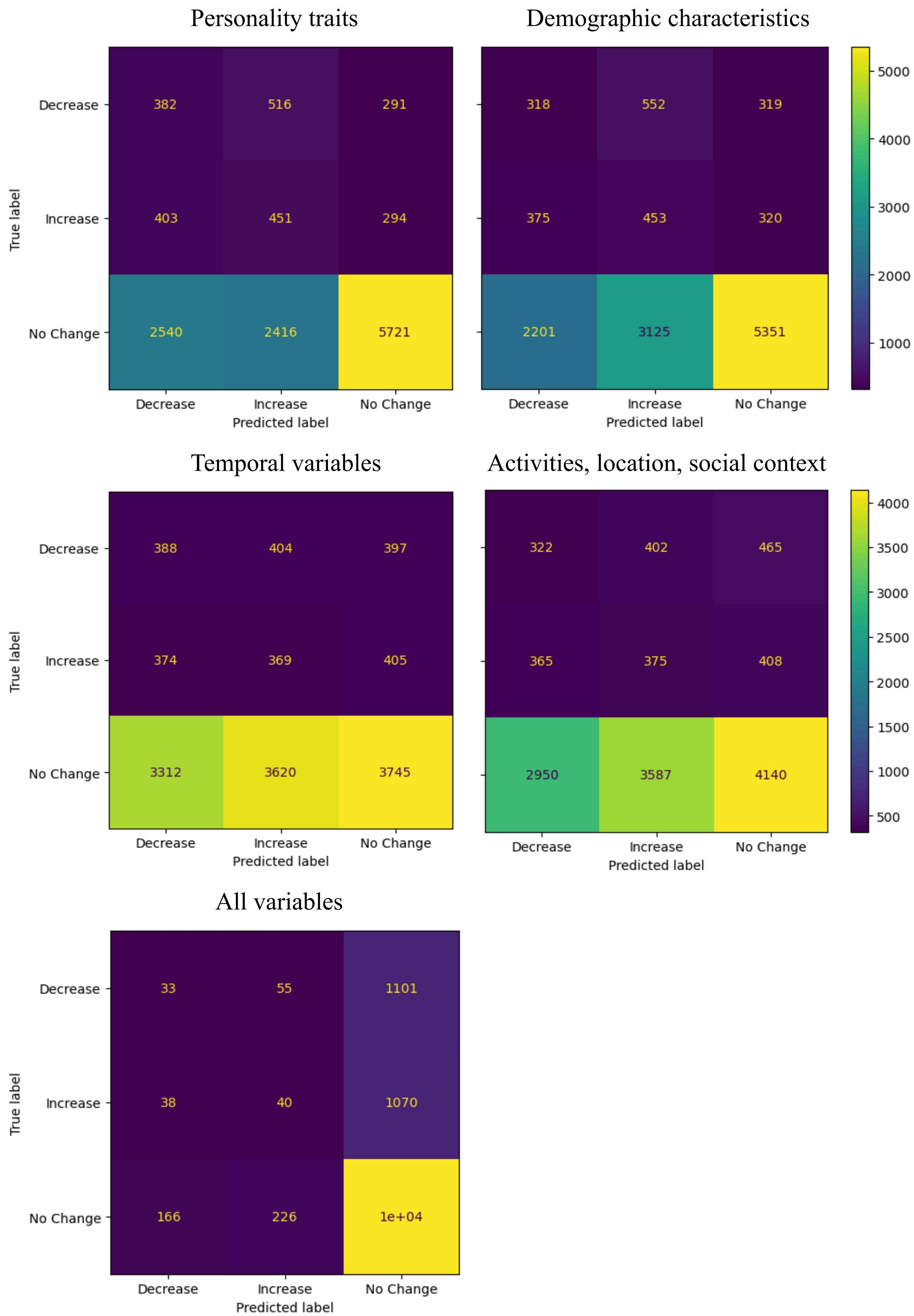
The all variables model achieves high accuracy and F1 scores for the dominant class but fails to generalize to minority classes. This suggests that the model prioritizes overall accuracy by focusing disproportionately on the majority class.

Personality traits and demographic variables achieve the best balance between accuracy and F1 scores for minority classes. This suggests these variables have some predictive value for mood changes, though improvements are needed.

Temporal variables and contextual factors like activities and social context alone do not provide sufficient predictive power, likely due to their lack of interaction with individual-specific variables.

While Random Forest models show potential for predicting mood change, particularly with personality traits and demographic variables, their performance on minority classes remains limited.

Graph 10: Confusion matrix for the Random Forest models



We can see that the first four models predict the decrease and increase classes more times than they actually are, especially the temporal variables, and activities, location, social context models. The all variables model predicts the no change class more ofter than the other logistic regression models.

Table 3: Features importance for the all variables Random Forest model

Feat.	Importance	Feat.	Importance
Sunday	0.027396	withw2_Roommates	0.004039
Saturday	0.027260	Pconformity	0.003902
Leisure	0.025631	Intrapersonal	0.003894
Monday	0.025000	Popen	0.003876
Tuesday	0.024672	Pselftran	0.003860
Thursday	0.023860	withw2_Classmates	0.003796
Friday	0.023293	Spiritual	0.003774
Wednesday	0.023178	Conscientiousness	0.003745
what2_Study/workgroup	0.020675	Psecurity	0.003736
withw2_Alone	0.020095	Openness	0.003718
what2_Eating	0.017177	Ppromotion	0.003716
what2_Watching/TV/ YouTube	0.017047	Psuprapersonal	0.003695
17:00	0.014817	Environmental	0.003679
16:30	0.014601	Musical	0.003642
16:00	0.014486	Pachieve	0.003596
18:00	0.014363	Phedon	0.003596
11:00	0.013914	Pnormative	0.003577
21:00	0.013726	Punivers	0.003541

22:00	0.013694	Extraversion	0.003513
15:30	0.013616	Bodykines	0.003436
17:30	0.013420	Pinteractive	0.003403
withw2_Relatives	0.013302	residence_Trento	0.003372
19:00	0.013224	Pself	0.003339
21:30	0.013158	08:00	0.003228
14:00	0.013138	Pstim	0.003210
11:30	0.013039	Pexcitements	0.003167
22:30	0.013026	01:00	0.003114
14:30	0.012840	Linguistic	0.003100
18:30	0.012680	what2_Travel	0.003094
15:00	0.012592	Ppower	0.003049
12:30	0.012583	Pspatial	0.002953
13:00	0.012449	Pexistence	0.002782
12:00	0.012442	dep Engineering	0.002643
19:30	0.012381	Female	0.002597
10:00	0.012276	Agreeableness	0.002583
10:30	0.012234	Pbenov	0.002581
20:30	0.012121	Male	0.002547
what2_Lecture	0.011980	cohort_21	0.002395
09:30	0.011610	degree_BSc	0.002380
13:30	0.011562	01:30	0.002343
20:00	0.011524	dep Natural Sciences	0.002305

where2_HomeApartment/ room	0.011459	degree_MSc	0.002259
23:00	0.011237	cohort_20	0.002211
what2_DistantCommunication/SeekingInternet	0.010934	residence close to university	0.002153
23:30	0.010301	where2_Classroom/ Uni_Library	0.002118
09:00	0.009516	dep Social Sciences	0.002031
what2_Householdcare/ Shopping	0.009260	cohort_19	0.001908
what2_Cooking	0.008083	dep Law	0.001892
00:00	0.008069	withw2_Colleagues/ Other	0.001853
08:30	0.007793	cohort_22	0.001849
withw2_Friends	0.007659	residence far from university	0.001780
what2_Sociallife/ Happy Hour	0.007250	dep Business/ economics	0.001705
what2_Social media	0.006229	07:30	0.001698
where2_RelativesHome	0.005975	cohort_24	0.001546
withw2_Partner	0.005942	02:00	0.001535
what2_Listeningmusic/ Reading	0.005594	cohort_23	0.001465
where2_AnotherIndoor	0.005429	cohort_25-26	0.001162
00:30	0.005336	07:00	0.001134
Neuroticism	0.005326	dep Humanities	0.000979
Intrapersonal	0.005011	cohort_17-18	0.000834

where2_House/friends/others	0.004910	residence_Rovereto	0.000743
Pselfenh	0.004807	cohort_27-30	0.000577
Pconserv	0.004750	dep Medicine	0.000544
what2_Work/Other	0.004412	cohort_31	0.000526
Ptradition	0.004265	nationality_Foreign	0.000521
Logicmath	0.004247	nationality_Italian	0.000517
where2_AnotherOutdoor	0.004061	dep International Relations	0.000000

This table highlights the features' importance for the Random Forest model trained on all variables to predict mood change. Feature importance reflects the relative contribution of each predictor to the model's performance.

The top-ranked features are dominated by temporal variables, particularly days of the week (e.g., Sunday, Saturday, Monday) and specific times of the day (e.g., 17:00, 16:30, 18:00). This suggests that mood dynamics are strongly tied to temporal patterns, reflecting the influence of structured routines and cultural or societal norms.

For instance: Sunday and Saturday likely capture the influence of leisure and relaxation associated with weekends, when people are more likely to engage in activities that positively or negatively impact mood. Specific hours of the day, particularly late afternoons and evenings, may represent key moments for emotional fluctuations, possibly due to transitions between work, leisure, and social activities.

Activities such as Leisure, Study/Workgroup, and Eating rank highly, emphasizing their importance in shaping mood. Leisure is the third most important feature, reinforcing its role as a key driver of mood, likely due to its association with relaxation and enjoyment. Study/Workgroup and Eating highlight the emotional impacts of academic and social interactions, as well as the physiological and psychological benefits of meal times. Watching TV/YouTube also features prominently, reflecting its role as a common leisure activity that can influence mood, positively or negatively, depending on content and context.

Social context variables, such as Alone, Relatives, and Friends, are critical for mood prediction. Alone ranks highly, suggesting that solitude significantly affects mood, potentially amplifying introspection or loneliness. Relatives and Friends capture the positive emotional impacts of social interactions, emphasizing the importance of supportive relationships.

While location variables such as Home/Apartment/Room and Relatives' Home are present in the importance rankings, their lower positions indicate that location alone may not be as predictive of mood as activities or temporal factors.

Personality traits, such as Neuroticism, Conscientiousness, and Extraversion, appear lower in the rankings. This suggests that while individual differences in personality contribute to mood dynamics, their predictive power is secondary to situational and temporal factors in this dataset.

Features such as Gender, Degree, and Residence appear near the bottom of the rankings, indicating that demographic characteristics have limited direct influence on mood prediction in this context. Similarly, Department and Nationality show negligible importance, suggesting that academic or cultural differences are not primary drivers of mood changes within this sample.

Temporal features are the most influential predictors, underscoring the importance of time-based patterns in mood dynamics. Activities and social contexts are critical, highlighting the need to account for what people are doing and with whom when modeling mood. Personality traits and demographic characteristics, while contributing to individual differences, play a less central role compared to situational factors. The prominence of specific hours (e.g., late afternoon and evening) and weekend days suggests targeted opportunities for mood interventions and personalized well-being strategies.

These findings align with prior research emphasizing the importance of integrating temporal, activity-based, and social-contextual data for accurate mood prediction. Future studies could explore interactions between these factors to deepen understanding of mood dynamics and improve predictive models.

Table 4: Performance on the test set for Gradient Boosting models

	Accuracy	F1 No Change	F1 Increase	F1 Decrease
Personality traits model	0.50	0.67	0.21	0.16
Demographic model	0.45	0.62	0.17	0.16
Temporal variables model	0.28	0.40	0.14	0.15
Activities, location, social context model	0.32	0.46	0.14	0.14
All variables model	0.55	0.72	0.18	0.17

This table evaluates the performance of Gradient Boosting models for predicting mood change across various feature sets. The metrics include Accuracy and F1 scores for the three mood change classes: no change, increase, and decrease.

The personality traits model's accuracy is 50%, suggesting moderate predictive power. The F1 no change is 0.67, reflecting strong performance for the dominant class. The F1 increase and decrease are 0.21 and 0.16, indicating improved performance for minority classes compared to Random Forest and Logistic Regression. Personality traits are moderately effective in predicting mood changes, particularly for identifying shifts from the dominant class (no change) to minority classes (increase and Decrease).

The demographic variables model's accuracy is 45%, lower than the personality traits model. The F1 no change is 0.62, showing reduced performance for the dominant class. The F1 increase and decrease are 0.17 and 0.16, similar to the personality traits model. Demographic variables, while static, capture some mood patterns but are less predictive than personality traits. Their utility may improve when combined with other dynamic factors.

The temporal variables model's accuracy is 28%, the lowest among all models. The F1 no change is 0.40, indicating poor performance for the dominant class. The F1 increase and decrease scores are low (0.14 and 0.15). Temporal variables alone provide minimal predictive value for mood changes, likely because they lack context or individual-specific information.

The activities, location, and social context model's accuracy is 32%, slightly better than the temporal variables model. The F1 no change is 0.46, reflecting moderate performance for the dominant class. The F1 increase and decrease scores are 0.14, indicating limited predictive power for minority classes. While activities, location, and social context are relevant, their predictive utility remains limited when used in isolation.

The all variables model's accuracy is 55%, the highest among all models. The F1 no change is 0.72, indicating strong performance for the dominant class. The F1 increase and decrease are 0.18 and 0.17, reflecting moderate improvements for minority classes compared to other models. The inclusion of all variables provides the best overall performance. Gradient Boosting effectively handles complex interactions and non-linearities in the data, capturing subtle patterns that improve predictions for both dominant and minority classes.

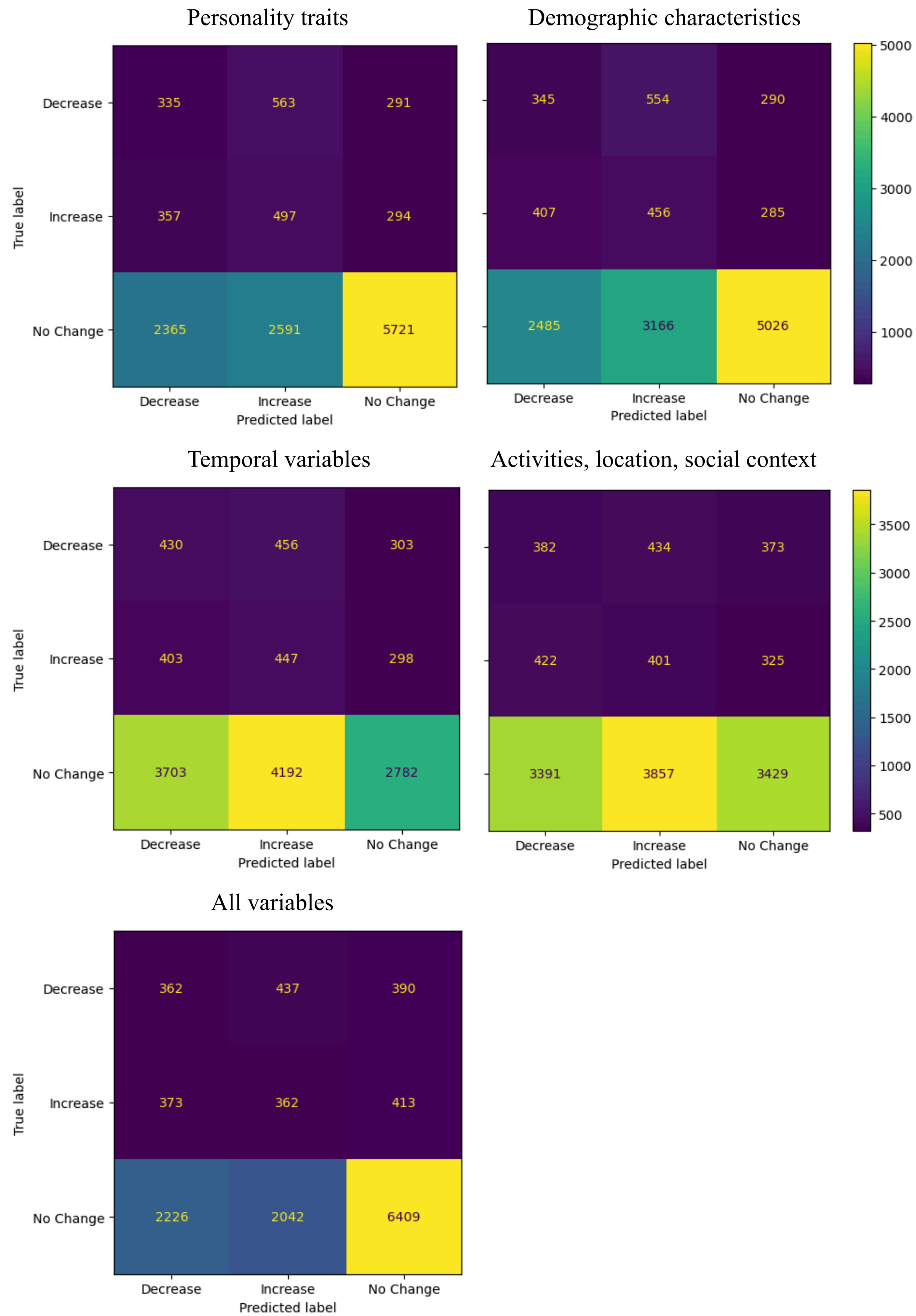
The all variables model consistently outperforms other models, highlighting the importance of combining static (e.g., demographics, personality traits) and dynamic (e.g., activities, temporal factors) predictors for mood change.

While Gradient Boosting performs better than Logistic Regression and Random Forest for minority classes, the increase and decrease labels remain challenging to predict, as evidenced by their relatively low F1 scores.

Models using only personality traits, demographics, temporal variables, or activities perform poorly compared to the combined model. This suggests that mood change is influenced by a complex interplay of multiple factors.

Gradient Boosting models demonstrate strong potential for predicting mood changes, particularly when all variables are combined. However, further efforts are needed to improve predictions for minority classes (increase and decrease) through advanced techniques and feature engineering. The results highlight the importance of using diverse and comprehensive predictors to capture the complexity of mood dynamics.

Graph 11: Confusion matrix for the Gradient Boosting models



We can see that the all the models predict the decrease and increase classes more times than they actually are, especially the temporal variables, and activities, location, social context models.

Table 5: Features importance for the all variables Gradient Boosting model

Feat.	Importance	Feat.	Importance
Ppromotion	0.017693	23:30	0.006714
dep Law	0.017133	what2_Work/Other	0.006671
Environmental	0.016995	where2_House/friends/ others	0.006634
Neuroticism	0.016729	21:00	0.006548
Interpersonal	0.014502	what2_Lecture	0.006541
Psuprapersonal	0.013955	what2_Eating	0.006508
Pconformity	0.013468	Tuesday	0.006356
Bodykines	0.013168	Thursday	0.006322
Musical	0.012769	22:30	0.006318
residence_Trento	0.012340	Pbenov	0.006316
Pselfenh	0.012080	15:30	0.006285
Linguistic	0.012054	Monday	0.006186
Pnormative	0.012031	10:00	0.006159
Pconserv	0.011750	18:30	0.006156
Pstim	0.011670	23:00	0.006131
Pselftran	0.011644	cohort_31+	0.006131
Logicmath	0.011506	what2_Travel	0.006117
Pinteractive	0.011372	13:30	0.006110

Ptradition	0.011103	11:30	0.006100
Openness	0.011033	Wednesday	0.006090
Phedon	0.010936	what2_Watching/TV/ YouTube	0.006071
Popen	0.010911	21:30	0.005990
cohort_19	0.010514	16:30	0.005985
Intrapersonal	0.010119	what2_Householdcare/ Shopping	0.005977
Punivers	0.010114	20:30	0.005956
Spiritual	0.009972	17:30	0.005931
Psecurity	0.009820	09:30	0.005834
Conscientiousness	0.009597	what2_Cooking	0.005775
dep Engineering	0.009487	Saturday	0.005735
Pexcitements	0.009480	17:00	0.005693
dep Humanities	0.009424	withw2_Roommates	0.005683
cohort_20	0.009026	Friday	0.005682
Ppower	0.009025	what2_Leisure	0.005608
cohort_17-18	0.009001	what2_DistantCommuni cation/SeekingInternet	0.005607
nationality_Italian	0.008744	what2_Sociallife/ Happy Hour	0.005606
cohort_23	0.008740	19:30	0.005543
where2_RelativesHome	0.008740	withw2_Classmates	0.005540
Pexistence	0.008565	16:00	0.005538
Spatial	0.008474	what2_Social media	0.005436

degree_BSc	0.008426	00:30	0.005375
residence_Rovereto	0.008396	22:00	0.005358
Pself	0.008309	13:00	0.005338
where2_HomeApartment/room	0.008284	Sunday	0.005313
far from university	0.008013	what2_Listeningmusic/Reading	0.005271
dep Business/economics	0.007983	00:00	0.005270
Female	0.007955	what2_Study/workgroup	0.005207
cohort_25-26	0.007781	12:30	0.005146
dep Social Sciences	0.007770	where2_Classroom/Uni_Library	0.005116
Agreeableness	0.007730	08:00	0.004908
Extraversion	0.007654	20:00	0.004862
withw2_Alone	0.007438	14:00	0.004754
dep Natural Sciences	0.007396	where2_Another Outdoor	0.004747
18:00	0.007350	cohort_27-30	0.004665
08:30	0.007255	dep Medicine	0.004571
cohort_21	0.007237	07:00	0.004520
Pachieve	0.007134	withw2_Colleagues/Other	0.004505
cohort_22	0.007125	11:00	0.004487
where2_Another Indoor	0.007103	09:00	0.004445
withw2_Partner	0.007061	07:30	0.004175

19:00	0.006889	12:00	0.003889
10:30	0.006867	01:00	0.003591
withw2_Relatives	0.006833	01:30	0.003429
15:00	0.006817	02:00	0.001842
withw2_Friends	0.006799	Male	0.000000
14:30	0.006796	nationality_Foreign	0.000000
cohort_24	0.006779	dep International Relation	0.000000
close to university	0.006775	degree_MSc	0.000000

This table highlights the features' importance for the Gradient Boosting model trained on all variables to predict mood change. Feature importance reflects the relative contribution of each predictor to the model's performance.

Several personality traits and human values rank highly, reflecting their significant role in mood dynamics: Ppromotion (0.0177) emerges as the most influential feature, suggesting that individuals driven by self-promotion and achievement-oriented values may experience more pronounced mood changes. Neuroticism (0.0167), a trait associated with emotional instability, is a top predictor, aligning with its established link to mood fluctuations. Pconformity (0.0135) and Psuprapersonal (0.0139) further underscore the importance of individual value systems in shaping emotional responses. Traits like Interpersonal (0.0145) and Environmental (0.0170) highlight the influence of social and environmental sensitivities on mood dynamics.

Residence in Trento (0.0123) and Cohort (e.g., Cohort_19: 0.0105) suggest that geographic and temporal factors tied to the participants' university life play a role in mood changes. Department (e.g., Law: 0.0171) is notable, indicating that academic disciplines may influence emotional states, possibly through workload or social dynamics. Gender and Nationality have negligible importance, suggesting that these factors do not significantly contribute to mood changes in this dataset.

While temporal variables such as specific hours (e.g., 18:00: 0.0074, 19:00: 0.0069) are present, they rank lower compared to personality and value-based features. Days of the week (e.g., Saturday: 0.0057, Sunday: 0.0053) have moderate importance, reflecting the potential influence of weekend routines on mood.

Contextual variables such as with whom (e.g., With Relatives: 0.0068, With Friends: 0.0068) and where (e.g., Home/Apartment: 0.0082, Relatives' Home: 0.0087) highlight the importance of social and physical environments.

Activities such as Leisure (0.0056), Eating (0.0065), and Work/Other (0.0067) are moderately influential, reinforcing their emotional impact. Social contexts like With Friends (0.0068) and With Relatives (0.0068) further emphasize the role of interpersonal interactions in mood regulation.

Academic variables like Department (e.g., Humanities: 0.0094) and Degree (e.g., BSc: 0.0084) have limited importance, suggesting that broader personal and contextual factors overshadow structural academic differences. Nationality (Foreign: 0.0000) and Degree MSc (0.0000) indicate that these demographic features do not significantly affect mood changes in this dataset.

Personality traits and human values dominate, suggesting that intrinsic factors play a central role in mood changes. Demographic characteristics, while present, have limited predictive power compared to personality and contextual variables. Temporal and contextual factors provide complementary insights but are less influential than individual traits and values. The importance of activities and social contexts underscores the need to consider situational dynamics in mood prediction. The negligible importance of certain demographic variables, such as gender and nationality, highlights the uniformity of mood predictors across these dimensions in this dataset.

6. Conclusions

The study explored the complex interplay of daily activities, social context, and location in predicting mood changes using a combination of regression and machine learning models. The results highlight the importance of integrating diverse predictors and advanced analytical techniques to capture the nuances of mood dynamics.

Across all models, predicting the no change class was significantly more accurate than predicting increase or decrease classes. This imbalance reflects the dominance of the no change class in the dataset, making minority classes more difficult to predict. Despite these challenges, the models demonstrated the potential for meaningful insights, particularly when combining diverse predictors.

Personality traits and human values emerged as critical predictors of mood changes, particularly in the Gradient Boosting model. Features like Neuroticism, Ppromotion, and Pconformity highlight the influence of emotional stability, achievement orientation, and adherence to social norms on mood dynamics. These intrinsic factors consistently outperformed demographic and contextual variables, underscoring their central role in shaping emotional responses.

Temporal variables, such as the day of the week and specific hours of the day, were influential in Random Forest models. Weekend days (e.g., Sunday and Saturday) and late afternoons or evenings (e.g., 17:00, 18:00) were particularly relevant, reflecting the emotional impact of structured routines and transitions between work, leisure, and social interactions.

Contextual variables, including social context (e.g., with relatives or friends) and activities (e.g., leisure, eating, and study/workgroup), were moderately important. These findings emphasize the need to consider situational dynamics, such as interpersonal interactions and daily routines, in mood prediction.

Logistic Regression models demonstrated moderate accuracy for the no change class but struggled with increase and decrease. Regularized models like Ridge and Lasso improved balance across classes but still fell short in capturing minority mood changes.

Random Forest models showed stronger performance for minority classes compared to Logistic Regression, although the all variables model overfit to the dominant class.

Gradient Boosting models consistently outperformed other methods, achieving the highest accuracy and F1 scores across all classes. Its ability to handle non-linear relationships and interactions made it the most effective model for predicting mood changes.

Activities, social context, and temporal variables were the top ranked features for importance in the Random Forest model, and personality traits and human values were the most important features in the Gradient Boosting model.

Demographic variables like gender, nationality, and academic department had negligible importance, suggesting that mood changes are more influenced by intrinsic and situational factors than static demographic characteristics.

These findings underscore the importance of personalized and context-aware approaches to mood prediction. By integrating personality traits, human values, and situational factors, models can better capture the complexity of mood dynamics.

While this study provides valuable insights, it also highlights areas for improvement: investigating how personality traits, activities, and temporal variables interact could deepen understanding of mood dynamics. Testing models in diverse populations and settings would improve generalizability and robustness. Trying different methods to predict minority classes better.

This study demonstrates the feasibility and value of using diverse predictors and advanced machine learning techniques to understand mood changes. By building on these findings, future research can refine predictive models and contribute to more effective mood prediction systems.

7. Bibliography

Assi, K., Meegahapola, L., Droz, W., Kun, P., De Götzen, A., Bidoglia, M., ... & Gatica-Perez, D. (2023, April). Complex daily activities, country-level diversity, and smartphone sensing: A study in denmark, italy, mongolia, paraguay, and uk. In Proceedings of the 2023 CHI conference on human factors in computing systems (pp. 1-23).

Canzian, L., & Musolesi, M. (2015, September). Trajectories of depression: unobtrusive monitoring of depressive states by means of smartphone mobility traces analysis. In Proceedings of the 2015 ACM international joint conference on pervasive and ubiquitous computing (pp. 1293-1304).

LiKamWa, R., Liu, Y., Lane, N. D., & Zhong, L. (2013, June). Moodscope: Building a mood sensor from smartphone usage patterns. In Proceeding of the 11th annual international conference on Mobile systems, applications, and services (pp. 389-402).

Meegahapola, L., Droz, W., Kun, P., De Götzen, A., Nutakki, C., Diwakar, S., ... & Gatica-Perez, D. (2023). Generalization and personalization of mobile sensing-based mood inference models: an analysis of college students in eight countries. Proceedings of the ACM on interactive, mobile, wearable and ubiquitous technologies, 6(4), 1-32.

Rachuri, K. K., Musolesi, M., Mascolo, C., Rentfrow, P. J., Longworth, C., & Aucinas, A. (2010, September). EmotionSense: a mobile phones based adaptive platform for experimental social psychology research. In Proceedings of the 12th ACM international conference on Ubiquitous computing (pp. 281-290).

Sano, A., & Picard, R. W. (2013, September). Stress recognition using wearable sensors and mobile phones. In 2013 Humaine association conference on affective computing and intelligent interaction (pp. 671-676). IEEE.

Servia-Rodríguez, S., Rachuri, K. K., Mascolo, C., Rentfrow, P. J., Lathia, N., & Sandstrom, G. M. (2017, April). Mobile sensing at the service of mental well-being: a large-scale longitudinal study. In Proceedings of the 26th international conference on world wide web (pp. 103-112).

Wang, R., Chen, F., Chen, Z., Li, T., Harari, G., Tignor, S., ... & Campbell, A. T. (2014, September). StudentLife: assessing mental health, academic performance and behavioral trends of college students using smartphones. In Proceedings of the 2014 ACM international joint conference on pervasive and ubiquitous computing (pp. 3-14).

The code used for this analysis is available on:
https://github.com/TommasoGrotto2/SHB