Personalized prediction of behaviors and experiences: An idiographic person-situation test

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Abstract

A longstanding goal of psychology is to predict the things people do and feel, but tools to accurately predict future behaviors and experiences remain elusive. In the present study, we used intensive longitudinal data (N = 104; total assessments = 5,971) and three machine learning approaches to investigate the degree to which three future behaviors and experiences – loneliness, procrastination, and studying – could be predicted from past psychological (i.e. personality and affective states), situational (i.e. objective situations and psychological situation cues), and time (i.e. trends, diurnal cycles, time of day, and day of the week) phenomena from an idiographic, person-specific perspective. Rather than pitting persons against situations, such an approach allows psychological phenomena, situations, and time to jointly predict future behaviors and experiences. We find (1) a striking degree of prediction accuracy across participants, (2) that a majority of participants' future behaviors are predicted by both person and situation features, and (3) that the most important features vary greatly across people.

Keywords: idiographic, personality, prediction, machine learning, ESM

Statement of Relevance

Understanding and predicting behaviors and experiences is an integral part of everyday life. Situations clearly impact behavior, but individuals also have unique styles in their behaviors. Despite this, the psychological study of behavior / experiences typically examines person and situation factors separately or assumes situations have similar behavioral or experiential consequences across people. But people exhibit different behaviors or have different experiences in the same contexts and similar behaviors in different contexts, indicating reciprocal person-situation relationships. In this study, we built personalized prediction models to predict future occurrences of procrastination, loneliness, and studying to test the extent to which people differed in their person- and situation-level antecedents. We found that these behaviors varied in how predictable they were for each person as well as that the person and situation features that best predicted each future behavior / experiences varied widely across people. Such variability suggests that one-size-fits-all methods for predicting, explaining, and changing behavior / experiences are misguided at best and wholly wrong at worst.

Personalized Prediction of Behavior and Experiences: An Idiographic Person-Situation Test

A longstanding goal of psychology is to describe (e.g., Titchener, 1898), predict (e.g., Meehl, 1954), and explain (e.g., Fodor, 1968) the things people do and experience. Despite this persisting emphasis, accurately predicting future socioemotional behaviors and experiences remains elusive. Indeed, most of the existent research on prediction examines broad life outcomes (e.g., Beck & Jackson, 2021; Joel et al., 2020). While such broad life outcomes result from accumulating behaviors and experiences (e.g., Hampson, Goldberg, Vogt, & Dubanoski, 2007), how predictable those behaviors are is unknown.

We argue that the elusiveness of accurate predictions of future behaviors stems from an almost exclusive focus of a between-person perspective. In the present study, we offer an alternative person-specific, idiographic approach to behavior / experiences prediction, where the antecedents of everyday behavior / experiences are allowed to vary across people. We use three machine learning approaches to investigate the degree to which seven future behaviors and experiences, three of which we will focus on (future loneliness, procrastination, and studying) can be predicted from psychological phenomena (i.e. personality and affective states), situations (i.e. objective situations and psychological situation cues), and time (i.e. trends, diurnal cycles, time of day, and day of the week).

An Individualized, Idiographic Approach to Assessment

A major assumption of measurement in psychology is that a measured construct is the same across people. A personality characteristic like Extraversion is Extraversion for everyone, and how it is related to Neuroticism is the same for everyone. If this assumption is violated, and it almost always is (Borsboom, Mellenbergh, & van Heerden, 2003; Fisher, Medaglia, & Jeronimus, 2018; Molenaar, 2004), then it hard to say whether or not Extraversion predicts behavior / experiences at the level of a person. Indeed, doing so would be to make an incorrect within-person interpretation of a between-person model (Borsboom et al., 2003). Alternatively, idiographic approaches sidestep such assumptions by focusing on a single individual, attempting to identify variables that are meaningful for them, which may not be meaningful for another person (Beck & Jackson, 2020a).

To what extent are idiographic approaches necessary? A growing body of work demonstrates that the within-person structure of emotion and personality differs across people (Beck & Jackson, 2020b; Borkenau & Ostendorf, 1998; Molenaar, 2004). Across people, measures of the Big Five demonstrate five factors, while within-person, they range from two to seven and have different content within them. Thus, common taxonomies used to describe populations may not describe an individual.

Similarly, taxonomic work on situations is only beginning (Parrigon, Woo, Tay, & Wang, 2017; Rauthmann et al., 2014). In part, this is because of the great range in behaviors exhibited within similar situations, which makes identifying coherent patterns that are found between-person difficult. It is likely that situations impact a person largely idiosyncratically (i.e. idiographically) for each person (Mischel, 2004). Simply – there is little reason to believe individuals should respond to the "same" situations similarly. Even if they do, there is almost certainly heterogeneity in why individuals behave similarly. Consider, for example, small talk while at work. The same behavior in the same environment could be fueled by goals to get ahead and get along – like avoiding an awkward interpersonal situation (get along) or making a long-term beneficial social connection (get ahead). Differences in person factors differ both across people and within them, making the interpretation of the situation quite subjective (i.e. idiographic).

The Person-Situation Debate (Still)

Predicting behavior / experiences using person and situation factors has mostly been ignored as a lingering consequence of the Person-Situation Debate (e.g., Barrick & Mount, 2005), which implied that the threshold on predicting single behaviors was low. The “personality coefficient” of .3 was seen as an upper bound of what is possible in behavioral prediction and is typically resolved by focusing on aggregating behaviors to increase predictive validities (Epstein, 1979), discussing the relevance of a .3 correlation (Funder, 2009; Roberts, 2009), or focusing on strong situations (Snyder & Ickes, 1985). However, these discussions typically concern a one-to-one predictor-behavior / experiences association. If instead a behavior / experiences is multi-determined from many sources, theoretical estimates can go much higher than .3, though currently this is only theoretical (Ahadi & Diener, 1987).

Another longstanding question in predicting behavior / experiences asks whether person or situation factors impact behavior / experiences more (Epstein & O’Brien, 1985). But most approaches hold either person or situation features constant to examine the association between the other and behavior / experiences (Kenrick & Funder, 1988). In other words, rather than viewing the triad of personality, situations, and behavior / experiences simultaneously, most studies examine these in isolation (Funder, 2006). Of those that do examine person and situational features simultaneously, findings indicate the importance of both as *independent* but not interactive influences (Sherman, Rauthmann, Brown, Serfass, & Jones, 2015), leading people to continue studying these in isolation. Thus, it remains unclear how situations coalesce with person factors to impact behavior / experiences.

The Present Study

We argue that by adopting an idiographic, machine learning-based prediction approach that incorporates information about persons, situations, and time relative only to a single person's experience will allow us to accurately predict future behavior and experiences (Renner, Klee, & von Oertzen, 2020). In the clinical psychology domain, previous research has indicated that future behaviors, like smoking (Fisher & Soyster, 2019; Soyster et al., 2021) and food craving (Butter et al., 2020) (1) can be predicted with high levels of accuracy using these methods and (2) that the degree of predictability and the important features across people vary considerably. Thus, in the domain of psychology more broadly, we believe that machine learning methods can be used to understand (1) the degree to which we can predict behavioral and experiential outcomes, (2) individual differences in how predictable such outcomes are, (3) whether certain domains (i.e. persons, situations, and time) out-predict others, (4) which features play the strongest role, and (5) whether and to what degree individuals differ in which features play the strongest role.

Method

This study was preregistered on the Open Science Framework (OSF; https://osf.io/4nm5p) and all data, analysis scripts, and results are available on both the OSF (https://osf.io/8ebyx/) and GitHub (https://github.com/emoriebeck/behavior-prediction). More details on the analyses and visual results depictions are available online at https://emoriebeck.github.io/behavior-prediction/ and in the R Shiny webapp at https://emoriebeck.shinyapps.io/behavior-prediction/. All data are completely de-identified. This study was approved by the Institutional Review Board at Washington University in St. Louis (#201806124), and all data were collected in alignment with the APA ethics code. Components of these data have been published elsewhere (Beck & Jackson, 2021b; Jackson & Beck, 2021).[1]

Participants

Participants were 208 (71.96% female; M_{age} = 19.51, SD_{age} = 1.27) undergraduates at Washington University in St. Louis who enrolled in a study between October 2018 and December 2019. 69 identified as white, 67 as Asian, 34 as Black, and 30 other race/ethnicity or mixed race/ethnicity (8 declined to answer). Nine participants were excluded for not completing any ESM surveys. The remaining participants completed a total of 8,403 surveys (*M* = 42.23; *SD* = 24.01; range 1-109). See Table S1 in the online materials for additional information. An additional 85 participants were excluded for having fewer than 40 ESM measurements, and 10 were excluded for having too little variance in one or both outcome measures[2]. The remaining 104 participants (72.82% female; M_{age} = 19.49, SD_{age} = 1.31) completed an average of 57.41 assessments (*SD* = 16.33; range 40-109). 32 identified as white, 33 as Asian, 14 as Black, and 16 as other (9 declined to answer).

[1] The data used in the present study were collected as a part of a personalized intervention study targeting one social (procrastination) and one emotional (loneliness) behavior or experience among college students. In this longitudinal burst study, participants completed baseline surveys and a wave of ESM and then were later contacted with the opportunity to be part of the intervention component. Due to delays and the onset of the COVID-19 pandemic, a number of participants became ineligible for the intervention component of the study, leaving more than 200 participants with data designed to help understand antecedents and consequences of procrastination and loneliness in students' lives. Rather than simply starting over, we decided to use these data to refine and validate our personalized prediction procedure before resuming the study with a new cohort of participants. In the present study, we chose to focus on procrastination and loneliness in order to validate our predictions of these socioemotional behaviors and experiences. However, thanks to helpful comments during the review process, we now include five additional outcomes, feeling sick, feeling tired, studying, arguing with a friend / family member, and interacting with a friend / family member. These results are available in the online materials on the OSF and GitHub as well as the R Shiny webapp.

[2] Participants were excluded on an outcome-by-outcome basis – that is, if a participant had too little variance in outcome #1, they were excluded from those analyses, but if they had enough variance in outcome #2, they were included in those analyses. The 10 participants here are those who had too little variance *across* outcomes.

Measures

Participants responded to a battery of trait and ESM measures as part of the larger study (see the supplementary codebooks in the online materials). The present study focuses on a subset of preregistered ESM measures that were used to estimate idiographic prediction models.

ESM Measures

Personality and Affect. Personality was assessed using the full BFI-2 (Soto & John, 2017) using a planned missing data design (Revelle et al., 2016; https://osf.io/pj9sy/). Items capturing affect were a subset of the PANAS-X (Watson & Clark, 1999) with items redundant with the BFI-2 removed. Each item was answered relative to what a participant was just doing on a 5-point Likert-like scale from 1 “disagree strongly” to 5 “agree strongly.”

Situations. Binary situation indicators were derived by asking research assistants to provide list of the common social, academic, and personal situations in which they found themselves. From these, we derived a list of 20 unique situations. Separate items for arguing with or interacting with friends or relatives were composited in overall argument and interaction items. Participants checked a box for each event that occurred in the last hour (1 = occurred, 0 = did not occur). Psychological features of situations were measured using the ultra-brief version of the “Situational Eight” DIAMONDS scale (S8-I; Rauthmann & Sherman, 2015) on a 3-point scale from 1 “not at all” to 3 “totally.”

Timing Features. Time features were created from the time stamps collected with each survey based on approaches used in other studies of idiographic prediction (Fisher & Soyster, 2019; Butter et al., 2020). To create these, we created time of day (4; morning, midday, evening, night) and day of the week dummy codes. Next, we created a cumulative time variable (in hours) from first beep to create linear, quadratic, and cubic time trends as well as one and two period sine and cosine functions across each 24 period (e.g., 2 period sine = $\sin\frac{2\pi}{12} * \ cumulative\ time_t$ and 1 period sine = $\sin\frac{2\pi}{24} * \ cumulative\ time_t$).

Outcomes. Procrastination, loneliness, and studying were assessed by asking participants to check a box if it had occurred in the last hour (1 = occurred, 0 = did not occur). Each will be lagged such that time *t* features will predict time *t*+1 procrastination, loneliness, and studying.[3]

Procedure

Participants responded to two types of surveys: trait and state (Experience Sampling Method; ESM) measures, for which they were paid separately. More information on the procedure of this study sample have been reported elsewhere (Beck & Jackson, 2021b; Jackson & Beck, 2021) and are available in the online materials.

Analytic Plan

The present study used three machine learning classification models: (1) Elastic Net Regression (ENR; Friedman, Hastie, & Tibshirani, 2010), (2) The Best Items Scale that is Cross-validated, Correlation-weighted, Informative and Transparent (BISCWIT; Elleman, McDougald, Condon, & Revelle, 2020), and (3) Random Forest Models (RF; Kim et al., 2019). More details on these methods and the procedure can be found in the online materials but are summarized below.

Because we have a large number of features to test, we chose methods with variable selection procedures and methods for reducing overfitting. To both reduce the number of indicators used in each model and to test which group of indicators are the most predictive of

[3] In addition to future procrastination, loneliness, and studying, we also examined four other future outcomes. These outcomes, as well as studying, were deviations from our preregistration, to replicate our main conclusions based on suggestions received during the review process. The full results of these models are available in the online materials. On the whole, these unpreregistered results were largely congruent with the results of the preregistered loneliness and procrastination models in the aggregate, with a few exceptions that we will note in later sections.

future procrastination, loneliness, and studying, we will also examine these in several sets: (1) Psychological indicators (personality + affect) (25), (2), Situation indicators (binary + DIAMONDS) (25), and (3) Full set (personality + affect + binary situations + DIAMONDS) (49). Each of these will also be tested with and without the 18 timing indicators, for a total set of six combinations of the 68 features.

In each of these methods, we used cumulative rolling origin forecast validation,[4] which was comprised of the first 75% of the time series (i.e. training data), and held out the remaining 25% of the data set for the test set. In the rolling origin forecast validation, we used the first one-third of the training data time series as the initial set, five observations as the validation set, and set skip to one (to reduce the number of folds to roughly equate 10-fold cross-validation), which resulted in 10-15 rolling origin "folds." For all training and test sets, the outcomes were lagged such that each outcome was predicted by previous time point features (roughly 4 hours previously). Tuning results are available for each participant, feature set, outcome, and model in the online materials and webapp ("Model Tuning Figures").

Out of sample prediction was tested based on classification error and area under the ROC (receive operating characteristic) curve (AUC) in the test set (the last 25% of the time series). Classification error is a simple estimate of the percentage of the test sample that was correctly classified by the model. In addition, the AUC will capture the trade-off between sensitivity and specificity. An AUC of .5 indicates binary classification at chance levels. AUC curves are available in the online materials and webapp ("ROC").

[4] We preregistered the use of 10-fold cross-validation on the training set. Because of how 10-fold cross-validation separates and combines folds, this would have resulted in validation sets that temporally occurred before observations in the other nine folds. As an alternative, we elected to use rolling origin validation. In rolling origin, the validation set always occurs after the earlier "rolls" (as opposed to folds).

ENR uses *L1* (Ridge) and *L2* (LASSO) regularization to shrink coefficients based on a penalty (λ) that is tuned to minimize error using cross-validation. We tuned based on penalty and mixture (set to 10 values each). ENR was performed using the `tidymodels` package (Kuhn & Wickham, 2020) in `R` to estimate the ENR models by calling the `logistic_reg()`, setting the engine as `"glmnet"` (`mode="classification"`; Friedman et al., 2010).

The Best Items Scale that is Cross-validated, Correlation-weighted, Informative and Transparent (BISCWIT) is a correlation-based machine learning technique. Using the `best.scales()` function in the `psych` package (Revelle, 2020), we used rolling origin validation to choose the best number of items to be retained. Weighted scores were calculated by extracting the correlations from the best scales object and using it in the `scoreWtd()` function to create the correlation weighted scores.

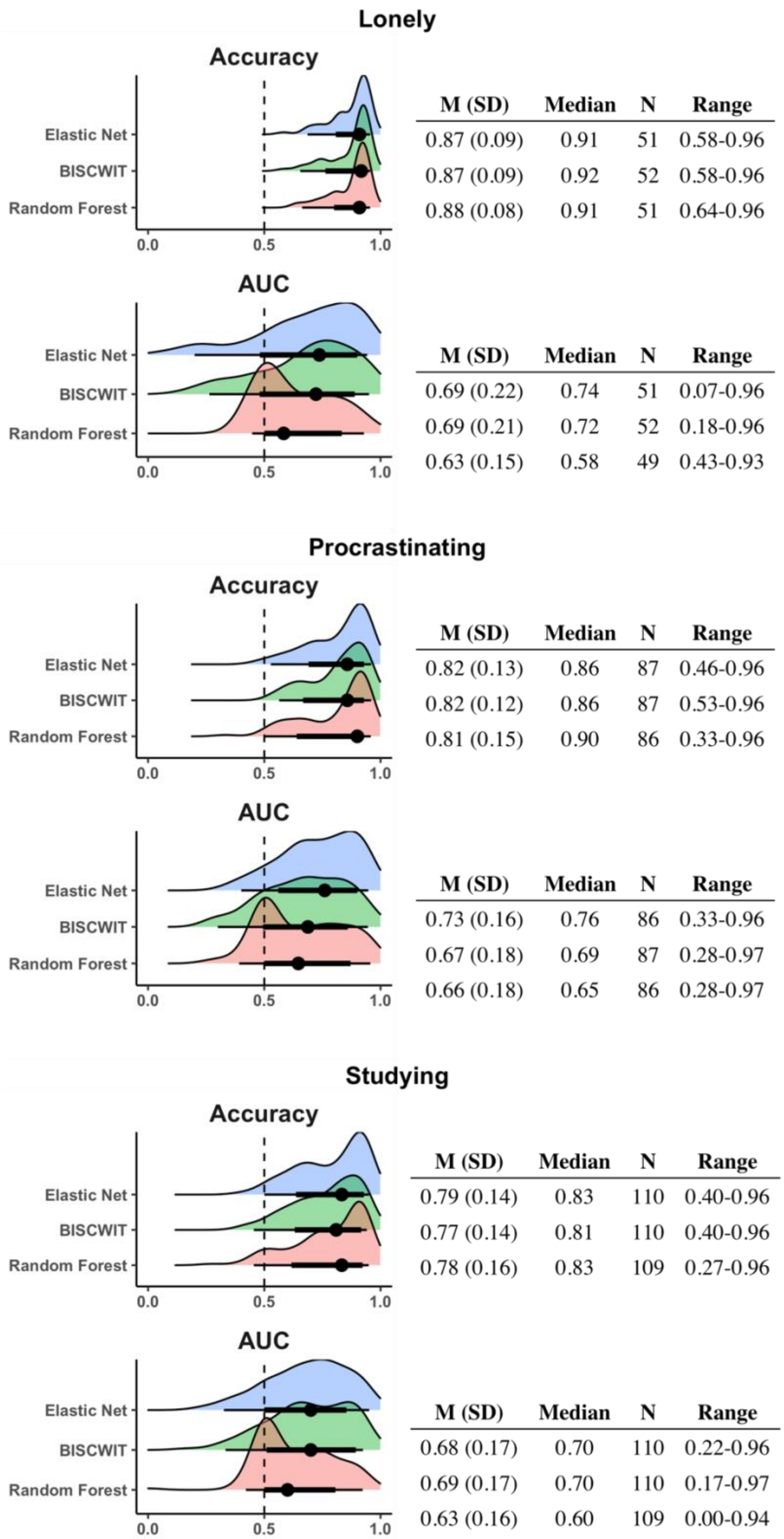
RF models are a variant of decision tree classification algorithms that utilize ensemble methods. Because RF uses bagging (i.e. bootstrapping with aggregation), we performed a series of steps that make bootstrapping appropriate with time series data. Models were tuned using `mtry` (i.e. the number of predictors that will be randomly sampled at each split when creating tree models) and `min_n` (i.e. the minimum number of data points in a node that is required for the node to be split further), which were each set to 10 values. We used the `tidymodels` package in `R` to estimate the RF models by calling the `rand_forest()`, setting the engine as `"ranger" (mode="classification"`; Wright & Ziegler, 2017), with `importance="permutation"` in order to extract variable importance.

Results

Can we predict future procrastination, loneliness, and studying?

First, we tested to what extent we could predict future incidences of procrastination, loneliness, and studying for each person by their previous assessments using ENR, BISCWIT, and RF. Figure 1 presents histograms and descriptive statistics of accuracy and AUC across the full sample for each outcome and model. The same figures for all other outcomes are available in the online materials and webapp ("Sample-Level Performance Distributions"). As is clear in the figure, predictive accuracy was high overall, with mean accuracy of .87 (Median .91 to .92) for future loneliness, between .82 and .83 (Median .88 to .89) for future procrastination, and between .77 to .79 (Median .81 to .83) for future studying. Similarly, AUC was also well above the .5 threshold with means ranging from .70 to .76 (Median .75 to .80) for future loneliness, .69 to .70 (Median .70 to .75) for future procrastination, and .63 to .68 (Median.65 to .76) for future studying. Participant-level descriptives across models, feature sets, and outcomes are available in the online materials and webapp ("Model Performance Tables"). [5]

[5] Of the additional four outcomes we tested, the results largely converged. Three (argument, sick, and tired) has median accuracy between .81 and .92. Interaction had a lower accuracy, with median accuracies between .69 and .72 (SDs = .14 - .17).



Lonely — Accuracy

M (SD)	Median	N	Range
0.87 (0.09)	0.91	51	0.58-0.96
0.87 (0.09)	0.92	52	0.58-0.96
0.88 (0.08)	0.91	51	0.64-0.96

Lonely — AUC

M (SD)	Median	N	Range
0.69 (0.22)	0.74	51	0.07-0.96
0.69 (0.21)	0.72	52	0.18-0.96
0.63 (0.15)	0.58	49	0.43-0.93

Procrastinating — Accuracy

M (SD)	Median	N	Range
0.82 (0.13)	0.86	87	0.46-0.96
0.82 (0.12)	0.86	87	0.53-0.96
0.81 (0.15)	0.90	86	0.33-0.96

Procrastinating — AUC

M (SD)	Median	N	Range
0.73 (0.16)	0.76	86	0.33-0.96
0.67 (0.18)	0.69	87	0.28-0.97
0.66 (0.18)	0.65	86	0.28-0.97

Studying — Accuracy

M (SD)	Median	N	Range
0.79 (0.14)	0.83	110	0.40-0.96
0.77 (0.14)	0.81	110	0.40-0.96
0.78 (0.16)	0.83	109	0.27-0.96

Studying — AUC

M (SD)	Median	N	Range
0.68 (0.17)	0.70	110	0.22-0.96
0.69 (0.17)	0.70	110	0.17-0.97
0.63 (0.16)	0.60	109	0.00-0.94

Figure 1. Histograms of classification accuracy and Area Under the Receiver Operator Curve (AUC) for participants' best models.

Are there individual differences in the idiographic range of prediction across people?

Figure 2 presents the median, 66%, and 95% range of classification accuracy for a random sample of 25 participants, ordered by the median accuracy (other outcomes as well as AUC for all outcomes are available in the online materials and webapp [“Person-Level Performance Distributions”]). As is clear in the figures, accuracy varies both across people and within them. In other words, although there are between-person differences in the degree of accuracy, there are also within-person differences, depending on which features are used.

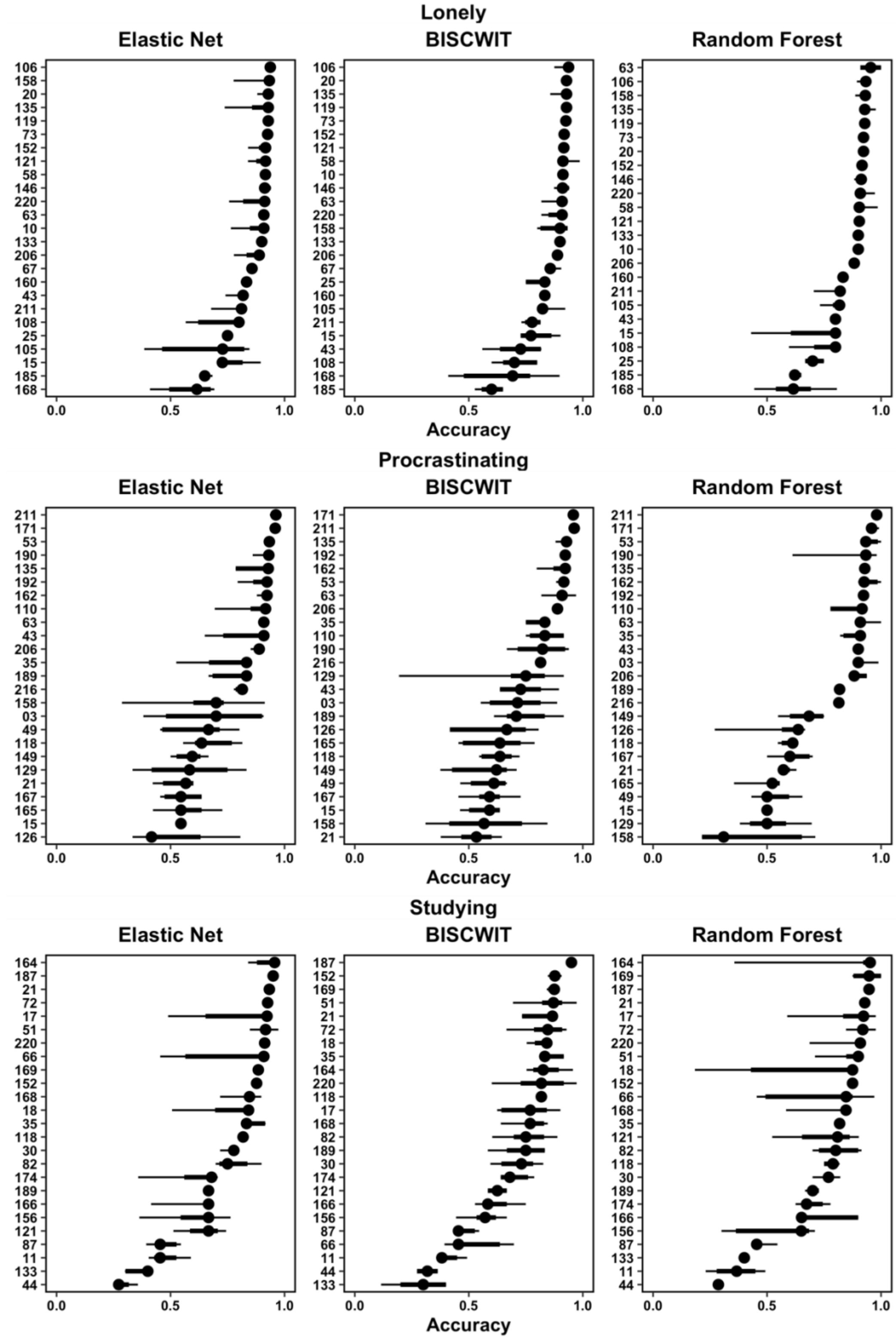


Figure 2. Person-level distributions (dot = median, wide line = 66% interval, thin line = 95% interval) of classification accuracy for 25 sample participants predicting future procrastination, loneliness, and studying.

Do Psychological, Situational, Time, or Full Feature Sets Perform Best?

Table 1 presents the number of and percentage of participants whose best model was for each feature set. As is clear, feature sets without time performed better than those with time. Second, relative to AUC, using accuracy as the selection metric was more likely to indicate that the full feature set performed best. Third, with some slight differences, relative proportions were similar across the three methods. Finally, for accuracy but not AUC, only RF indicated that situation feature models performed better than psychological feature models. We next examined the breakdown of selected features for each participant. As is clear in Figure 3, which shows proportions of features for all participants' best models for each method, there were individual differences in the proportion of psychological, situational, and time features. Some participants' best models included exclusively psychological or situational features, with most showing a varying mixture of both. Similar patterns were displayed across all outcomes, which are included in the online materials and web app ("Feature Proportions").

Table 1

Frequencies of the Full, Psychological, and Situation Feature Sets with or Without Time Being the Best Model for a Participant

		Accuracy						**AUC**					
		Elastic Net		**BISCWIT**		**Random Forest**		**Elastic Net**		**BISCWIT**		**Random Forest**	
Set	**Time**	**#**	**%**	**#**	**%**	**#**	**%**	**#**	**%**	**#**	**%**	**#**	**%**
Lonely													
Full	No	35	68.6%	33	63.5%	22	43.1%	13	25.5%	12	23.1%	14	28.6%
	Yes	5	9.8%	5	9.6%	2	3.9%	7	13.7%	3	5.8%	4	8.2%
Psychological	No	9	17.6%	7	13.5%	6	11.8%	8	15.7%	19	36.5%	10	20.4%
	Yes	0	0	3	5.8%	1	2.0%	9	17.6%	5	9.6%	2	4.1%
Situations	No	1	2.0%	4	7.7%	20	39.2%	8	15.7%	8	15.4%	13	26.5%
	Yes	1	2.0%	0	0	0	0	6	11.8%	5	9.6%	6	12.2%
Procrastinating													
Full	No	48	55.2%	38	43.7%	34	39.5%	14	16.3%	14	16.1%	24	27.9%
	Yes	12	13.8%	9	10.3%	4	4.7%	6	7.0%	6	6.9%	8	9.3%
Psychological	No	15	17.2%	17	19.5%	14	16.3%	19	22.1%	23	26.4%	18	20.9%
	Yes	6	6.9%	7	8.0%	1	1.2%	12	14.0%	10	11.5%	12	14.0%
Situations	No	5	5.7%	12	13.8%	29	33.7%	19	22.1%	18	20.7%	17	19.8%

Table 1

Frequencies of the Full, Psychological, and Situation Feature Sets with or Without Time Being the Best Model for a Participant

		Accuracy						AUC					
		Elastic Net		BISCWIT		Random Forest		Elastic Net		BISCWIT		Random Forest	
Set	**Time**	**#**	**%**	**#**	**%**	**#**	**%**	**#**	**%**	**#**	**%**	**#**	**%**
	Yes	1	1.1%	4	4.6%	4	4.7%	16	18.6%	16	18.4%	7	8.1%
Studying													
Full	No	56	50.9%	45	40.9%	38	34.9%	22	20.0%	17	15.5%	34	31.2%
	Yes	18	16.4%	6	5.5%	8	7.3%	9	8.2%	14	12.7%	9	8.3%
Psychological	No	17	15.5%	26	23.6%	14	12.8%	19	17.3%	27	24.5%	17	15.6%
	Yes	9	8.2%	13	11.8%	4	3.7%	23	20.9%	19	17.3%	12	11.0%
Situations	No	6	5.5%	12	10.9%	36	33.0%	22	20.0%	18	16.4%	22	20.2%
	Yes	4	3.6%	8	7.3%	9	8.3%	15	13.6%	15	13.6%	15	13.8%

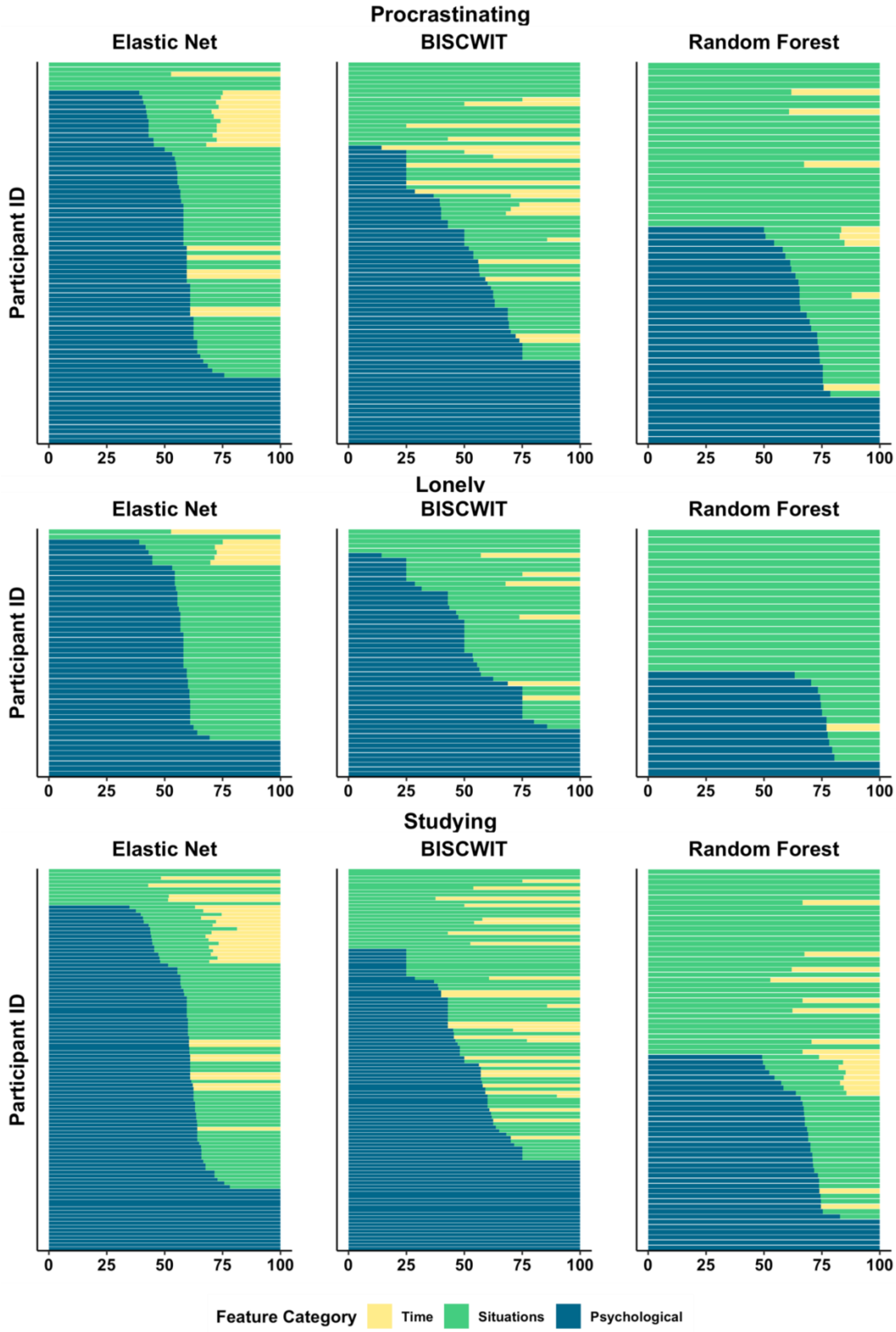


Figure 3. Sequence plots of the percentage of features from the Psychological, Situational, and Time Features Sets for each participant for each outcome and model.

Which features are most associated with future Procrastination, Loneliness, and Studying?

To examine which features were most important, we extracted the top five features and calculated the proportion of the sample that had each feature in their top five. In Figure 4, larger, darker circles indicate that a higher proportion of individuals had this feature in their top five, while smaller, lighter circles indicate that a smaller proportion of individuals had this feature in their top five. Overall, most features were not shared by a majority of participants, with the maximum proportion of participants sharing a single feature of 40% (energy level predicting arguing with a friend or family member). Across outcomes, the results were very similar, although which features were most frequent varied across outcomes, as can be seen in the online materials and web app ("Feature Frequency").

Figure 4 also has several takeaways relative to categories of features.[6] First, across models, timing features were less frequent, with the exception linear, quadratic, and cubic trends (T12-T14) across the ESM period and a 24-hour sinusoidal diurnal cycle for ENR. Second, for ENR and BISCWIT, psychological features were slightly more frequent than situation features. Third, one consequence of the higher frequency of situation feature RF models being selected than for the other two models was that situation features were both more frequent as well as more variable (more different sized circles) for the RF models than for ENR or BISCWIT (more similarly sized circles). Finally, and perhaps most crucially, this figure makes clear that person and situation characteristics were both key in predicting each outcome, with neither "dominating" the feature space.

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[6] This pattern was largely replicated in the additional five behaviors and experiences. Across these, the prevalence of any feature was heavily right skewed, ranging from 0 (38.14% of all timing frequencies) to 17.72 (M = 2.40, Median = 1.80, SD = 2.87). The non-zero frequencies were largely driven by two outcomes, interacting with family or friends and studying. However, the mean frequencies of timing features relative to psychological and situational features across these outcomes remained low.

Lastly, there are several specific features in Figure 4 of note. For both outcomes in Figure 4, there were some frequent features that made face value sense. For example, the Extraversion feature Energy Level, the Openness features Intellectual Curiosity and Aesthetic Sensitivity, and internet use were relatively frequent predictors of future procrastination across all models. Some were less intuitive, with, for example, happiness being infrequently predictive of future procrastination. For RF, some situational features were also very frequent, with, for example, perceptions of situations from the DIAMONDS as inviting Sociality or being pOsitive or Negative predicted future procrastination. Similarly, for future loneliness, the Extraversion feature Sociability, the Neuroticism Feature Emotional Volatility. For RF, the perception of a situation as pOsitive or Negative was the most frequent predictor, suggesting that the perceived valence of participants' current situations was predictive of future loneliness approximately four hours later. Finally, for studying, the most frequent features were quite similar to those for procrastination, with Sociality and Intellect from the DIAMONDS scale frequently predictive of future studying in RF as well as relatively more frequent timing features than for loneliness.

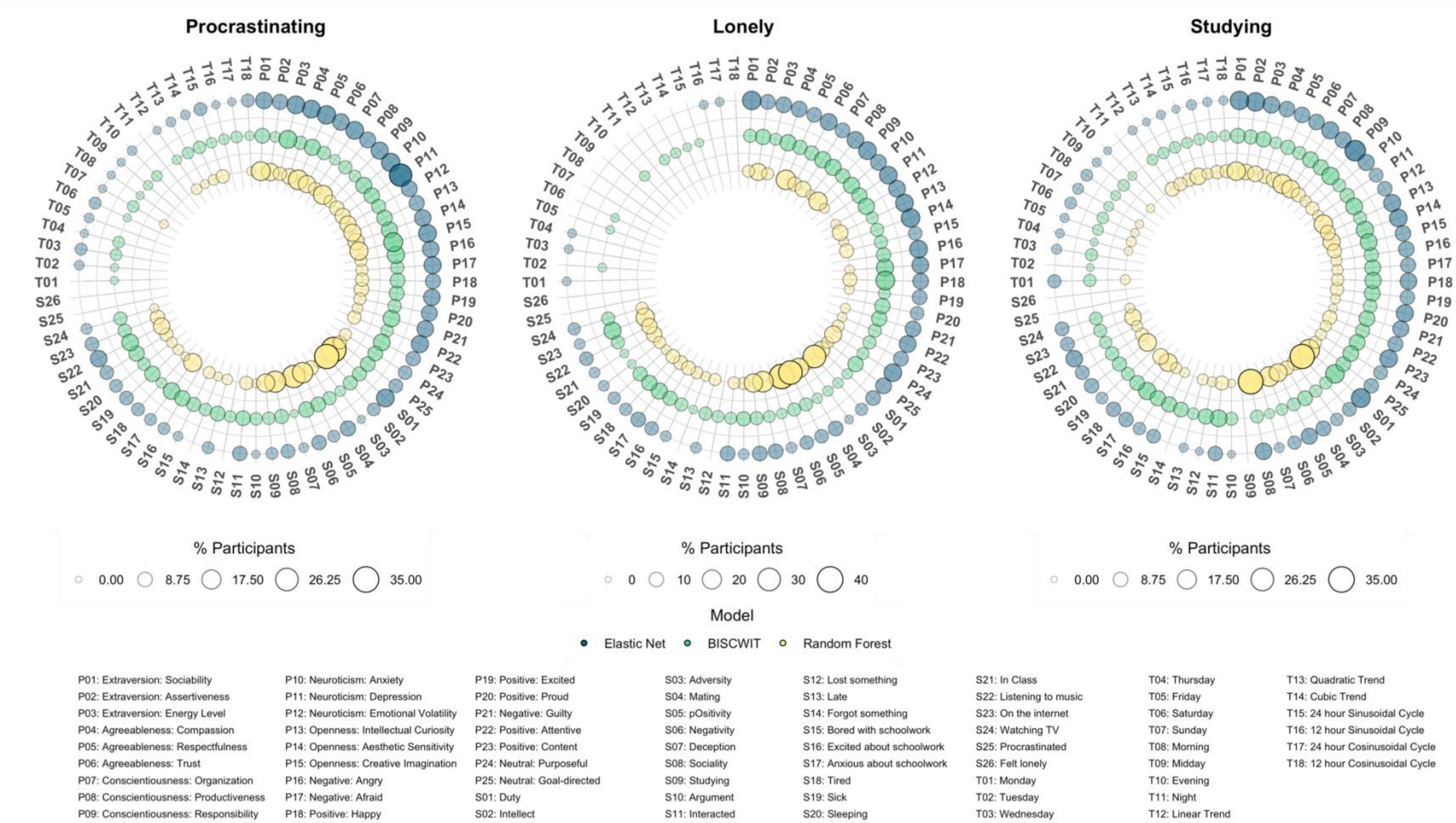

Figure 4. Percentage of each feature appearing as a top five variable importance feature across the full sample for future Procrastination (left), Loneliness (middle), and Studying (bottom). Larger, darker circles indicate higher percentages, while smaller, lighter circles indicate lower percentages. Each features' corresponding label is listed in the right side of the figure.

Do people vary in the which features are most important?

To demonstrate how people differ in which features were important participants' profiles of retained features along with their variable importance are available in the online materials and webapp for each participant, outcome, and model ("Participant Coefficient Plots"). In addition, Figure 5 presents the profiles of all participants' coefficients in their best models for BISCWIT (all combinations of outcomes and models are available in the online materials and webapp ["Participant Coefficient Profiles"]) for future procrastination. From the figure, it is clear that only a relatively small number of participants' best models had timing features. Moreover, even common features varied widely across people in presence, direction, and magnitude without exception. No two profiles are the same even just in which features were included, let alone in direction and magnitude of the associations.

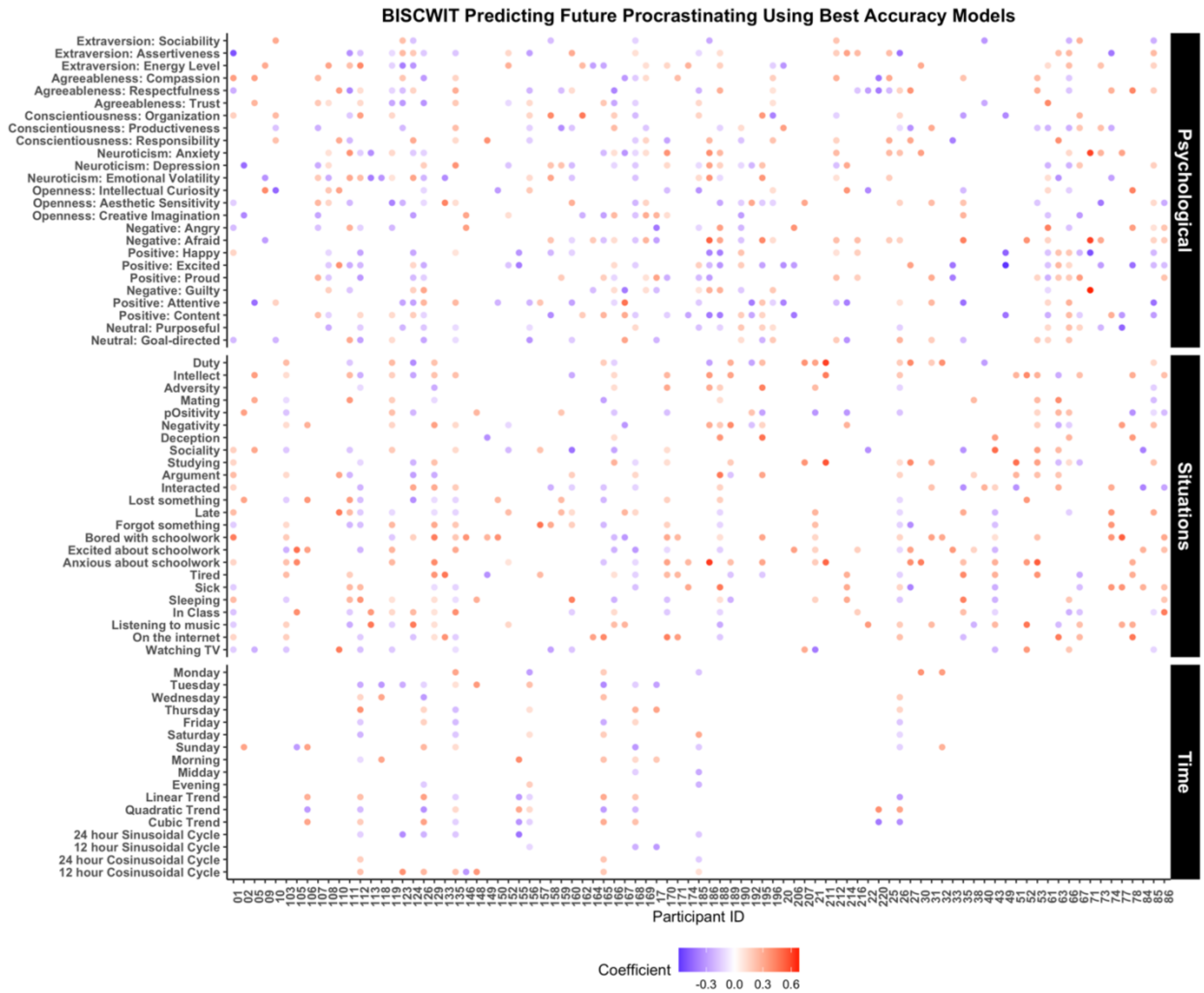

Figure 5. Coefficient profile for all participants' best BISCWIT models predicting future procrastination.

Discussion

The current study investigated personalized, idiographic prediction models for seven socioemotional behaviors and experiences, three of which we focused on (feeling lonely, procrastinating, and studying in the future) and four of which are detailed in the online materials (interacting, arguing, feeling tired, and feeling sick in the future). Rather than assuming that antecedents of different outcomes were shared, our idiographic approach built N=1 personalized prediction models. Overall, three main conclusions emerged: First, psychological, situational, and time variables accurately predicted future everyday behaviors and experiences. Second, psychological and situational variables were both important, almost equally so, with neither being a predominant antecedent of behavior / experiences. Third, individual differences reigned supreme –people differed on how predictable outcomes were, which domains performed best, and which features were most important. Moreover, across the three behaviors and experiences, one experiential and two performative, the results were quite consistent. These findings indicate the utility of an idiographic approach to psychological assessment relative to standard between-person approaches that are routinely used.

On Predicting More Behaviors More of the Time

We found accurate out-of-sample prediction of future procrastination, studying, and feelings of loneliness when using a suite of psychological and situational factors. Predicting individual experiences and behaviors has long eluded psychologists. However, the results of the present study suggest this is because of two assumptions: (1) that the same psychological and situational antecedents should predict the same behaviors across people and (2) that psychological or situational features should out-predict the other. Neither of these assumptions holds. While there are between-person individual differences in future loneliness, procrastination, and studying, there was also within-person variability in terms of how and when people demonstrated these behaviors / experiences. Typical prediction models within psychology have largely focused on which between-person features predict life outcomes or other aggregated behaviors (e.g., Beck & Jackson, 2021a; Joel et al., 2020; Puterman et al., 2020). Here, in alignment with a growing emphasis on precision medicine approaches to improving physical health, well-being, and productivity, we demonstrate that within-person features are also predictable by psychological and situation features. These dynamic features tend to be less studied, which has resulted in little knowledge about why people vary within-person in these behaviors. Our findings suggest that from a fairly prescribed set of personality, situational, and time features, we can identify *when* someone is going to procrastinate, study, or feel lonely at a future timepoint – not just if they tend to procrastinate, study, or feel lonely *in general*.

Notably, predictions were made assuming individuals have unique antecedents of each outcome. Although this equifinality is often described in theoretical models, it is rarely implemented in statistical models. Instead, statistical models use a circumscribed set of predictors that are assumed to impact people similarly, depending on their rank-order on the predictor (e.g., Borsboom et al., 2003). For example, procrastination is associated with Conscientiousness (Jackson et al., 2009). Typically, this suggests if people are feeling low in Conscientiousness markers (responsibility, organization) they would be more likely to procrastinate. However, we found that markers of Conscientiousness were not important antecedents of procrastinating for everyone, nor were they the most important in general (with 10-15% of the sample having Conscientiousness features as important predictors). People procrastinate, study, and feel lonely for many different reasons. As a result, prediction models that assume similar associations between predictors and outcomes for everyone may underestimate potential predictive validity.

In general, we found individual differences in every aspect of the models – in accuracy, in feature sets, and in the importance of specific features. For some people, we could very accurately predict future behaviors, while for others, we could not. Similarly, people differed in which and to what degree the domains were important. Together these findings paint a picture of a psychological system that is highly unique to an individual. Although there is a longstanding consensus that behavior is the output of such highly unique dynamic psychological systems that are impacted by situational features (Mischel & Shoda, 1995), these have remained elusive and often ignored in practice. Thus, the present study is an initial demonstration of the empirical validity of such thinking. Participants differ in the important situational and psychological features that predict future behavior / experiences.

Pragmatically, that people differed in (1) which features were predictive of future procrastination, studying, and loneliness and (2) the proportion of these that were situational and psychological features has implications for behavioral prediction in applied contexts, such as outpatient clinical work, worker performance and well-being, and more. The results of the present study suggest that using a very short, standard battery of psychological and situational indicators may not well capture the antecedents of these or other behaviors but that machine learning approaches are useful as feature selection tools when used in conjunction with larger batteries. However, what this study did not address is the use of true idiographic assessment in which participants respond to unique, tailored batteries of items rather than (or in addition to) standard batteries. It is possible that such approaches may be useful in reducing participant burden and improving overall prediction. However, we expect that such an approach would only broaden the realm of antecedents in behaviors, highlighting the broad range of individual differences within and across people in psychological and situational antecedents.

The Person-Situation Debate Revisited

Half a century ago, the seeming limits of behavioral prediction that sparked the Person-Situation Debate and led to research being formulated around the question of whether person or situation features matter more. While most agree that both matter, there are few examples of demonstrating the joint importance of them for the same outcome (c.f., Sherman et al., 2015). We found evidence that person and situation features were both important for most individuals, with only a minority demonstrating that person or situation features alone were most predictive of future procrastination, loneliness, and studying. In other words, the Person-Situation Debate was always a false debate. The dynamic relations among person, situation, and behavior / experiences and indicate that attempts to understand behavior / experiences must incorporate both (Funder, 2006) – at least for most people.

Not only are person and situation variables important, but they were also more important than time variables. Given that people have natural cycles of behavior / experiences that are regimented by time of day and day of week (Mathews, 1988; Larson, 1985), it would be natural to expect that behavior / experiences largely vary within and across people as a function of these cycles. For example, people work less on the weekends and at night, which is a change in their behavior / experiences. Similarly, time of day and day of week govern situations people can enter. Although across the three focal outcomes (future procrastination, studying, and loneliness) as well as the five additional outcomes we tested as robustness checks models without time were less likely to be selected, there was some variability across outcomes. For example, timing features were proportionally more prevalent for procrastination, interacting with friends/family members, and studying than they were for feeling lonely, tired, or sick. Although it may be expected that work-related behaviors, like procrastination and studying, may be associated with time, that feeling tired was not strongly associated with day of the week, time of day, diurnal cycles, and more was more surprising. It is possible that time variables were less important because they were already captured by the more proximal person or situational features. In other words, time is likely important but works through person and situation variables rather than being a separate factor. However, the full pattern of results across the seven tested outcomes does not paint a clear picture of when this is true.

Limitations and Conclusion

This study is not without its limitations. First, relatively low variance in each of the outcomes led us to drop a number of participants from analyses. Thus, the participants in the present study are only representative of participants who experienced somewhat frequent loneliness, procrastination, and studying, as well as the other outcomes. Second, we examined prediction over a two-week interval for most participants, so long-term prediction accuracy is unclear. Finally, this study was the first in a line of planned research focusing on individual differences in the accuracy, antecedents, and timing of prediction models of future behaviors and experiences. These future studies must address challenging questions about the long-term consistency of antecedents, their consequences, and more.

The current study created personalized prediction models to help understand antecedents of future loneliness, procrastination, and studying. We found psychological and situational predictors did well in predicting within-person variations in these behaviors. However, in contrast to many years of methodological orthodoxy, the antecedents of these behaviors differed greatly across people. Thus, there is a need for more personalized assessments – not just longer assessments – but assessments that are tailored and important for the individual. Behavior / experiences appears to be highly predictable, so our next task is identifying personalized antecedents.

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