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Examining 81 Predictors of Self-Esteem Using Machine Learning

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ABSTRACT

The purpose of this study was to identify and rank the most important predictors of self-esteem. Data were drawn from the Midlife in the United States (MIDUS) study, a nationally representative survey of American adults. A total of 81 potential predictors, including psychological, sociodemographic, and health-related variables, were included. The Random Forest machine learning algorithm was used for data analysis. Environmental mastery emerged as the strongest predictor, followed by negative affect, sense of personal growth and positive affect. Agency-related and affective variables ranked among the top predictors, surpassing socio-demographic, health-related, relational and status-related factors. These findings are inconsistent with some theoretical frameworks that emphasise social validation and status as primary drivers of self-esteem, suggesting that self-esteem is more strongly linked to personal agency, a subjective sense of growth and affective experiences. The results contribute to ongoing theoretical development and offer direction for future theorising and empirical research on the nature and predictors of self-esteem.

1 | Introduction

Self-esteem is defined as 'an overall assessment of the value of one's self or self-worth' (Jordan et al. 2017, p. 4738). Psychological theories emphasise the crucial role of self-esteem as a desirable trait. Research has consistently demonstrated that self-esteem is positively correlated with desirable outcomes in various life domains, including relationships, academic performance, career, mental health and physical well-being (Orth and Robins 2022). Given the importance of self-esteem, researchers have sought to identify its key predictors. However, the existing literature on predictors of self-esteem is fragmented and scattered across numerous studies, often examining only a limited number of potential predictors in each study.

From an evolutionary perspective, self-esteem functions as a key indicator of social acceptance and quality of relationships. It reflects responses to major social challenges, including mate selection and social status, suggesting that self-esteem evolved to monitor performance across diverse social challenges (Kirkpatrick and Ellis 2001). For example, according to sociometer theory, self-esteem functions as a 'sociometer', providing a gauge of an individual's standing within their social groups (Leary 2012). In essence, self-esteem acts as an internal gauge that reflects how well we meet our fundamental need for social belonging by processing social feedback and transforming it into a self-evaluation (Fisher et al. 2016). Empirical evidence supports this notion by showing that positive relationship outcomes are associated with higher self-esteem, and that self-esteem is responsive to social acceptance and rejection (Cameron and Stinson 2017).

While evolutionary theories of self-esteem emphasise its social function, other lines of research have explored self-esteem as a manifestation of a sense of competence and agency. One such line of inquiry investigated the predictive power of agency and communion orientations on self-esteem. Wojciszke et al. (2011)

demonstrated that agency orientation is a more robust predictor of self-esteem than communion orientation. Subsequent studies in this line of research have generally supported the primacy of agency over communion (e.g., Chen et al. 2017; Hauke and Abele 2020; Wojciszke and Sobiczewska 2013). Therefore, self-esteem may reflect not only the perceived quality of one's social relationships and sense of belonging but also one's sense of agency.

Additionally, research underscores the need to consider a broader range of potential predictors of self-esteem, including those linked to affective experiences. Self-esteem is conceptualised as an emotionally charged self-evaluation (Liu and Zhang 2021) and, as such, is susceptible to the influence of an individual's emotional predispositions and experiences. Experimental studies have shown that inducing a sad mood can lower self-esteem (Brown and Mankowski 1993). Moreover, the tendency to experience negative feelings, as measured by neuroticism, is a strong predictor of low self-esteem (Robins et al. 2001). Similarly, terror management theory regards self-esteem as a buffer against existential anxiety. This theory offers an existential perspective on self-esteem and highlights its role in coping with death anxiety and in the search for meaning and significance (Arndt et al. 2007). According to this theory, awareness of mortality generates anxiety, which individuals mitigate through self-esteem derived from meeting the standards prescribed by their cultural worldview. Therefore, for a comprehensive examination of the predictors of self-esteem, it is essential to consider positive and negative affective experiences.

Another group of theories posits that social status (the extent to which one is respected and admired) plays a pivotal role in shaping self-esteem. Theoretical frameworks, such as dominance theory (Barkow 1980) and hierometer theory (Mahadevan et al. 2016), each grounded in evolutionary rationales, support this prediction. Importantly, these theories suggest that the objective foundations of social status, particularly socioeconomic status (SES) indicators such as income and education, should also be predictive of self-esteem (Gregg et al. 2021). Empirical research supports this notion, revealing that SES (Twenge and Campbell 2002) is predictive of self-esteem. Other characteristics such as gender (Zuckerman et al. 2016) and health status (von Soest et al. 2018) are also linked to self-esteem. Consequently, demographic variables and health-related factors should be integrated into a comprehensive predictive model of self-esteem.

1.1 | The Present Study

Previous research and theoretical frameworks have identified several key categories of variables that influence self-esteem, including agency, communion, affective tendencies and SES. However, a notable gap in the literature is that no single study has comprehensively examined the relative contributions of variables across all these domains. Instead, previous studies have typically focused on specific domains without considering other categories of predictors (Furnham and Robinson 2022). For example, research on agency and communion has often treated these constructs as broad motivational orientations rather than comprehensively examining the specific variables associated with agency and communion (e.g., Wojciszke et al. 2011). Variables such as autonomy, extraversion, environmental mastery, and social potency represent different facets of agency. However, it remains unclear which of these variables is the most robust predictor of self-esteem. A more comprehensive investigation is needed to clarify the complex relationships between these variables and self-esteem, and to critically evaluate the theoretical claims.

This study aimed to conduct a comprehensive analysis of a large set of potential predictors of self-esteem, including 81 psychological (e.g., related to agency, communion and affective experiences), social, demographic and health-related variables in a national American sample. The primary objective was to elucidate the key predictors of self-esteem and shed light on the nature of the relationship between these predictors and self-esteem. Given that it is unrealistic to assume linear relationships between all predictors and self-esteem, the Random Forest algorithm was employed as an alternative to linear regression. Random Forest is a type of machine learning (ML) technique that excels in handling a large number of predictors, non-parametric data, linear as well as non-linear relationships, and takes into account interactions between variables without requiring prior specification (Hastie et al. 2009; Garson 2022). Random Forest has been recommended as a suitable method for analysing tabular data in psychological research (Fife and D'Onofrio 2022; Pargent et al. 2023). The interpretability of Random Forest analyses is enhanced using variable importance measures and partial dependence plots (PDPs). Variable importance scores are assigned to input features based on their predictive power, providing a ranking of features according to their impact on the model performance (Hassija et al. 2023). PDPs provide a graphical visualisation of the marginal effect of a predictor on the predicted outcome, illustrating the relationship between a specific feature and the target variable while accounting for the effects of other features (Petch et al. 2021).

2 | Methods

2.1 | Participants

This study utilised data from the third wave of the Midlife in the United States (MIDUS) dataset, a nationally representative sample of American adults (Ryff et al. 2019). The MIDUS 3 survey was conducted between 2013 and 2014 with 3294 participants, spanning a wide age range of 39 to 93 years (mean age = 63.64 years, standard deviation = 11.35). Approximately 55% of the participants were female. More information about the methods and data can be found at https://midus.wisc.edu/data/index.php.

2.2 | Variables

The dependent variable, self-esteem, was measured using a seven-item version of the Rosenberg Self-Esteem Scale (Rosenberg 1965). To select the predictor variables, those exhibiting low internal consistency, significant missing data (such as work-related variables), or those deemed less relevant to the research objectives (such as medical history variables) were removed. Self-acceptance was also excluded because of its substantial empirical and conceptual overlap with self-esteem. Following the application of these criteria, 81 potential predictors

TABLE 1 | Variables used in the study.

Short name	Full label
SelfEsteem	Self-esteem
Age	Age
Female	Female gender
Education	Highest level of education completed
Income	Household total income
Non_white	Non-White race
WaistHipRatio	Waist-to-hip ratio
BodyMassIndex	Body Mass Index
ChronicConditions	Number of chronic conditions
Medicines30Days	Number of prescription medicines taken in 30 days
ChildrenInHousehold	Number of children living in household
IndividualsInHousehold	Number of individuals living in household
LifeSatisfaction	Life satisfaction
HealthSelfLocus	Health locus of control—self
NegativeAffect	Negative affect
PositiveAffect	Positive affect
BasicADLs	Basic activity of daily living
InstrumentalADLs	Instrumental activity of daily living
Intellectual	Personality in intellectual ageing context
AlcoholProblem	Alcohol problem
Autonomy	Autonomy
EnvironmentalMastery	Environmental mastery
PersonalGrowth	Personal growth
PositiveRelations	Positive relations with others
PurposeInLife	Purpose in life
PersonalMastery	Personal mastery
PerceivedConstraints	Perceived constraints
Agency	Agency
Agreeableness	Agreeableness
Extraversion	Extraversion
Neuroticism	Neuroticism
Conscientiousness	Conscientiousness
Openness	Openness
WellBeingtrait	Well-being
SocialPotency	Social potency
Achievement	Achievement
SocialCloseness	Social closeness
Reactivity	Reactivity
Aggression	Aggression
Alienation	Alienation
Control	Control
Traditionalism	Traditionalism
HarmAvoidance	Harm avoidance
Optimism	Optimism
Pessimism	Pessimism
SelectivePrimary	Selective primary control
Compensatory	Compensatory primary control
SelectiveSecondary	Selective secondary control
Disengage	Disengage
SelfProtect	Self-protect
GoalAdjustment	Adjustment of goals
SelfDirectedness	Self-directedness and planning
LiveForToday	Live for today
SelfSufficiency	Self-sufficiency
PositiveReinterpretation	Positive reinterpretation
ActiveCoping	Active coping
PlanningCoping	Planning
VentingEmotion	Venting of emotion
DenialCoping	Denial
BehavioralDisengagement	Behavioural disengagement
UseFoodToCope	Use food to cope
Generativity	Generativity
MeaningfulnessSociety	Meaningfulness of society
SocialIntegration	Social integration
SocialContribution	Social contribution
SocialActualization	Social actualization
QualityOfNeighborhood	Perceived quality of neighbourhood
InequalityInHome	Perceived inequality in home
SupportFromFamily	Support from family
StrainFromFamily	Strain from family
ProvidingSupportFamily	Providing support for family
SupportFromFriends	Support from friends
StrainFromFriends	Strain from friends
InequalityInFamily	Perceived inequality in family
Spirituality	Spirituality
ReligiousIdentification	Religious identification
PrivateReligiousPractices	Private religious practices
SpiritualCopingA	Seeking comfort through spiritual practices
SpiritualCopingB	Relying on divine forces
DailySpiritualExperiences	Daily spiritual experiences
Mindfulness	Mindfulness
LifetimeDiscrimination	Lifetime discrimination

were retained, which are listed and defined in Table S1. Table 1 lists the short and full variable labels. To address potential redundancy among variables, a unique variable analysis (Christensen et al. 2023) was conducted using the weighted topological overlap measure (Nowick et al. 2009). This analysis identified seven variables with very high associations, which were subsequently discarded: childreninhousehold, instrumentaladls, compensatory, activecoping, strainfromfamily, privatereligiouspractices and spiritualcopingb. Additionally, the variable female was suggested for removal due to its strong association with waisthipratio. However, female was retained while waisthipratio was eliminated. After the removal of these variables, a Spearman correlation analysis of the remaining variables revealed that the correlation of 0.711 between perceived constraints and

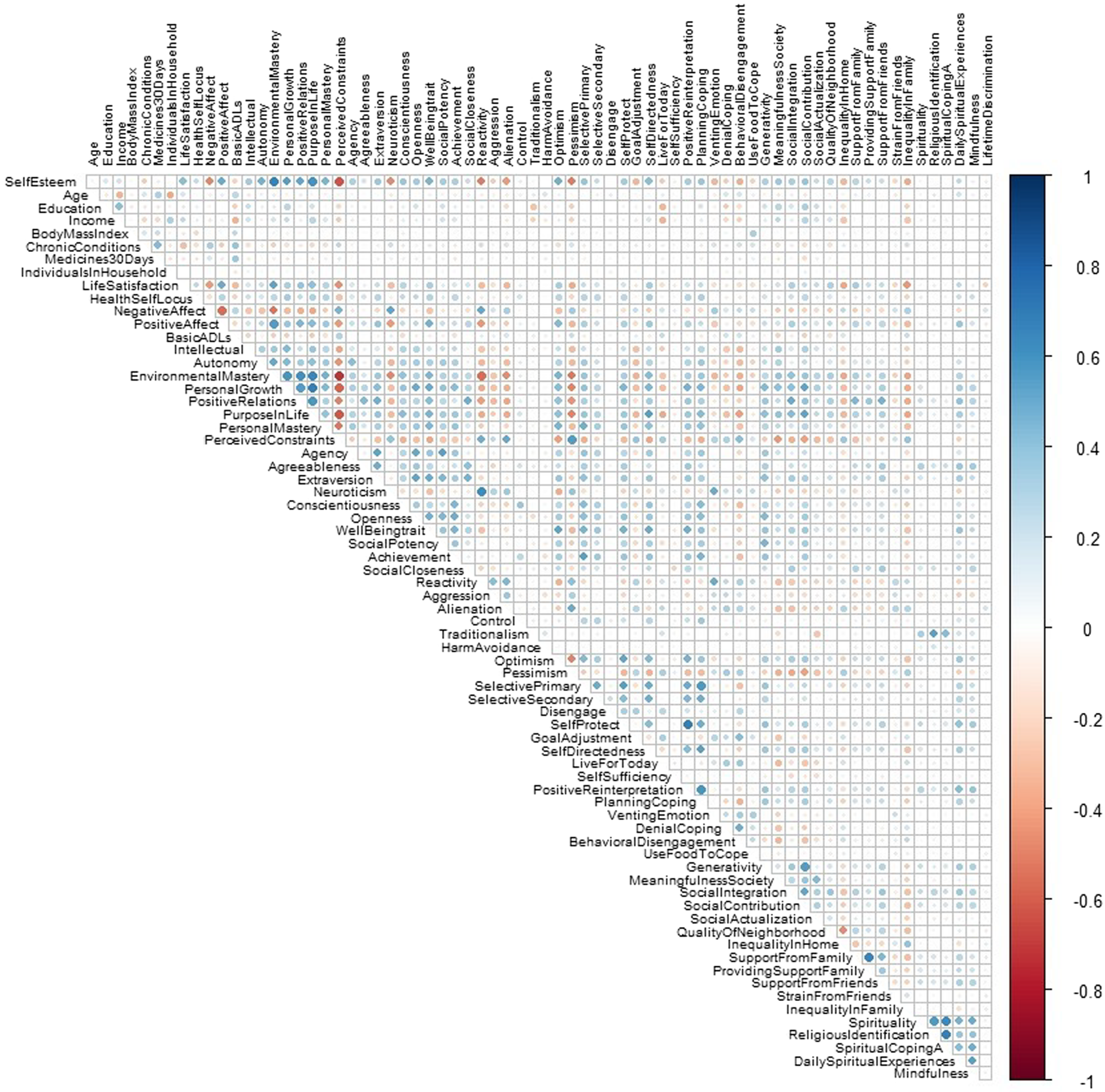

FIGURE 1 | Correlations.

environmental mastery was the largest correlation coefficient in the dataset, indicating that multicollinearity was not a serious issue (Tabachnick and Fidell 2014).

To address missing data, participants with more than 30% missing values (i.e., more than 21 variables) were excluded, resulting in the removal of 386 participants (363 respondents had 69 missing values). Next, an additional 13 participants with missing values on the outcome variable were removed, yielding a final sample of 2895. The descriptive statistics for the variables before imputation are presented in Table S2. The missing rate for individual variables was generally low, not exceeding 15.4% (for inequality in the family), with an average missing rate of 1.15% across all variables. The R package *missRanger* (Mayer 2024) was used to impute the missing values, employing 500 trees. *missRanger* is a multivariate imputation algorithm based on Random Forests that offers a faster alternative to the MissForest algorithm (Stekhoven and Bühlmann 2011). Table S3 presents descriptive information for the variables in the final imputed dataset. Figure 1 shows the Spearman correlation matrix for the non-binary variables of the study.

3 | Results

3.1 | Feature Elimination

Models that incorporate a large number of predictors may suffer from overfitting (Meiri and Zahavi 2004). Although Random Forest models are relatively resilient to noisy variables, removing

TABLE 2 | Eliminated and selected predictors based on simulated annealing.

Eliminated variables (43)
Age, Female, Education, Income, Non_white, LifeSatisfaction, HealthSelfLocus, Intellectual, Autonomy, PositiveRelations, PurposeInLife, PersonalMastery, PerceivedConstraints, Agreeableness, Neuroticism, Openness, WellBeingtrait, SocialCloseness, Reactivity, Aggression, Traditionalism, HarmAvoidance, SelectiveSecondary, Disengage, GoalAdjustment, LiveForToday, SelfSufficiency, PlanningCoping, Generativity, MeaningfulnessSociety, SocialIntegration, SocialContribution, SocialActualization, QualityOfNeighborhood, InequalityInHome, ProvidingSupportFamily, SupportFromFriends, StrainFromFriends, Spirituality, SpiritualCopingA, DailySpiritualExperiences, Mindfulness, LifetimeDiscrimination
Selected variables (30)
BodyMassIndex, ChronicConditions, Medicines30Days, IndividualsInHousehold, NegativeAffect, PositiveAffect, BasicADLs, AlcoholProblem, EnvironmentalMastery, PersonalGrowth, Agency, Extraversion, Conscientiousness, SocialPotency, Achievement, Alienation, Control, Optimism, Pessimism, SelectivePrimary, SelfProtect, SelfDirectedness, PositiveReinterpretation, VentingEmotion, DenialCoping, BehavioralDisengagement, UseFoodToCope, SupportFromFamily, InequalityInFamily, ReligiousIdentification

noncontributory predictors can improve model performance (Garson 2022). Accordingly, feature selection analysis with simulated annealing was performed (Henderson et al. 2003; Kuhn and Johnson 2020). The *caret* package (Kuhn 2008) was used to implement this analysis with Random Forest (100 iterations and five-fold cross-validation repeated five times), identifying predictors that did not significantly contribute to model performance. Table 2 presents the results of this analysis, including the eliminated and selected variables. Only the selected variables ($N = 30$) were included in the final Random Forest analysis.

3.2 | Random Forest

The optimization of model hyperparameters is a crucial step in ML, as it can affect the performance of the model. In Random Forest, this process involves adjusting hyperparameters such as *mtry*, which controls the number of predictors sampled at each split, and *nodesize*, which determines the minimum size of terminal nodes and thus influences model complexity and generalisation (Biau and Scornet 2016). To optimise these hyperparameters, a range of values was explored. A range of 5–25 was explored for *mtry*, and a range of 2–10 was explored for *nodesize* (Genuer and Poggi 2020; Boehmke and Greenwell 2019). To ensure model stability, the number of trees was set to 1000, exceeding the typical default of 500. A grid search with five-fold cross-validation was performed using the *mlr3* package (Lang et al. 2019) with a resolution of 20, testing 180 models with different combinations of *mtry* and *nodesize* values. The best-performing model was found to have $mtry = 7$ and $nodesize = 5$. These two values were then used in the final Random Forest analysis.

The *randomForestSRC* package (Ishwaran and Kogalur 2024) was used to perform Random Forest regression using the optimised hyperparameter values. The results showed that the models achieved strong performance with 30 predictors, with out-of-bag (OOB) R-squared values of 0.595 and OOB mean squared error (MSE) of 20.431, respectively. This R-squared value is considered strong in the context of social sciences (Whittier et al. 2020). An inspection of the cumulative OOB error rate suggested that 1000 trees were sufficient for the analysis. The permutation variable importance scores for all predictors were calculated, as shown in Figure 2. AlcoholProblem, Control, Medicines30Days, IndividualsInHousehold, and BodyMassIndex were found to have null predictive power for self-esteem. However, the remaining variables demonstrated varying degrees of predictive contribution. PDPs are shown in Figures 3 and 4. These plots show the shape of the relationship between the predictors and self-esteem. These relationships exhibit varying degrees of deviation from linearity for many variables, which supports the choice of Random Forest over traditional regression models (Garson 2022).

It is noteworthy that Random Forest has a built-in cross-validation mechanism, leveraging OOB samples to assess performance without requiring external cross-validation. During the training, each tree is constructed using a bootstrap sample of the data, leaving out approximately one-third of the observations. These omitted observations, known as OOB samples, serve as a validation set, enabling the evaluation of model performance on unseen data (Hastie et al. 2009).

4 | Discussion

The results indicate that, in order of importance, the strongest predictors of self-esteem were environmental mastery, experienced negative affect, personal growth, experienced positive affect, and dispositional optimism/pessimism. These findings suggest that self-esteem is most strongly related to one's sense of competence in coping with life demands, coupled with emotional tendencies and a subjective sense of growth.

4.1 | Primary Role of Agency-Related Factors

The results strongly support models that emphasise the primacy of agency for self-esteem. Environmental mastery (the ability to effectively manage and adapt to environments and situations) emerged as the strongest predictor of self-esteem, followed by other agency-related variables, including personal growth, agency trait and self-directedness appearing among the top predictors. This aligns with previous research demonstrating a robust relationship between agency orientation and self-esteem (Wojciszke et al. 2011; Chen et al. 2017; Hauke and Abele 2020).

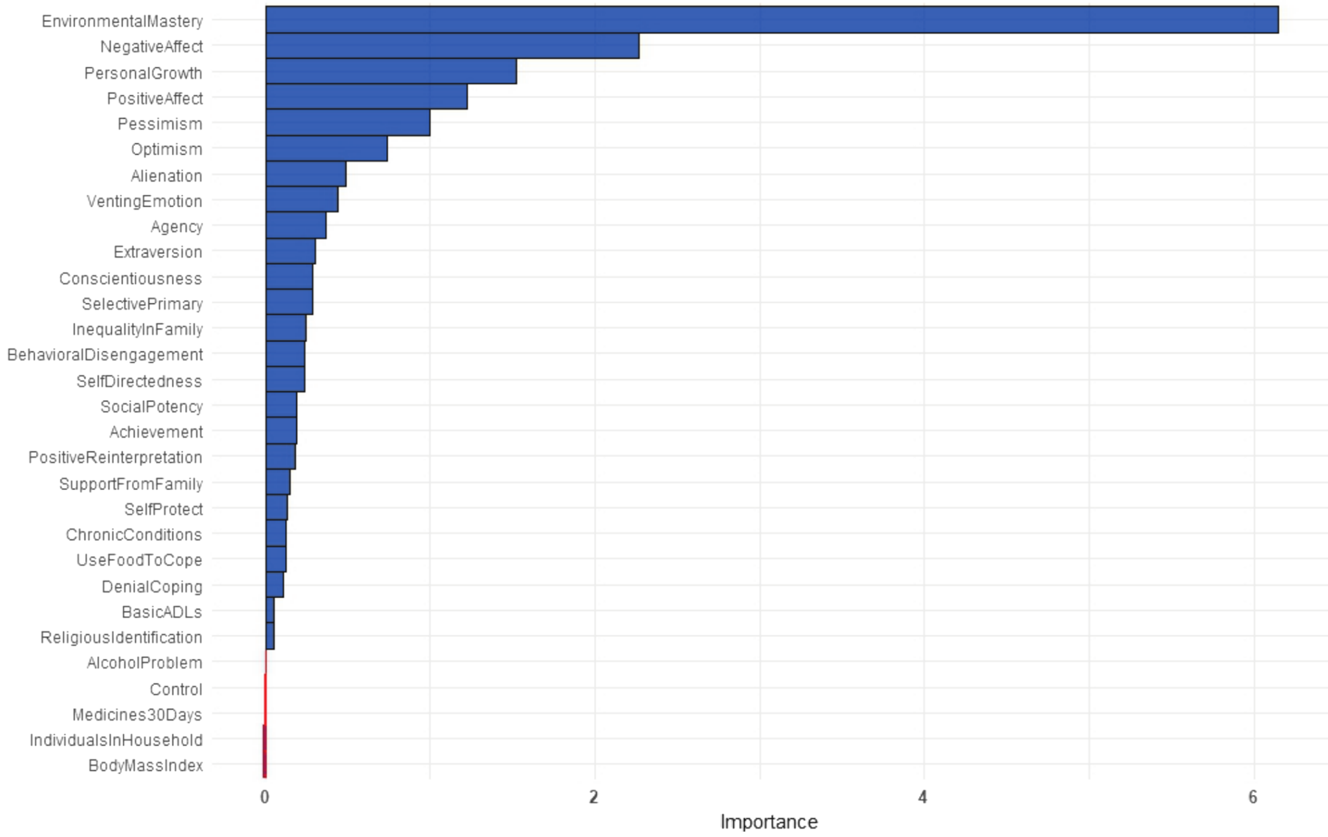

FIGURE 2 | Variable importance.

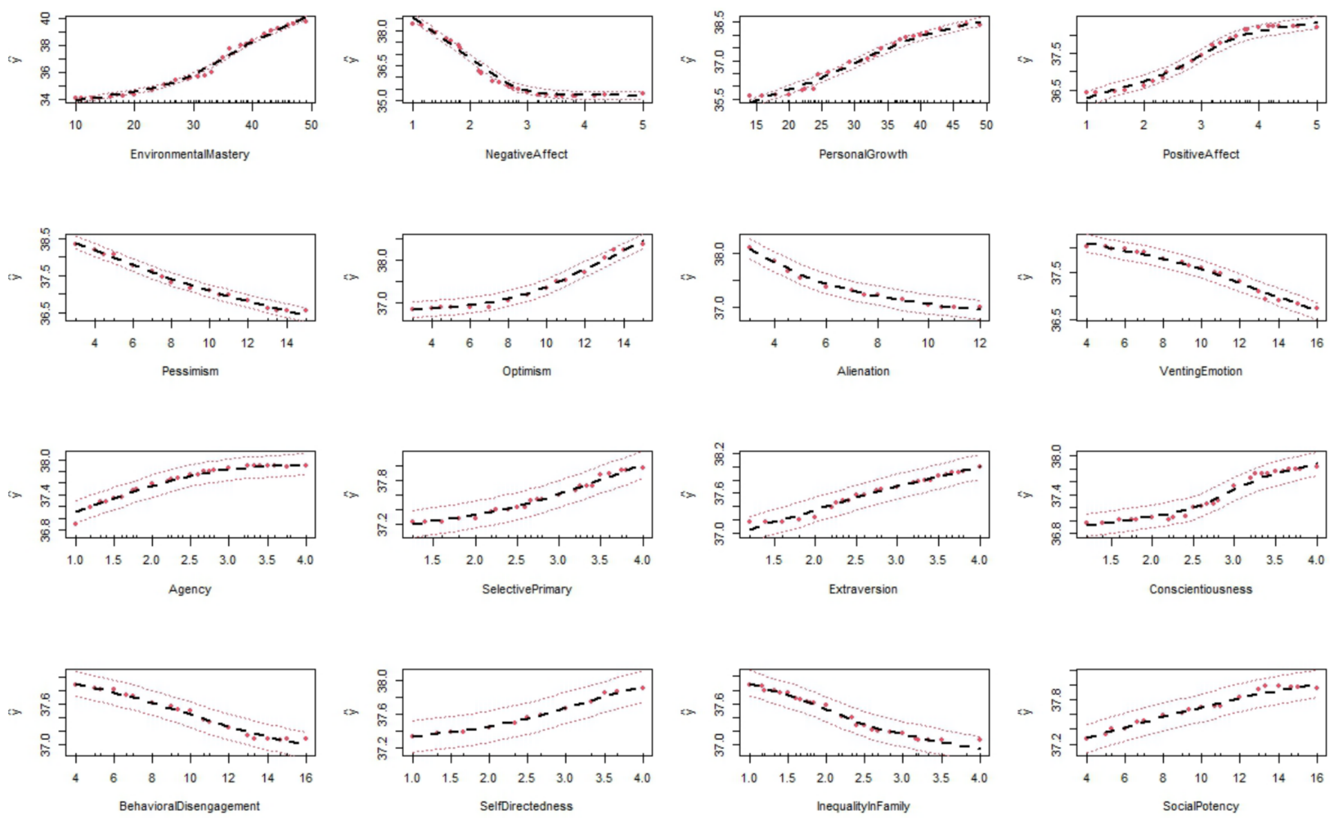

FIGURE 3 | Partial dependence plots for the top 16 predictors.

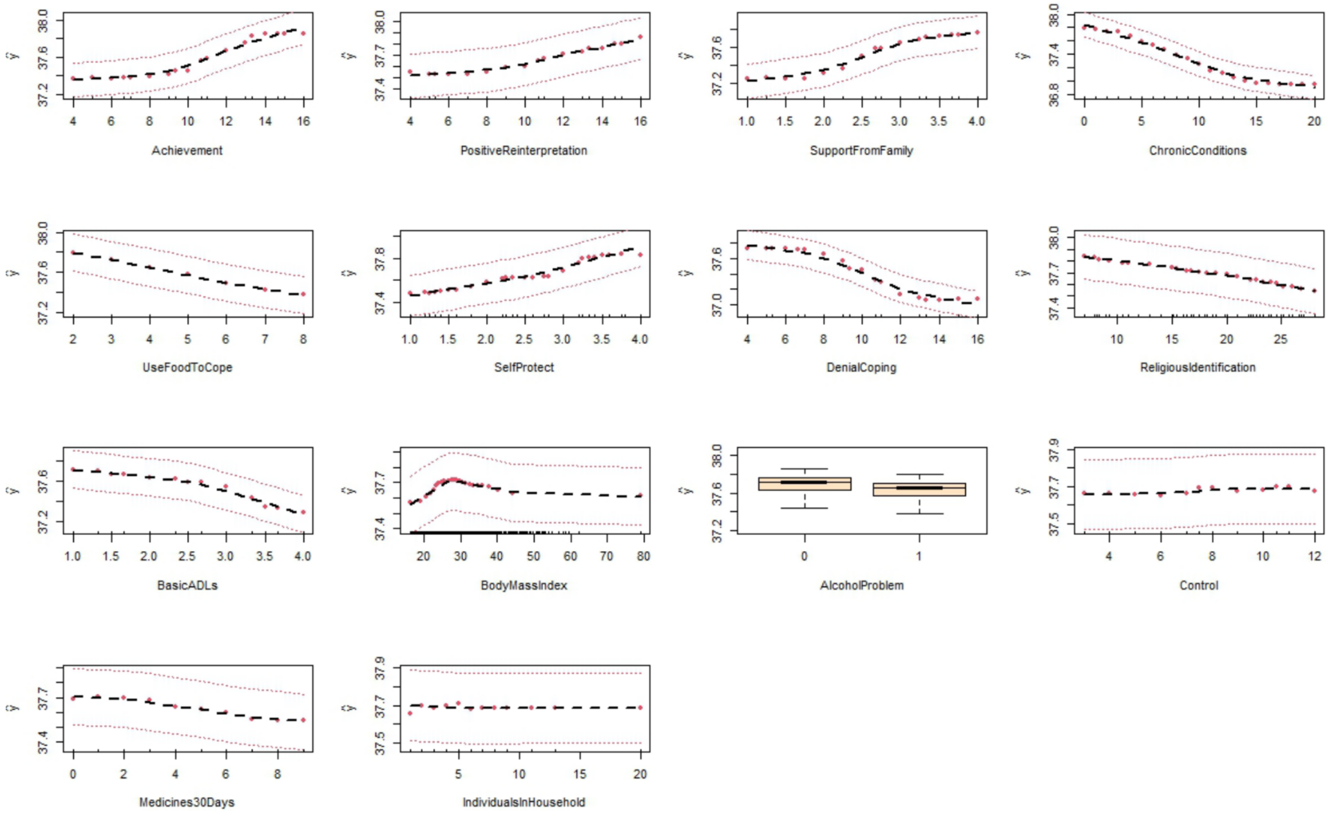

FIGURE 4 | Partial dependence plots for the weaker predictors.

These variables represent conceptually related yet distinct facets of personal agency. Environmental mastery reflects one's perceived ability to effectively manage and adapt to one's environment. Personal growth captures the ongoing process of developing and realising one's potential. Agency refers to the ability to act independently and assertively, while self-directedness includes goal-setting, planning, and a sense of purpose. Although these constructs are theoretically and empirically related, their emergence as distinct top predictors suggests that each contributes a unique variance to the prediction of self-esteem. In addition to highlighting the unique importance of these agency-related constructs, the results shed light on the specific dimensions of agency that are more strongly associated with self-esteem. Environmental mastery and personal growth had the highest predictive values, suggesting that the ability to navigate one's environment and a continuing sense of realising one's potential are particularly salient for self-esteem. By contrast, assertiveness and goal orientation are two aspects of agency that show relatively less predictive power. The conceptual proximity of these variables underscores the need for further empirical and theoretical work to clarify their distinct roles and the psychological mechanisms linking the different aspects of agency to self-esteem.

4.2 | Affective Factors

The results also highlighted the significant role of affective experiences in predicting self-esteem, with negative affect emerging as the second most important predictor, along with positive affect and pessimism/optimism and venting (the tendency to intensely experience and express negative emotions in response to a problem or difficulty) among the top predictors. This finding provides strong support for models and lines of research emphasising the affective nature of self-esteem judgements (Brown and Marshall 2001) and aligns with previous research showing the impact of mood on self-evaluations (Brown and Mankowski 1993). The high ranking of both positive and negative affect suggests that self-esteem may be more strongly influenced by emotional dispositions than previously recognised in some theoretical frameworks. Consequently, it seems prudent to place greater emphasis on the affective underpinnings of self-worth and self-evaluation in theoretical frameworks of self-esteem. Moreover, it is likely that various other factors, such as social exclusion and rejection, exert an indirect influence on self-esteem by affecting an individual's affective state (Rimes et al. 2023).

4.3 | Sociometer Theory: Mixed Support

The findings provide mixed support for sociometer theory (Leary 2012). While social-related variables such as alienation and social potency appeared among the significant predictors, they ranked lower than the agency-related and affective factors. This suggests that while social acceptance and relationship quality contribute to self-esteem, their influence may be less direct or powerful than that proposed by the sociometer theory. The relatively lower ranking of support from family and other social variables indicates that self-esteem might be more strongly tied to agency and emotional experiences than social acceptance. These findings complement, rather than contradict, the assumptions of sociometer theory, providing a more comprehensive understanding of the complex factors at play.

4.4 | Status and Demographic Factors: Limited Support

The present findings provide limited support for theories that emphasise the role of social status and demographic factors in self-esteem formation. In general, the demographic variables were ranked relatively low in importance. This is inconsistent with the predictions of some theories (Barkow 1980; Mahadevan et al. 2016), which posit a stronger role for status-related variables (Gregg et al. 2021). The absence of traditional SES indicators (e.g., income and education) among the top predictors suggests that objective status markers are less crucial for self-esteem than are psychological factors.

4.5 | Summary of Theoretical Implications

These findings suggest a need to integrate and broaden existing theories of self-esteem determinants. While some evolutionary frameworks often emphasise social validation, acceptance and status as primary drivers of self-esteem, the present results indicate a more complex picture in which personal agency, a sense of personal growth and emotional well-being are more central. The prominence of these predictors suggests that self-esteem, although often conceptualised as a 'sociometer', also reflects an individual's sense of personal agency, growth and emotional well-being. These findings emphasise the need for an integrated framework that highlights the importance of personal agency, a sense of continuous growth and emotional stability, while still acknowledging the roles of social validation and status. This expanded perspective may offer a more accurate and comprehensive account of self-esteem's psychological foundations.

Notably, several theoretically important variables (e.g., autonomy, life satisfaction, purpose in life) were excluded during the feature elimination process because of their limited unique contribution to the prediction of self-esteem within the full multivariate context. Their exclusion does not imply that these constructs are unimportant for self-esteem. Rather, it reflects the relative strength of their predictive power when considered along with a large set of competing variables. These constructs may emerge as significant predictors in models focused on a narrower set of predictors. The goal of this analysis was to identify the strongest predictors in a high-dimensional setting, in which only variables contributing significant unique variance over all other predictors were retained, thereby facilitating the development of a more parsimonious model. Thus, the exclusion of these variables does not reflect their lack of theoretical importance but rather their limited empirical contribution when assessed alongside a broader range of competing predictors. These results also provide nuances to existing theoretical models. For example, while subjective well-being is recognised as important for self-esteem, the present findings revealed that the affective components of subjective well-being (i.e., positive and negative affect) are more predictive of self-esteem than the cognitive aspects of subjective well-being (i.e., life satisfaction).

4.6 | Practical Implications

Although the correlational nature of the findings precludes definitive causal conclusions, the results offer valuable insights that can inform evidence-based interventions to enhance self-esteem. The findings suggest that practitioners, educators, and mental health professionals might benefit from recalibrating their approaches to enhancing self-esteem. Self-esteem interventions might be more effective when they prioritise three key areas that emerge as robust predictors: environmental mastery, personal growth orientation, and emotional regulation capabilities. This would shift the focus from external validation to internal development, emotional regulation, and environmental management. Notably, the findings revealed that specific coping strategies were predictive of self-esteem levels. Selective primary control, characterised by direct action and persistent effort in pursuing goals, emerged as a positive predictor, whereas behavioural disengagement, manifested through withdrawal and reduced effort when facing challenges, showed a negative relationship with self-esteem. These contrasting patterns suggest that interventions aimed at enhancing self-esteem might benefit from explicitly teaching active coping strategies while helping individuals identify and minimise tendencies towards disengagement when facing difficulties. Such insights can inform the development of targeted and effective self-esteem enhancement programs.

4.7 | Limitations

Some limitations of this study should be considered when interpreting the findings. First, this study relied on cross-sectional, correlational data, which inherently limits the ability to draw causal inferences. These analyses reflect predictive rather than causal modelling (Kuhn and Johnson 2013). The goal was to quantify the relative contributions of variables to the prediction of self-esteem without establishing a temporal precedence or causal direction. Accordingly, the findings identify variables that are predictive of self-esteem but should not be interpreted as evidence of causal links. Moreover, the cross-sectional design precluded the examination of directionality. Some variables identified as predictors (e.g., positive affect) may also function as self-esteem outcomes (Joshanloo 2022). Future research using longitudinal or experimental designs is necessary to clarify the direction and potential reciprocity of these associations.

Second, this study relied on Random Forest's built-in OOB validation to estimate the model performance. OOB validation is a robust internal validation method that leverages the inherent bootstrapping procedure of Random Forest to provide unbiased estimates without the need for a separate holdout sample. However, the absence of an external validation or replication sample limits the generalisability of the findings beyond the present dataset. While OOB estimates are well established for internal model evaluation, future research should replicate these results in independent samples to confirm the stability and generalisability of the identified predictor importance rankings.

The third limitation concerns the self-reported nature of the measures. All variables, including self-esteem and its predictors, were assessed using self-report questionnaires, which may be subject to biases such as social desirability. This may have artificially influenced the relationships between the variables. Future studies could benefit from incorporating multiple assessment methods, including behavioural measures, peer ratings, and objective indicators of the variables.

Fourth, although the sample was nationally representative of the American population, the findings may not be generalisable to other cultural contexts. Given that self-esteem construction and expression can vary across cultures (Cai et al. 2007), the prominence of agency-related constructs as predictors of self-esteem in this study reflects patterns that may be particularly characteristic of individualistic cultural contexts such as the United States. In collectivist societies, self-esteem may be shaped to a greater extent by communal values, relational harmony, and social obligation (Ng et al. 2003). Thus, the centrality of agency in self-esteem formation observed here may not be generalisable across different cultural contexts. Future cross-cultural research is needed to examine whether different sociocultural environments prioritise distinct psychological foundations of self-esteem.

Finally, this study focuses on global self-esteem as a unitary construct. However, research suggests that self-esteem can be domain-specific, and that different predictors might be more or less important for different domains of self-worth. Future research should examine how the identified predictors relate to domain-specific self-esteem measures, potentially revealing more nuanced patterns of relationships.

5 | Conclusion

This study provides a comprehensive examination of the relative importance of diverse predictors of self-esteem, offering crucial insights that reshape our understanding of these predictors. The findings revealed a clear hierarchy of predictors in which personal agency, particularly environmental mastery and personal growth, along with emotional experiences, emerged as the strongest determinants of self-esteem, surpassing socio-demographic, health-related, relational, and status-related factors. This pattern suggests that self-esteem is fundamentally grounded in the subjective experience of personal effectiveness, sense of continuous development, and affective well-being. While the results do not negate the role of social factors in self-esteem, they suggest a more nuanced understanding in which social acceptance and relatedness are not the primary factors. These findings have important implications for both theory and practice, suggesting a need for integrative theories and indicating that interventions aimed at enhancing self-esteem might be most effective when focused on developing personal agency, fostering growth experiences, and building emotional regulation skills. Future research could build on these insights by examining how these relationships unfold over time and across different cultural contexts.

Ethics Statement

This study was conducted in accordance with the ethical standards outlined in the 1964 Declaration of Helsinki and its subsequent amendments. It utilises secondary data from the MIDUS project. Ethical approval for the MIDUS project was granted by the University of Wisconsin–Madison Ethics Committee on November 22, 2016 (#2016-1051).

Consent

Informed consent was obtained from all the participants.

Conflicts of Interest

The author declares no conflicts of interest.

Data Availability Statement

The MIDUS data and materials are publicly available. For more information, see https://midus.wisc.edu/data/index.php.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Data S1. Supporting Information**.