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Research Article

Key Predictors of Generativity in Adulthood: A Machine Learning Analysis

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Abstract

Objectives: This study aimed to explore a broad range of predictors of generativity in older adults. The study included over 60 predictors across multiple domains, including personality, daily functioning, socioeconomic factors, health status, and mental well-being.

Methods: A random forest machine learning algorithm was used. Data were drawn from the Midlife in the United States (MIDUS) survey.

Results: Social potency, openness, social integration, personal growth, and achievement orientation were the strongest predictors of generativity. Notably, many demographic (e.g., income) and health-related variables (e.g., chronic health conditions) were found to be much less predictive.

Discussion: This study provides new data-driven insights into the nature of generativity. The findings suggest that generativity is more closely associated with eudaimonic and plasticity-related variables (e.g., personal growth and social potency) rather than hedonic and homeostasis-oriented ones (e.g., life satisfaction and emotional stability). This indicates that generativity is an inherently dynamic construct, driven by a desire for exploration, social contribution, and personal growth.

Keywords: MIDUS, Personality, Random forests, Successful aging, Well-being

The global demographic scene has been undergoing profound change, at least in the developed world, with the proportion of older adults steadily increasing (Harper, 2014). This shift presents both challenges and opportunities for societies around the world. As we face these rather new challenges, it is imperative to deepen our understanding of the factors that contribute to healthy and successful aging (Menassa et al., 2023). Generativity, as "concern in establishing and guiding the next generation" (Erikson, 1963, p. 240), includes goals and actions positively affecting future generations, including parenting, grandparenting, teaching, and mentoring (McAdams & de St. Aubin, 1992; Schaie, 2016). Viewed as particularly significant in midlife and old age (Villar, 2011), generativity is widely acknowledged as a contributing factor to successful aging and mental well-being during later life stages (Becchetti & Bellucci, 2020; Busch & Hofer, 2019; Gruenewald, 2024; Reinilä et al., 2023). That is, not only does generativity contribute to societal well-being, but also enhances personal satisfaction and psychological health later in life. As our population ages, understanding the predictors and mechanisms of generativity becomes increasingly important to foster a society in which older adults can thrive and continue to make meaningful contributions (Glass et al., 2004).

Although generativity is recognized as important in adult development and well-being, our current understanding of it and its predictors remains limited. Existing studies have typically focused on a narrow set of predictors, often examining factors such as personality traits (Blatný et al., 2019), religion and spirituality (Brady & Hapenny, 2010), demographic characteristics (Doerwald et al., 2020), and psychological strengths (Kashy & Morash, 2021). Although these studies provide valuable insights, they may overlook key determinants of generativity. There is a lack of comprehensive research that examines a wide range of predictors across multiple domains. This study addresses this gap by using a machine learning technique to analyze over 60 diverse variables across domains such as personality, daily functioning, socioeconomic factors, health status, and mental well-being. The study is primarily exploratory, taking advantage of a large data set to uncover new insights into generativity.

Machine Learning For Exploratory Research

Although psychological science has traditionally relied on theory-driven deductive research (Jebb et al., 2016), the increasing availability of large data sets with numerous variables has highlighted the need for more data-driven inductive approaches that can make better use of these resources (Van Lissa, 2022). This shift is particularly valuable because relationships among multiple variables may not be fully predictable based on current theoretical knowledge, and comprehensive psychological theories that can effectively explain complex phenomena are scarce (Woo et al., 2016).

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By incorporating exploratory methods, researchers can generate novel insights and address gaps in current psychological theory (Chen & Wojcik, 2016), allowing for both the testing of existing theories and the discovery of unexpected patterns that can lead to new theoretical developments (Yarkoni & Westfall, 2017). This study exemplifies such an exploratory, data-driven approach, focusing on predictive rather than causal modeling, with the fundamental goal of facilitating insight, and informed decision-making even without a complete understanding of the underlying mechanisms (Bzdok et al., 2018).

Machine learning techniques offer unique advantages for exploratory research, particularly when dealing with complex data sets that can challenge traditional statistical methods. In contrast to traditional approaches, which are often limited by strict parametric assumptions, many machine learning algorithms exhibit greater adaptability, effectively handling nonparametric data and producing reliable results even in complicated, high-dimensional data sets (Jiang et al., 2020). A key advantage of machine learning is its ability to identify nonlinear relationships and interactions between variables without the need for explicit prior specification (Fokkema et al., 2022). This feature is particularly valuable in psychological research, where complex nonlinear patterns are common but may be missed by standard linear methods. In addition, machine learning algorithms can efficiently process high-dimensional data with a large number of predictors (Sun, 2024). Another advantage of machine learning is its ability to provide a more thorough assessment of model performance through methods such as cross-validation. In these methods, the model's performance is assessed not on the same data set used for training, but rather on unseen data sets. This not only leads to more accurate estimates of predictive ability but also helps researchers avoid overfitting, which can negatively impact the generalizability of results (Yarkoni & Westfall, 2017).

The Present Study

Previous research has successfully applied machine learning to aging studies, yielding novel insights. For example, Casanova et al. (2020) used machine learning to identify the strongest predictors of cognitive decline among nearly 30 demographic, health, and genetic variables. Similarly, (Yu et al., 2022) applied machine learning to determine key drivers of active aging in older adults in China, examining predictors across paid and unpaid work, caregiving, and social activities. Despite the growing interest in machine learning applications within aging research, generativity remains an understudied concept. This study sought to fill this gap by using data from the Midlife in the United States (MIDUS) project. The MIDUS survey includes a generativity scale and an exceptionally diverse range of variables, reflecting the project's interdisciplinary approach to understanding the complexities of aging (Radler, 2014). By incorporating a wide range of demographic, health, social, psychological, affective, and well-being indicators, this data set offers a rich foundation for uncovering important predictors of generativity.

Previous research has linked generativity to both hedonic and eudaimonic well-being (Doerwald et al., 2020). Hedonic well-being encompasses the subjective experience of happiness, pleasure, and life satisfaction, whereas eudaimonic well-being reflects a deeper sense of fulfillment through the realization of human potential and living authentically (Ryan & Deci, 2001). This study includes both hedonic variables (e.g., positive and negative affect, well-being trait, and life satisfaction) and eudaimonic variables (e.g., purpose in life, personal growth, and self-acceptance) to examine their relative predictive power for generativity.

Also relevant is the distinction between two fundamental meta-traits of personality—plasticity and stability (DeYoung, 2010, 2014; Digman, 1997). Plasticity represents the tendency toward cognitive and behavioral exploration, flexibility, and engagement with novel experiences, and includes openness to experience and extraversion from the Big Five personality framework. This meta-trait reflects an individual's ability to adapt and grow in response to new situations and information. Stability, on the other hand, reflects the maintenance of goal-directed behavior, emotional equilibrium, and social integration across time and contexts, combining conscientiousness, agreeableness, and emotional stability (low neuroticism). This study includes variables related to both plasticity (e.g., personal growth, agency, extraversion, and openness) and stability (eg, neuroticism, control, and traditionalism) to determine their relative predictive power for generativity.

In sum, the present investigation aims to advance our understanding of generativity by examining its predictors through multiple theoretical lenses. Specifically, this study incorporates a comprehensive set of variables representing the broad psychological dimensions of hedonia and eudaimonia, as well as variables related to the meta-traits of plasticity and stability. The study sought to offer a novel perspective on how these variables might underlie generative tendencies. This comprehensive approach allows for a systematic comparison of which psychological domains are most predictive of generativity, potentially reconciling previously fragmented findings in the literature. Furthermore, a comprehensive set of variables spanning multiple domains was incorporated as potential predictors of generativity, including demographic, health-related, and spirituality- and religion-related factors, which have been linked to generativity in prior research (Brady & Hapenny, 2010; Carlson et al., 2000; Doerwald et al., 2020).

Method

Participants

The third wave of the Midlife in the United States (MIDUS) data set was utilized (Ryff et al., 2019). MIDUS 3 was conducted from 2013 to 2014, comprising a nationally representative sample of 3,294 American adults, with a mean age of 63.64 years (SD = 11.35, range: 39–93 years). About 55% of participants were female.

Variables

The outcome variable was measured using the Loyola Generativity Scale's contributions domain consisting of six items (McAdams & de St. Aubin, 1992; Rossi, 2001). The selection process for predictor variables involved excluding variables with low internal consistency reliability, extensive missing data (e.g., variables related to work-life), or those deemed theoretically less irrelevant to the research objectives (e.g., medical history variables or a large number of variables related to coping styles). The variable of social contribution (a dimension of social well-being) was also excluded because of its substantial overlap with generativity. After applying these criteria, the resulting data set included 70 variables. Supplementary Table 1 in Supplementary Material presents these variables and their definitions.

Missing Data Handling

To address missing data, participants with more than 30% missing values on the variables (i.e., more than 20 variables) were excluded, resulting in the removal of 382 participants. Notably, 363 of these respondents had 59 missing values. Next, an additional 82 participants with missing values on the outcome variable were removed, yielding a final sample of 2,830. Descriptive statistics for the variables before imputation are presented in Supplementary Table 2. As shown, the missing rate for individual variables was low, not exceeding 6.3% (for income), with an average missing rate of 0.8%. 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 and offers a faster alternative to the MissForest algorithm (Stekhoven & Bühlmann, 2011). Supplementary Table 3 presents the descriptive information for the variables in the final imputed data set.

Random Forest Analysis

In this study, random forest regression was performed using the package *randomForestSRC* (Ishwaran & Kogalur, 2024). Random forest analysis involves the construction of multiple decision trees during the training process, combining their predictive capabilities to generate more accurate and robust results (Hastie et al., 2009; Kalita, 2022). Random forests are particularly effective for handling many variables, capturing nonlinear relationships and interactions, and providing reliable predictions without overfitting (Chen & Ishwaran, 2012; Cutler et al., 2007; Fife & D'Onofrio, 2022; Pargent et al., 2023). The random forests regression algorithm has a built-in cross-validation mechanism known as out-of-bag (OOB) samples. This feature allows for performance evaluation without the need for separate cross-validation procedures (Hastie et al., 2009). More specifically, in the training phase, the algorithm creates multiple decision trees using random subsets of data. Each tree is trained on a different subset, called a bootstrap sample, leaving some data points out, known as OOB samples. These OOB samples are then used to assess the predictive performance of the model. This internal validation process helps to prevent overfitting and provides a more accurate estimate of the model's predictive ability than the in-sample estimates would (Hastie et al., 2009).

The application of machine learning in social sciences necessitates transparency and interpretability (Molnar, 2020). This study employs two key techniques to enhance model explainability for random forest: variable importance measures and partial dependence plots (PDPs). Variable importance techniques assign scores to predictors based on their predictive power (Hassija et al., 2023). This study utilizes permutation variable importance, measuring the increase in prediction error (mean-squared error, MSE) after permuting each variable's values (Fife & Rodgers, 2022; Hassija et al., 2023). PDPs provide a graphical visualization of the marginal effect of a predictor on the model's predicted outcome, accounting for other variables' effects (Petch et al., 2021). This aids in understanding potential nonlinear effects often overlooked in traditional methods.

The process of hyperparameter tuning involves optimizing the parameters that govern the learning process in machine learning models to enhance their performance. In random forests, hyperparameter tuning is typically used to optimize *mtry*, the number of predictors sampled at each split, and *nodesize*, the minimum size of terminal nodes, which controls the smallest number of observations assigned to a leaf, thus influencing model complexity and generalization (Biau & Scornet, 2016). In this study, the number of trees was set to 1,000 for both tuning and the final analysis, exceeding the typical default of 500 to ensure sufficient model stability. *Mtry*, the number of predictors considered at each split, typically defaults to one-third of the total predictors in random forest regression. With 34 final predictors (see later), the default would be approximately 11. For this analysis, a range of 5 to 20 was explored to investigate potential performance improvements. *Nodesize*, representing the minimum size of terminal nodes, influencing tree depth and complexity, was tuned within a range of 2 to 10 (default = 5) (Boehmke & Greenwell, 2019; Genuer & Poggi, 2020). A grid search with a resolution of 20 and 5-fold cross-validation was performed using the *mlr3* package (Lang et al., 2019). A total of 144 models were tested, and the best-performing model turned out to have an *mtry* of 13 and a *nodesize* of 2, which were used in the final analysis.

Results

Figure 1 shows the Spearman correlation matrix for nonbinary variables of the study. Figure 2 shows the Spearman correlations between all nonbinary variables and generativity.

Variable elimination

For the 70 included variables, variable redundancy was assessed using unique variable analysis (Christensen et al., 2023), which identifies variables with very high associations based on network analysis. This analysis applies the weighted topological overlap measure (Nowick et al., 2009) to an estimated network, where values exceeding 0.25 indicate high redundancy. The analysis identified five variables for removal because of extremely high associations with other variables: female, children_in_household, instrumental_adl, family_strain, and private_religious_practices. All these variables were removed except female. The variable female was flagged for potential removal due to its high correlation with waist_hip_ratio. However, it was decided to retain female and remove waist_hip_ratio instead. After removing these variables, a Spearman correlation analysis for the remaining 65 variables showed that the highest correlation in the whole data set was 0.751 between self-acceptance and environmental mastery, which does not indicate severe multicollinearity (Tabachnick & Fidell, 2014).

Although random forest (the machine learning algorithm used in this study) is generally robust to noisy variables, eliminating irrelevant predictors can enhance model performance (Garson, 2022). Accordingly, Recursive Feature Elimination was employed to systematically identify and eliminate predictors that did not significantly contribute to the model's performance (Kuhn & Johnson, 2019). Recursive feature elimination using random forests was performed using the *caret* package (Kuhn, 2008), employing 5-fold cross-validation. The results suggested dropping 30 of the predictors and keeping 34 of them for random forest regression. The removed variables

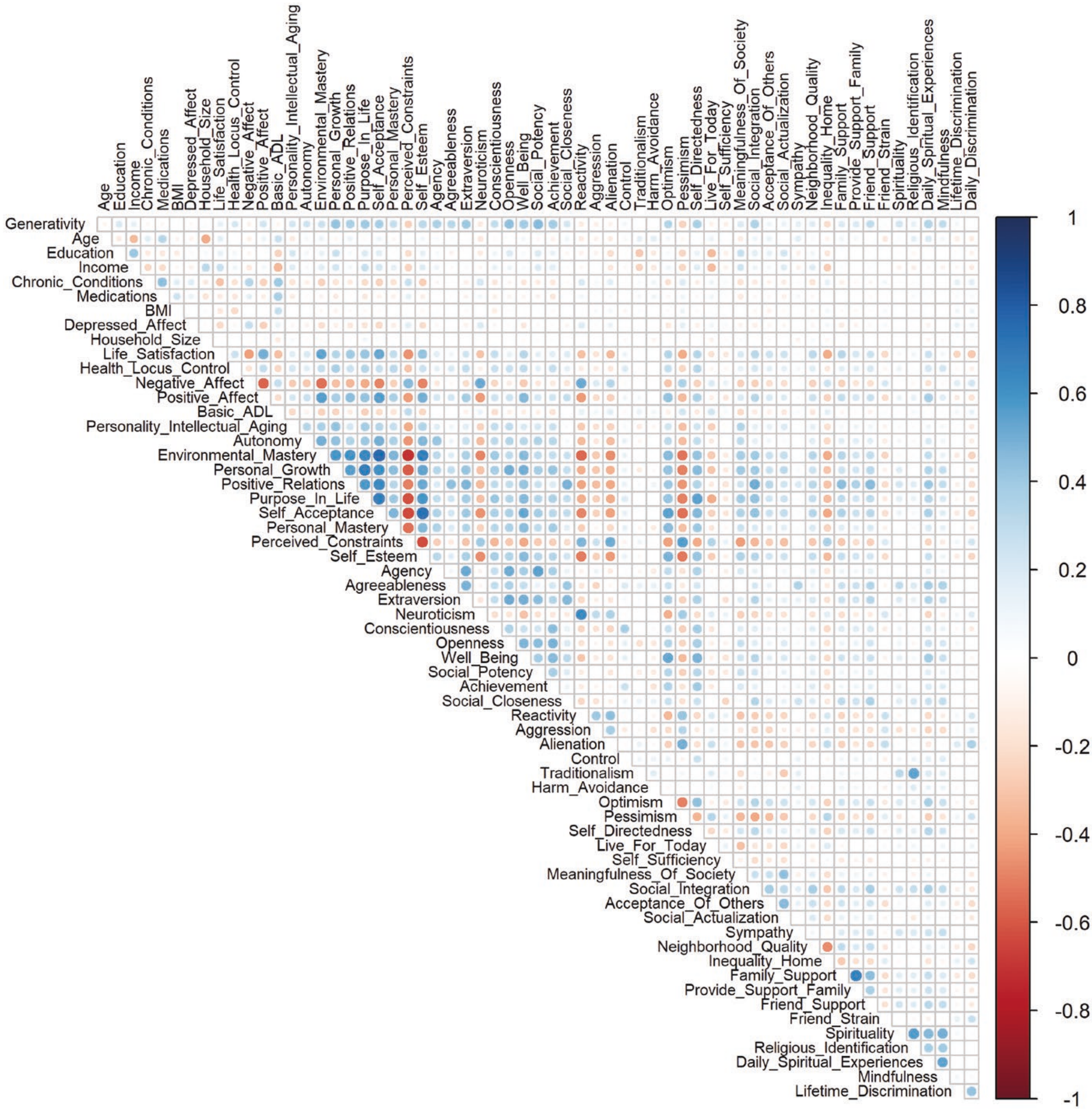

Figure 1. Correlations between nonbinary variables.

were female, income, non-White, chronic conditions, medications, BMI, depressed affect, household size, life satisfaction, health locus control, basic activity of daily living, personality intellectual aging, alcohol problem, neuroticism, reactivity, aggression, control, traditionalism, harm avoidance, pessimism, live for today, self-sufficiency, meaningfulness of society, acceptance of others, social actualization, neighborhood quality, family support, provide support family, friend strain, and daily discrimination.

Random Forest

A random forest analysis was conducted with 1,000 trees and optimized parameters based on the results of tuning (i.e., *nodesize* = 2, *mtry* = 13). The OOB R-squared of the model was 0.400, and the OOB MSE was 9.063. The *R*-squared value of about 40% can be considered strong in social sciences (Whittier et al., 2020). An inspection of the tree cumulative OOB error rate suggested that 1000 trees were sufficient as the error rate did not change much after 500 trees. Figure 3 presents the permutation variable importance scores for all 34 predictors. As shown, several variables emerged as particularly important. Social potency was the strongest predictor, followed by openness, social integration, personal growth, and achievement. Other strong predictors included purpose in life, extraversion, self-acceptance, daily spiritual experiences, agreeableness, educational level, mindfulness,

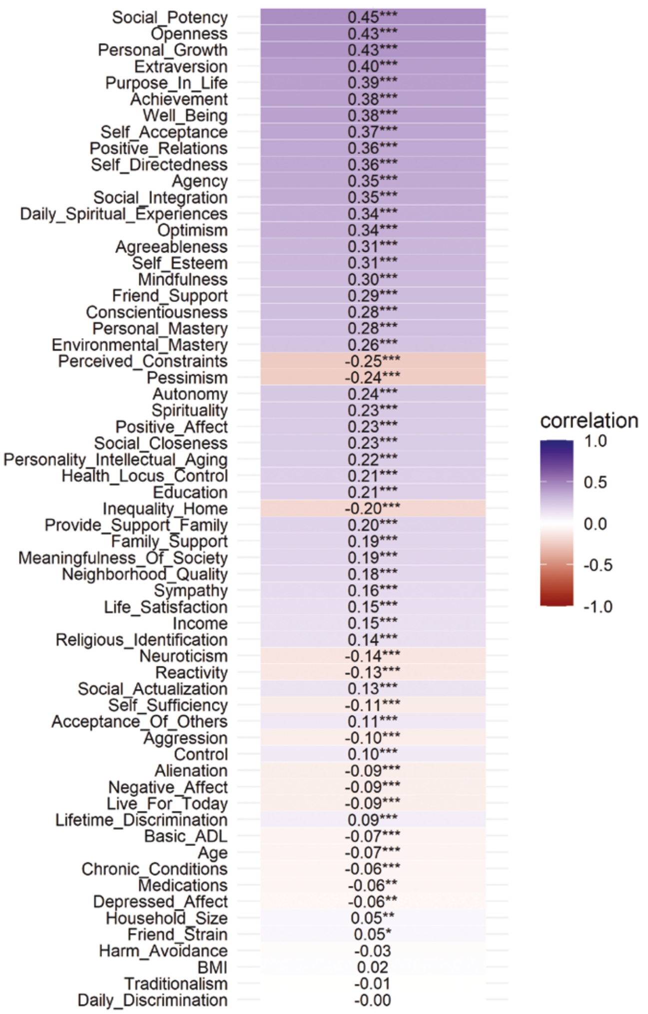

Figure 2. Correlations between nonbinary variables and generativity. ADL = Activities of Daily Living; BMI = body mass index. * $p < .05$. ** $p < .01$. *** $p < .001$

positive relations, friend support, and agency. PDPs for the top 16 most important variables are represented in Figure 4. All of these variables demonstrated a positive association with generativity, with some showing an approximately linear relationship and others deviating from linearity. Although the remaining variables also showed nontrivial associations with generativity, their contributions were to varying degrees smaller. The least important predictors were social closeness, autonomy, and positive affect. PDPs for variables ranked 16th through 34th in terms of their importance are presented separately in Supplementary Figure 1.

Supplementary Analysis

A random forest model was run with 1,000 trees and all 64 predictors, without feature elimination. The *mtry* parameter was tuned between 5 and 32, and *nodesize* between 2 and 10, using a grid search with fivefold cross-validation (resolution = 20). The optimal model had *mtry* = 32 and *nodesize* = 3, yielding an OOB R-squared of 0.394 and an OOB MSE of 9.149. Despite including 30 additional variables, this model's performance was not better than the main model in the study. As shown in Supplementary Figure 2, the top predictors remained largely unchanged across both models, indicating that excluding nonimportant predictors did not affect the ranking of the top predictors. These results underscore that feature elimination was instrumental in reducing noise without compromising model performance.

Discussion

Unimportant Predictors

A substantial number of variables were eliminated from the final model in recursive feature elimination, suggesting that their predictive power for generativity was comparatively limited alongside other predictors. Among the eliminated variables were a diverse range of factors spanning demographic characteristics, health indicators, psychological traits, and social factors. Demographic variables such as gender, race, and income were not retained in the final model. Thus, the women-are-more-generative hypothesis (Chen et al., 2022) was not supported by this analysis, where a large set of predictors were included. Health-related variables, including chronic conditions, medication use, and BMI, were also eliminated. Although health status undoubtedly plays a role in overall functioning in old age (Michel & Sadana, 2017), its direct impact on generativity appears to be less pronounced when considered alongside other factors.

Interestingly, several psychological constructs often associated with well-being and functioning were also excluded due to their limited contribution. These include depressed affect, life satisfaction, and various personality traits such as neuroticism, reactivity, and pessimism. Social and community-related variables like neighborhood quality, family support, and daily discrimination were also eliminated. The elimination of these variables does not necessarily negate their importance for generativity or in the broader context of adult development. Rather, it suggests that in the presence of other, more predictive factors, that are discussed later, their unique contribution to explaining variability in generativity is diminished.

Important Predictors

The emergence of social potency (i.e., assertiveness, persuasiveness, and inclination towards leadership roles) as the strongest predictor underscores the fundamentally social nature of generativity. This finding aligns with and extends Erikson's original conceptualization of generativity as a concern for guiding the next generation (Erikson, 1982). It suggests that the capacity to effectively influence and engage with others is crucial for generative behaviors. The prominence of social potency indicates that generativity is not merely about the desire to contribute, but also about having the social skills and confidence to enact that desire in meaningful ways. The second most important variable was openness. This likely facilitates generativity by promoting receptiveness to diverse experiences and perspectives, which may enhance one's ability to connect with and mentor others across various domains. The strong predictive power of social integration further reinforces the idea that generativity is deeply embedded in social contexts. Social integration provides the necessary network and opportunities for generative actions to take place. The significance of a sense of continued personal growth and achievement (e.g., ambitiousness and industriousness) as strong predictors points to an intrinsic motivational component of generativity. This suggests that generativity may be partly driven by a broader orientation towards self-improvement and accomplishment. Individuals who are

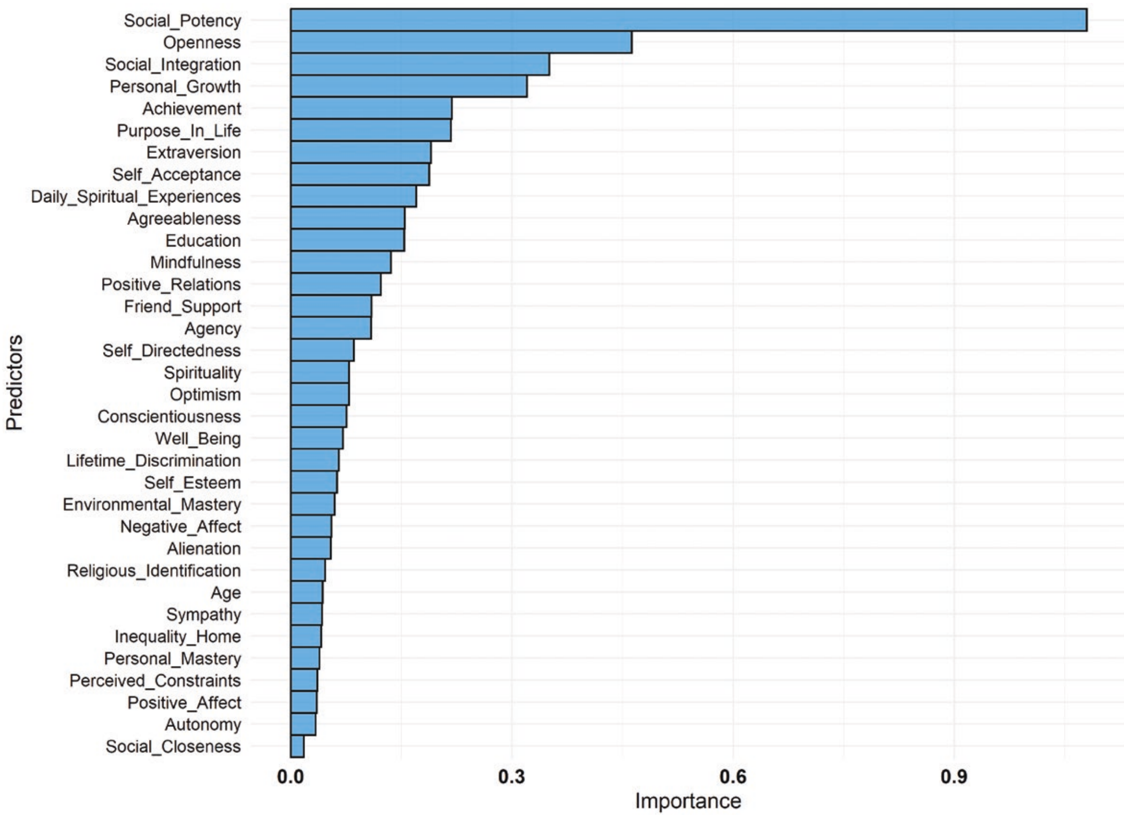

Figure 3. Variable importance.

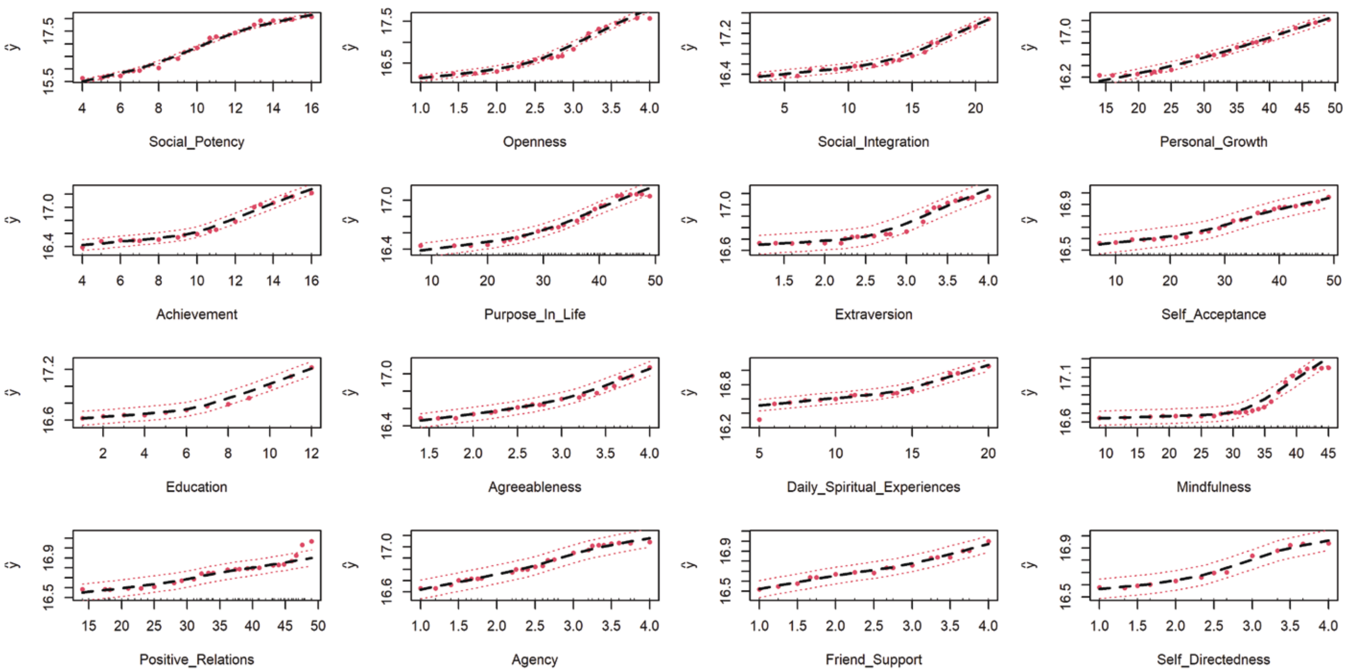

Figure 4. Partial dependence plots for the 16 most important variables.

invested in their own development may be more inclined to foster growth in others, viewing generative acts as extensions of their personal growth journey.

Purpose in life and self-acceptance emerge as key components, suggesting that generativity is closely tied to eudaimonic well-being and a coherent life narrative (Joshanloo, 2022). This is complemented by the significance of extraversion and agreeableness, which again highlight the crucial role of positive social interactions in generative behaviors. The inclusion of daily spiritual experiences adds a transcendent dimension, indicating that connecting to something greater than oneself may motivate generative actions.

A comparative analysis of the retained and eliminated predictors offers novel insights into the nature of generativity. The selected variables predominantly encompass psychological strengths, social engagement factors, and personal growth indicators, suggesting that generativity is closely tied to an individual's psychological resources and social connectedness. Notably, the retained predictors include traits like social potency, openness, extraversion, and achievement, indicating that proactiveness, social aptitude, and receptiveness to new and challenging experiences play crucial roles in generative behaviors. The presence of variables such as purpose in life, personal growth, and self-directedness underscores the importance of intrinsic motivation and a sense of personal life purpose in fostering generativity. In contrast, the eliminated variables included more concrete factors like demographic characteristics, physical health indicators, and specific life circumstances. This suggests that generativity may be more strongly influenced by malleable psychological and social factors rather than fixed demographic or health-related variables. Notably, education and age were the only demographic predictors of generativity, which is consistent with Keyes and Ryff's (1998) emphasis on these two variables in determining generativity.

Theoretical Implications

The examination of key predictors indicates that generativity is more strongly associated with eudaimonic variables (e.g., personal growth, social integration, purpose in life) than with hedonic ones (e.g., positive and negative affect), suggesting a closer conceptual alignment between generativity and eudaimonia than hedonia. These results imply that generativity is more reliant on a sense of purpose, meaning, and contributing to something larger than oneself than on the pleasures and positive emotions associated with hedonic well-being (Ryan & Deci, 2001). The results also provide compelling evidence for a distinction in the predictors of generativity, aligning well with the theoretical distinction between stability and plasticity in personality theories (DeYoung, 2010, 2014; Digman, 1997). The emergence of factors such as social potency, agency, openness, personal growth, and achievement as strong predictors of generativity, in contrast to the relative unimportance of variables such as neuroticism, stress reactivity, harm avoidance, and life satisfaction, offers robust support for the plasticity dimension of personality as a key predictor of generative contribution.

These findings present a compelling portrait of generativity as fundamentally growth-oriented and self-expansive in nature. The stronger associations between generativity and eudaimonic well-being and plasticity, rather than hedonic well-being and stability, suggest that generativity is more closely aligned with psychological striving and exploration than with a quest for emotional comfort and maintaining homeostasis. These findings indicate that generativity represents a dynamic, exploratory orientation toward life—one characterized by openness to new experiences, active engagement with new possibilities, and a quest for personal growth and fulfillment. Consistent with the growth-oriented nature of plasticity and eudaimonia (Joshanloo, 2023), the present study suggests that generativity also embodies a growth orientation marked by a proactive willingness to influence others, step beyond one's comfort zone, and pursue self- and other-improvement through active engagement.

Generativity has been portrayed as an active and dynamic process in previous research as well. For example, Erikson conceptualized generativity as a creative and productive influence in adult development, serving as an antithesis to "stagnation" (Erikson, 1982). McAdams (2019) concludes that individuals who are generative often display strong motivational inclinations towards not only communion (love) but also agency (power). Generativity and its related activities are rightfully considered essential components of active aging (Villar, 2024). Generativity serves as a mechanism for enhancing well-being by promoting increased social interaction (connecting with others), cognitive engagement (mentally stimulating tasks), and physical activity (particularly when involving productive efforts) (Gruenewald, 2024).

In sum, a key theoretical implication of the findings is the emphasis on the active nature of generativity, framing it within exploration-seeking dimensions of human behavior, rather than those oriented toward stability and homeostasis. This perspective underscores generativity's role in fostering dynamic engagement with life and supporting ongoing personal and social contribution growth throughout adulthood.

Practical Implications

The exploratory findings of this study suggest potential directions for interventions and policies that might promote generativity. The patterns observed indicate that social skills, personal growth, openness to experience, and sense of purpose could be relevant areas for intervention development. These could be considered within the framework of "eudaimonic interventions," which aim to enhance psycho-social skills rather than solely target mood improvement (Van Dierendonck & Lam, 2022; Vella-Brodrick, 2016). Eudaimonic interventions targeting purpose in life and self-acceptance could also play a crucial role in fostering generativity. These interventions aim to promote the development of a coherent life narrative and enhanced self-understanding, which are foundational to generative behaviors. Prior research has demonstrated a significant link between self-acceptance and generativity (Joshanloo, 2022), suggesting that generativity is deeply rooted in an individual's sense of identity and self-concept. This connection aligns with the emphasis on ego integrity in the generativity literature (Villar & Zacarés, 2024), underscoring the importance of a well-integrated sense of self and a coherent life story (McAdams, 2019).

The psychological factors identified in this study exist within a complex web of environmental and circumstantial influences, making isolated interventions potentially challenging (Wahl & Gitlin, 2019). Psychological elements related to eudaimonic well-being are deeply embedded within broader life experiences and sociocultural contexts, including experiences of age discrimination and other socioeconomic factors, which can significantly shape psychological development and expression (Ryff et al., 2003). Given this interconnectedness of psychological constructs with contextual factors, interventions targeting isolated psychological variables without addressing their broader sociocultural and environmental context may yield limited results. Although the findings identify potential areas for intervention, future research should examine how these psychological factors interact with systemic conditions, social structures, and environmental factors to better inform comprehensive intervention strategies that acknowledge both individual and contextual dimensions of human development in later stages of life.

Limitations

There are important limitations to acknowledge, some of which are highlighted here. First, the cross-sectional design restricts the ability to draw causal inferences. Although potential predictors of generativity were identified, it cannot be definitively determined whether these factors lead to generativity or whether individuals high in generativity are more likely to develop these characteristics. However, the primary goal of the study was to identify predictive factors rather than to establish causality. Another limitation is that the selection of variables was constrained by the availability of data in the MIDUS data set. Although the data set is comprehensive, it may not include all relevant predictors of generativity. It is possible that other important factors, not captured in MIDUS, could further explain generativity. Future research should consider incorporating additional variables, possibly drawn from alternative theoretical frameworks or new areas of psychological research. Furthermore, although the model explained 40% of the variance in generativity—a strong result for the social sciences—this leaves a significant portion of unexplained variance. This suggests that additional factors, which were not measured in this study, may also play a role in explaining generativity.

Finally, it is important to recognize that generativity is a multidimensional construct. For example, McAdams and de St. Aubin (1992) conceptualized it as encompassing several psychosocial features, including cultural demand, inner desire, action, and narrative. This study focused primarily on the contribution component, which is central to generativity. However, other dimensions of generativity warrant further investigation in their own right to provide a more complete picture of this construct.

Conclusion

This study offers a novel, data-driven understanding of the factors that predict (and potentially contribute to) generativity in adulthood by using an exploratory approach to analyze a wide range of potential predictors. The results indicate that social competence, personal growth, and psychological skills are central to fostering generative behaviors, with social potency, openness, and social integration emerging as key predictors. The findings suggest that generativity might be best understood as a growth-oriented psychological process that combines purposeful striving (eudaimonia) and adaptive flexibility (plasticity) in service of creating lasting contributions to future generations. This characterization extends previous conceptualizations by highlighting the dynamic, growth-oriented psychological infrastructure (rather than stability maintenance) that appears to underlie generative behavior. This study lays the groundwork for future research to further explore the dynamic nature of generativity across the lifespan and in diverse cultural contexts, providing new insights into how individuals contribute to the well-being of others and society as they age.

Supplementary Material

Supplementary data are available at *The Journals of Gerontology, Series B: Psychological Sciences and Social Sciences* online.

Funding

None.

Conflict of Interest

None.

Data Availability

Data and materials are publicly available. For more information see https://midus.wisc.edu/data/index.php. Analytic methods will be made available to other researchers upon request. This study was not pre-registered.

Ethics Approval

No new data were collected for this study, as it utilizes secondary data provided by the MIDUS project. For information regarding IRB approval for MIDUS, refer to: https://midus-study.github.io/public-documentation/IRB_Approval_Numbers.pdf.

Informed Consent

All participants provided informed consent before participating in the study.

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