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The association between mindfulness, psychological flexibility, and rumination in predicting mental health and well-being among university students using machine learning and structural equation modeling

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ABSTRACT

Objectives: This study explores the intricate relationships between mindfulness, psychological flexibility, rumination, and their combined impact on mental health and well-being.
Methods: Random forest regression on survey data from 524 undergraduate students was used to identify significant predictors from a comprehensive set of psychological variables. Neural networks were then trained on various combinations of these predictors to evaluate their performance in predicting mental health and well-being outcomes. Finally, structural equation modeling (SEM) was employed to validate a model based on the identified key predictors, focusing on pathways from mindfulness through psychological flexibility to rumination and well-being.
Results: The random forest analysis revealed that the mindfulness variables exerted their influence partially indirectly through psychological flexibility and rumination. The deep neural network analysis supported these findings and additionally showed that the mindfulness manifold model (consisting of self-awareness, self-regulation, and self-transcendence) was superior to the Five Facet Mindfulness Questionnaire variables in predicting mental health outcomes. The SEM analysis confirmed that psychological flexibility, particularly its avoidance and acceptance components, mediated the relationship between mindfulness and mental health. The hypothesized serial mediation pathway—mindfulness affecting psychological flexibility, which then influences rumination and subsequently mental health and well-being—was supported by the data. Self-transcendence was a particularly powerful predictor of mental health outcomes.
Conclusions: The findings underscore the critical role of psychological flexibility and rumination in mediating the effects of mindfulness on mental health and well-being, suggesting that enhancing mindfulness and psychological flexibility might significantly reduce rumination, thereby improving overall mental health and well-being.

1. Introduction

Mindfulness, defined by Kabat-Zinn (1994, pp. 3–4) as "paying attention in a particular way: on purpose, in the present moment, and non-judgmentally," is a cognitive skill that involves cultivating a heightened awareness and presence in the here and now, free from judgment and distraction. Recent research indicates that mindfulness training might enhance well-being by aiding in the detachment from automatic, unhealthy cognitive and behavioral patterns and instead fostering deliberate and self-affirmed behavioral regulation (Brown & Ryan, 2003; Ryan & Deci, 2000), thereby fostering a more balanced and fulfilling approach to personal challenges and daily activities that substantially boost overall mental health and life satisfaction (Hanley et al., 2015; Howell et al., 2008). In the current study, we propose that psychological flexibility and rumination, as two distinct yet interconnected constructs rooted in key components of mindfulness (e.g., self-acceptance and self-preoccupation), play a crucial role in enhancing well-being. Two conceptualizations of mindfulness will be utilized to understand the generalizability of these relationships, with machine learning used to arbitrate between the two. Additionally, this study will

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employ both traditional statistical methods and machine learning approaches to examine the mediators in the relationship between mindfulness and well-being.

1.1. Psychological flexibility as a mediator between mindfulness and wellbeing

One mechanism proposed to translate mindfulness into mental health and well-being (at least under its eudemonic guise) is psychological flexibility, as conceptualized in one form of mindful therapy, Acceptance and Commitment Therapy (ACT; Hayes et al., 2006). In this view, psychological flexibility is composed of six processes that are described as polar opposites, from maladaptive to adaptive: (a) cognitive fusion/defusion, (b) experiential avoidance/acceptance, (c) loss of flexible contact with the now/present-moment focus, (d) attachment to a conceptualized self/self as context, (e) values problems/chosen values, and (f) inaction, impulsivity, or avoidant persistence/committed action (Hayes et al., 2012). The claim is that high levels of flexibility allow individuals to engage with their internal experiences more objectively, enabling them to remain present, pursue goals, and adapt behaviors to align with their values (Hayes, 2004; Hayes et al., 2012). At least two of these components of flexibility—experiential acceptance and present-moment focus—are directly connected to mindfulness and might thus provide a mechanism to translate mindfulness into psychologically beneficial outcomes.

Interestingly, very few studies have explored this connection. The scarce empirical evidence indeed suggests that psychological flexibility mediates the effects of mindfulness interventions on a range of psychological symptoms and enhances life satisfaction (Duarte & Pinto-Gouveia, 2017; Hulbert-Williams et al., 2015; Mak et al., 2018; Ruiz, 2014). Negative mental preoccupation with internal experiences is frequently linked to negative emotions and hinders individuals from accepting and/or adapting to present stimuli (Dreisbach & Goschke, 2004). Higher levels of trait mindfulness could offer the flexibility needed to disrupt this pattern, guiding individuals towards embracing their emotions and adjusting to challenging circumstances. The current study measured flexibility using the Personalized Psychological Flexibility Index (PPFI; Daks & Rogge, 2020). This scale has a three-dimensional structure (Experiential Avoidance, Experiential Acceptance and Experiential Harnessing), which aligns well with Hayes's theoretical framework as outlined above; it also has excellent psychometric properties in a variety of populations (Cherry et al., 2021).

1.2. Rumination as a mediator between mindfulness and wellbeing

The psychological flexibility model posits a lack of reactivity and an increase in appropriate responsivity as a possible link between mindfulness to mental health and well-being. This claim evokes another well-known and broadly researched meditating mechanism between mindfulness and mental health/well-being, namely rumination. Rumination, that is, repetitive and unconstructive thought patterns that dwell on past negative emotion and self-criticism (Treynor et al., 2003), is linked to various negative emotional states, including depression and anxiety (McLaughlin & Nolen-Hoeksema, 2011). By cultivating mindfulness skills, individuals might become adept at directing attention to the present moment, which helps divert focus away from ruminative thoughts (Lewis et al., 2018; Résibois et al., 2018). Furthermore, mindfulness fosters a nonjudgmental attitude towards experiences, allowing individuals to be less judgmental (and perhaps by extension, less self-critical) in their thinking (Watkins & Roberts, 2020). Supporting this, longitudinal studies with adolescents found that lower individual levels of nonjudgment and nonreactivity predicted lower daily dysphoric affect through reduced rumination (Royuela-Colomer et al., 2021; Tumminia et al., 2020). Additionally, mindfulness practice fosters cognitive defusion, one aspect of flexibility, enhancing the ability to observe and recognize dysfunctional thought patterns like rumination, thereby reducing the self-critical thinking and enhance well-being (Alleva et al., 2014; Germer, 2009). Moreover, engaging in formal mindfulness practice has been associated with decreased rumination and symptom alleviation, further supporting the notion that mindfulness training may improve affective well-being by reducing rumination (for a meta-analysis, see Gu et al., 2015). Overall, a reduction in rumination appears to be a key mechanism through which mindfulness exerts its beneficial effects.

1.3. Relationship among psychological flexibility, rumination and mindfulness

Both psychological flexibility/inflexibility and rumination have been identified as mediators in the relationship between mindfulness and well-being, albeit with varying degrees of certainty in the evidence base. There is also evidence that these two variables may interact synergistically to influence the effectiveness of mindfulness interventions on well-being (Aydın, 2016; Genet et al., 2013; Perestelo-Perez et al., 2017). For example, research by Genet et al. (2013) reveals a strong correlation between psychological inflexibility and increased rumination, showing that affective inflexibility in diverting attention from negative emotional material was linked to higher rumination in daily life, whereas affective inflexibility in shifting away from positive emotional material was connected to lower rumination. Despite these and other findings, research exploring the potential mediating role of psychological flexibility and rumination in the correlation between mindfulness and well-being is sparse. This study seeks to address this gap by using a serial mediation model (depicted in Fig. 1) to examine how psychological flexibility and rumination may sequentially mediate the impact of mindfulness on well-being, thereby enhancing the understanding of the underlying mechanisms.

1.4. Conceptualizations of mindfulness: self-awareness, regulation, and transcendence (S-ART) and the five facet mindfulness questionnaire (FFMQ)

Complicating the research of mediational effects in mindfulness is that mindfulness itself is a multifaceted construct, and that multiple conceptualizations of the construct exist. The currently most often-used instrument to measure trait mindfulness is the Five Facet Mindfulness Questionnaire (FFMQ; Baer et al., 2006). Derived from factor-analytic analysis of existing scales, it assesses five key facets of mindfulness: Observing (noticing internal and external experiences), Describing (labeling these experiences), Acting with Awareness (focusing on present activities), Non-judgmental (maintaining a non-evaluative stance towards thoughts and feelings), and Non-reactivity (letting thoughts and feelings pass without engagement).

Recently, Verhaeghen (2019) proposed a broader measurement framework, based on Vago and Silbersweig's (2012) review of the literature and resulting conceptualization of mindfulness as a manifold of three core processes: self-awareness, self-regulation, and self-transcendence (S-ART). Self-awareness involves the ability to remain present and aware, self-regulation represents the ability to modulate one's behavior in accordance with desired goals, and self-transcendence pertains to the ability to identify with a broader perspective beyond the self, or de-centering. Thus, this framework focuses less on directly assessing individual facets of mindfulness and more on understanding their integrated impact on the self (Vago & Silbersweig, 2012).

Using factor-analysis on two independent samples, Verhaeghen (2019) concluded that self-awareness has a more active, reflective aspect (which was labeled reflective self-awareness) as well as a more passive, non-judging aspect (which was labeled controlled sense-of-self in the moment), and that self-regulation could be fruitfully subdivided into self-preoccupation (a concept close to rumination) and self-compassion. Additionally, results suggested a sequence of

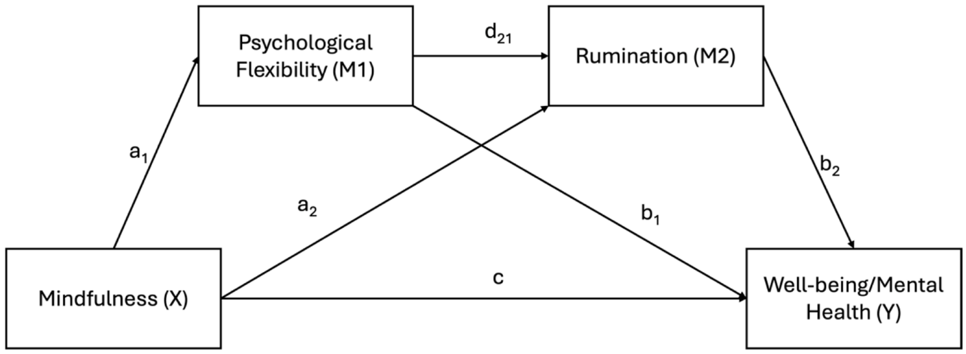

Fig. 1. Graphic representation of the four hypotheses. H1: There is an association between mindfulness and well-being (total effect c). H2: Individuals with higher trait mindfulness experience greater psychological flexibility, which is associated with higher well-being (indirect effect a_1b_1). H3: A higher level of mindfulness is associated with reduced rumination, which in turn is associated with improved well-being (indirect effect a_2b_2). H4: Psychological flexibility and rumination play a serial mediating role in the relationship between mindfulness and well-being (serial indirect effect $a_1d_{21}b_2$).

progressive processes in which self-awareness enhanced self-regulation, subsequently promoting self-transcendence (Miller & Verhaeghen, 2022; Verhaeghen, 2019). Crucially, the S-ART model was helpful in further elucidating the effects of what is traditionally understood as mindfulness on outcomes as diverse as depression, stress, anxiety, wisdom, emotional intelligence, moral attitudes, prejudice, and compassion (Caswell et al., 2022; Miller & Verhaeghen, 2022; Verhaeghen, 2019, 2021; Verhaeghen & Aikman, 2020). More specifically, self-regulation and self-transcendence often added additional explanatory variance to the outcomes over and beyond self-awareness, indicating their usefulness within both a clinical and positive psychology context. Thus, the S-ART model specifically highlights the transformation of emotional responses through practices aimed at enhancing self-transcendence, shifting away from a self-centered viewpoint to a more expansive, interconnected perspective. To gain a more comprehensive understanding of the connection between individuals' mindfulness levels and psychological flexibility, rumination, mental health and well-being, the current study will include both the FFMQ and the S-ART model and assess their relative contributions to the mediators (flexibility and rumination) and outcomes (mental health and well-being), using a machine learning framework.

1.5. Machine learning in psychological research

Machine learning algorithms were employed to investigate the relative usefulness of the two mindfulness models. The integration of machine learning algorithms, particularly Random Forest (RF) and neural networks, has become increasingly popular in psychological research due to their ability to handle large datasets and complex variable relationships effectively (Fife & D'Onofrio, 2023). RF is a versatile machine learning algorithm widely used for both classification and regression tasks, especially because it effectively reduces the risk of overfitting—a frequent issue with traditional regression models—-through its ensemble approach that aggregates predictions from multiple decision trees (Ao et al., 2019). RF models offer a robust framework for detecting complex interactions and excel as a nonparametric method when statistical assumptions, such as normal distribution, are untenable, particularly in cases where relationships between variables are often non-linear with intricate interactions (Henninger et al., 2023). Furthermore, RF models offer insights into variable importance, helping researchers identify and prioritize which predictors most significantly impact the dependent variables (King & Resick, 2014).

Neural networks are computational models inspired by the human brain's architecture, utilizing layers of interconnected neurons to process data and perform tasks such as pattern recognition and prediction. Particularly, the deep learning architectures of neural networks excel at capturing and describing nonlinear relationships within data by using nonlinear transformations in their hidden layers. This ability to extract features makes them highly effective for complex tasks that traditional linear models struggle to address.

1.5.1. Significance of this study

Given these advantages, employing machine learning algorithms like RF and neural networks in the current study enabled a comprehensive analysis of the relationships between the large set of variables in this study (mindfulness, flexibility, rumination, mental health and well-being), many of which cannot be easily consolidated by latent variables because of their internal manifold structure, like the S-ART variables. Machine learning algorithms might offer more insights into the hypothesized model and further reveal information about the intricate relationships between variables and the predictive power of the two mindfulness constructs. These analyses were followed up with theory-driven SEM analyses to test structural linear relationships between variables. Thus, the current study contributes a new methodology to cross-sectional psychological studies by combining novel machine learning algorithms with traditional statistical techniques. Both analysis methods which work complementarily to enhance the understanding of variable relationships. Furthermore, the study uncovers the complex relationships between mindfulness, rumination, and psychological flexibility, including their sub-components, using distinct concept-developed scales, and reveals the order of the variables.

1.6. Hypotheses

On the basis of the literature reviewed above, it can be hypothesized that mindfulness will be closely associated with psychological flexibility and rumination in our sample of university students, and that both of these variables will be linked to mental health and well-being. The formal hypotheses are as follows (the research models in Fig. 1 summarize the hypotheses):

H1: *There is an association between mindfulness and well-being.*

H2: *Individuals with higher trait mindfulness experience greater psychological flexibility, which is associated with higher well-being.*

H3: *A higher level of mindfulness is associated with reduced rumination, which in turn is associated with improved well-being.*

H4: *Psychological flexibility and rumination play a serial mediating role in the relationship between mindfulness and well-being.*

2. Methods

2.1. Participants and procedure

Participants were 524 undergraduate students at the Georgia Institute of Technology. After excluding incomplete questionnaires and participants with careless responses (e.g., excessively repetitive responses, or unrealistically quick completion times), the final sample consisted of 500 participants (mean age = 19.59, SD = 1.45); 49 % identified as women; 51 % as men. All participants were compensated with one hour of course credit. Following the completion of the set of surveys described below segment, which typically took about 25–30 min, participants were directed to a comprehensive demographics questionnaire that captured age, gender, and prior and present engagement with mindfulness meditation. Based on their responses to the mindfulness meditation question, participants were classified as either meditators or non-meditators. Meditator was defined as an individual who currently practices meditation at least once a week.

2.2. Measures

Mindfulness. The S-ART (Self-Awareness, Self-Regulation, and Self-Transcendence) measure contains several components (as derived from factor analysis in Verhaeghen, 2019). The subconstruct of self-awareness comprises two subscales: Reflective awareness and controlled sense-of-self in the moment (CSOSIM; a combination of mindfulness-in-the-moment and a strong sense-of-self) in self-awareness. Reflective awareness is measured as a composite of the *z*-scores of three scales: (a) the Observing subscale of the FFMQ (Cronbach's alpha = 0.7), (b) the Reflectiveness subscale of the Broad Rumination Scale (Cronbach's alpha = 0.80; BRS; Trani et al., in preparation), and (c) the Search for Insight/Wisdom of the Aspects of Spirituality Scale (Cronbach's alpha = 0.80; Bussing et al., 2007). The CSOSIM is measured as a composite of the *z*-scores of three scales: (a) the Acting with Awareness subscale (Cronbach's alpha = 0.83) from the FFMQ; (b) the Sense-of-Self Scale (Cronbach's alpha = 0.83; Flury & Ickes, 2007); and (c) the Nonjudging of inner experience subscale of the FFMQ (Cronbach's alpha = 0.88). Self-Regulation comprises two subcomponents, self-preoccupation and self-compassion. Self--preoccupation is measured as a composite of the *z*-scores of four scales: (a) the compulsivity subscale from the BRS (Cronbach's alpha = 0.79); (b) the worrying subscale from the BRS (Cronbach's alpha = 0.80); (c) the isolation subscale from the self-compassion scale, short form (SCS; Cronbach's alpha = 0.65; Raes et al., 2011); and (d) the over-identification subscale from the SCS (Cronbach's alpha = 0.67); Self-compassion is measured as a composite of the *z*-scores of four scales: (a) self-kindness subscale from the SCS (Cronbach's alpha = 0.65); (b) common humanity(Cronbach's alpha = 0.63); (c) mindfulness (Cronbach's alpha = 0.74); and (d) the de-centering subscale of the Experiences Questionnaire (Cronbach's alpha = 0.89; Fresco et al., 2007). Self-transcendence was measured as a composite of the z-scores of two subscales: (a) Joy and Love from the Dispositional Positive Emotion Scale (Cronbach's alpha = 0.82; DPES; Shiota et al., 2006); and (b) the meaningfulness subscale from the Resilience Scale (Cronbach's alpha = 0.83; RS; Lundman et al., 2007).

Anxiety. The State-Trait Anxiety Inventory (STAI; Spielberger, 1983) is a widely applied 40-item self-report scale. The State and Trait subscales (20 items each) provide distinct instructions for assessing current emotion status (Cronbach's alpha = 0.95) and enduring emotional states (Cronbach's alpha = 0.92), respectively .

Depression. The Maryland Trait and State Depression scale (MTSD; Chiappelli et al., 2014) consists of 36 questions. The state scale (Cronbach's alpha = 0.92) evaluates current feelings of depression, while the trait scale (Cronbach's alpha = 0.95) measures the frequency of these feelings throughout adulthood.

Well-being. The Psychological Well-being Scale-short version (PWB; Cronbach's alpha = 0.86; Ryff & Keyes, 1995) measures well-being and happiness.

Rumination. The Ruminative Response Scale (RRS; Nolen-Hoeksema & Morrow, 1991) is a self-assessment tool designed to evaluate an individual's rumination to depressive moods, encompassing 22 items (Cronbach's alpha = 0.94).

Flexibility. The Personalized Psychological Flexibility Index (PPFI; Kashdan et al., 2020) assesses the degree to which individuals continue striving towards their objectives even in the face of stressors and difficulties. This scale comprises 15 items centered around psychological flexibility within a three-factor model: experiential avoidance (Cronbach's alpha = 0.89), experiential acceptance (Cronbach's alpha = 0.79) and Harnessing (Cronbach's alpha = 0.74). To ensure participants provide responses that hold significance, they are initially prompted to identify a life goal that they are actively pursuing.

Personality. The Mini-International Personality Item Pool (Mini-IPIP Scale; Donnellan et al., 2006) contains 20 items and assesses the Big Five personality traits: extraversion (Cronbach's alpha = 0.80), agreeableness (Cronbach's alpha = 0.73), conscientiousness (Cronbach's alpha = 0.64), neuroticism (Cronbach's alpha = 0.70), and openness (Cronbach's alpha = 0.70).

3. Results

3.1. Correlation matrix

Fig. 2 shows the Pearson correlation matrix for the 19 variables. The correlation matrix indicates that the PWB and mental health factors are strongly correlated with RRS, PPFI avoidance, and SART factors (notably self-transcendence and self-compassion), as well as the FFMQ Nonjudging factor. Additionally, the interrelationship between RRS and PPFI avoidance is significant and strong.

3.2. Random forest

A random forest-based model was used to find the most important features (i.e., predictors) for each response variable. RF employs decision trees where the number of features used in the overall algorithm continuously splits into multiple nodes, with each node having a subset of the total features that best separates the data into subsets of homogeneous groups. The separation into different decision trees serves to detect the most important features. The feature importance is calculated by the mean decrease of the Gini Index, which indicates the net impurity decrease in the decision tree. Higher feature importance scores indicate that features or predictor variables have a larger influence on the response variable prediction and therefore would help make better predictions in a neural network. Fig. 3 shows the overall process of splitting the data into decision trees to extract the most important features from them. Table 1

During data preprocessing, all values were normalized using a standard scaling technique, transforming the data to unit variance prior to analysis for machine learning modeling. To build the random forest regressor model, the dataset was split into the response variables and predictor variables. The dataset was divided into 80 % training and 20 % testing with the random state being set to 42 (default hyperparameters of the random forest regressor model). Next, the model was trained and evaluated on its performance of generating accurate predictions for the response variable on the test set. To analyze which features among the predictor variables were most important for the prediction of the response variable, the feature importance scores were extracted for each variable with all features above 0.05 (5 %) being used for the neural network models (See Table 2). The normalization and random processes are performed using the scikit-learn library. Of the variables extracted by the random forest regressor, self-transcendence and RRS were always ranked as having feature importance scores of greater than 0.05 for all the response variables. Furthermore, the S-ART variables were among the most important features for the PPFI response variables. The FFMQ variables, in contrast, were not among the most important features of the psychological well-being variables.

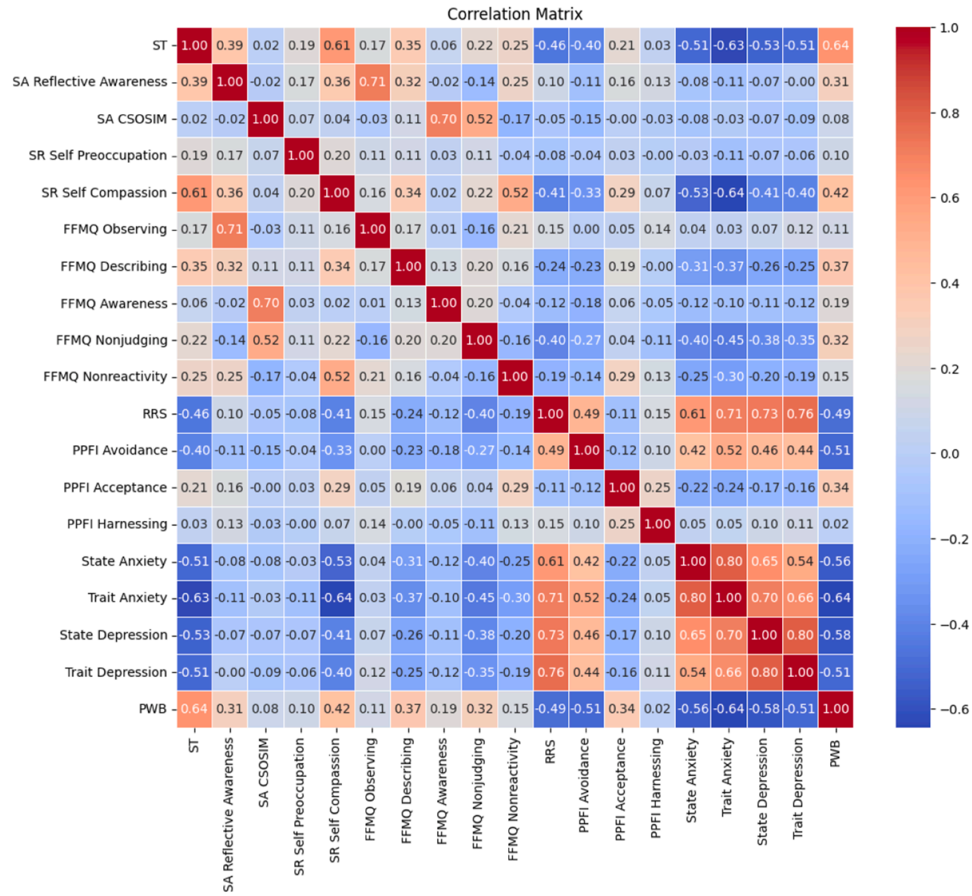

Fig. 2. Correlation Matrix for 19 Psychological Metrics
Note. ST = Self-Transcendence; SA = Self-Awareness; SR = Self-Regulation; C = Controlled Sense-of-Self in the Moment; PWB =Psychological Well-being; RRS = Ruminative Response Scale; PPFI = Personalized Psychological Flexibility Index.

3.3. Deep neural network

In the next step, six deep neural networks were implemented for each of the nine psychological variables for a total of 54 deep neural networks. The neural network analysis was conducted using the Keras in TensorFlow library. Each model was trained using the Adam optimizer and mean-squared error loss over 200 epochs, with a batch size of 32 and a validation split of 0.2. Hyperparameter tuning was conducted for each neural network model using grid search, optimizing batch size, training/testing split ratio, and optimizer type by iterating through all combinations of hyperparameters to identify the optimal configuration that minimized average cross-validation mean squared error (MSE). The model architecture consisted of multiple dense and dropout layers with L2 regularization, utilizing the ReLU activation function. To ensure robustness, 5-fold cross-validation was performed, with the model trained and evaluated on each fold of the validation split. The optimal hyperparameters were selected based on this process.

For each type of deep neural network, the nine psychological response variables were: PWB, RRS, state depression, trait depression, state anxiety, trait anxiety, PPFI Avoidance, PPFI Acceptance, and PPFI Harnessing. For each deep neural network model, the five well-being/mental health variables (PWB, state depression, trait depression, state anxiety, and trait anxiety) were excluded from being a predictor variable. The six different deep neural networks included the prediction of the response variable using the other 13 or 14 variables as predictor variables (the five well-being/mental health response variables had 14 predictor variables and the remaining four response variables had 13 predictor variables), the prediction of the response variable using only the five FFMQ variables as the predictor variables, the prediction of the response variable using only the five S-ART variables as the predictor variables, the prediction of the response variable using all of the predictor variables excluding the five FFMQ variables, the prediction of the response variable using all of the predictor variables excluding the five S-ART variables, and finally the prediction of the response variable using any predictor variables with an importance score above 0.05 from the random forest regressor model (see above). This process of implementing the six types of deep neural networks was repeated for each of the nine psychological response variables.

The final model was evaluated using root mean square error (RMSE; shown in Table 2), MSE (shown in **Table S1**), mean absolute error (MAE; shown in **Table S2**), R-squared (R^2; shown in **Table S3**), and mean directional accuracy percentage error (MDAPE; shown in **Table S4**) as quantifiable metrics. The Error Distribution Curves for each Neural Network Model are shown in Fig. 4. The neural network using the random forest regressor extracted variables performed the best for state depression (RMSE = 8.88), state anxiety (RMSE = 8.93), and trait anxiety (RMSE = 6.70). The neural network with only S-ART variables performed the best for PPFI Avoidance (RMSE = 5.80). The neural network using all 13 predictor variables performed the best for RRS (RMSE = 11.76) and PPFI acceptance (4.96). The neural network excluding the FFMQ variables performed the best for PWB (RMSE = 8.01) and trait depression (RMSE = 9.85). Thus, the results indicated that the best-performing models were the neural network that used the random forest regressor extracted variables. The neural networks using only the FFMQ variables were among the worst performing, as was also found in the random forest analysis. Therefore, the S-ART model, but not the FFMQ model, was retained for the subsequent SEM analysis. Additionally, this result shows that mindfulness significantly predicted

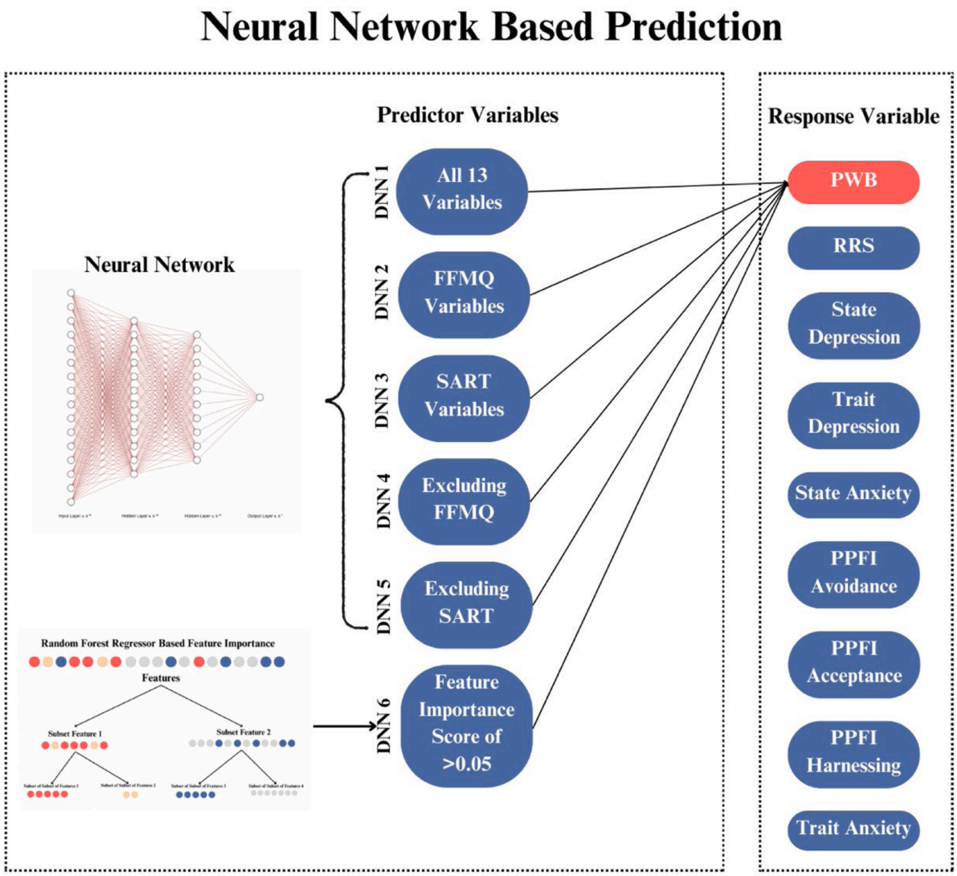

Fig. 3. Neural Network Based Prediction Workflow.

psychological flexibility, and that mindfulness and psychological flexibility were both strong predictors of rumination, additionally indicating a serial order of psychological flexibility and rumination for reference in the SEM analysis.

3.4. Structural equation path modeling

The present study employs the same analytical framework for structural equation modeling (SEM) as Verhaeghen (2019, 2021) and Verhaeghen and Aikman (2020, 2022), where a flow was posited (and confirmed) from self-awareness over self-regulation to self-transcendence and then on to the outcome variables. The analysis conducted using the lavaan package in R (Rosseel et al., 2012), structures this flow by implementing six tiers of variables. The first tier includes big five personality traits, meditator/non-meditator and gender as possible underlying factors affecting all other relationships. The second tier contains reflective awareness and CSOSIM within the self-awareness stage of the S-ART mindfulness manifold. The third tier comprises variables related to self-compassion and low self-preoccupation within the self-regulation stage. The fourth tier involves self-transcendence. The fifth tier includes the three psychological flexibility factors. The sixth encompasses rumination. The seventh tier includes variables related to mental health (state and trait anxiety, and state and trait depression) and psychological well-being. The baseline model incorporated the expected flow of influence from any lower tier to all higher tiers. Thus, all tier 1 variables were connected to all variables in tiers 2–6, all tier 2 variables are connected to all variables in tiers 3–6, and so on, implementing the flow described above.

This baseline model did not fit the data well, χ^2 ($df = 10$) = 61.13; comparative fit index (CFI) = 0.97; Tucker-Lewis index (TLI, also known as the non-normed fit index) = 0.71; RMSEA = 0.10; SRMR = 0.03. Given these unsatisfactory fit indices, the model was refined by removing all insignificant paths. The psychological flexibility Harnessing factor, despite its significant correlation with rumination, did not exhibit any significant paths with either the mindfulness factors or well-being variables; it was thus removed from the model. This adjustment, along with the removal of three additional paths that turned nonsignificant upon further examination, significantly improved the model fit. After these modifications, the final model demonstrated an excellent fit: χ^2 ($df = 79$) = 178.68; CFI = 0.98; TLI = 0.95; RMSEA = 0.02; SRMR = 0.04 (see Fig. 5 for the final model). The coefficients for the background variables (personality, gender and meditator/non-meditator) are shown in Table 3.

4. Discussion

The current study sought to identify, in a sample of university students, the influence of mindfulness on psychological well-being and mental health, and the potential mediating role of psychological flexibility and rumination in this relationship. Additionally, this study included two multi-faceted mindfulness scales with different conceptualizations (the FFMQ and the S-ART) to examine their respective effectiveness in predicting mental health and well-being. As hypothesized, mindfulness was related to psychological flexibility (specifically to two of its aspects, avoidance and acceptance, but not to harnessing), as well as to rumination, mental health, and well-being . Additionally, both the neural network analysis and the structural equation modeling identified a potential pathway for these effects: mindfulness → psychological flexibility → rumination → mental health and well-being. Longitudinal and/or intervention work would be necessary to confirm this ordering of variables.

A two-step approach was adopted for the analyses, first

Table 1
Random forest regressor based feature extracted variables.

Response Variable	ST	SA (Awareness)	SA (CSOSIM)	SR (SP)	SR (SC)	FFMQ (Observing)	FFMQ (Describing)	FFMQ (Awareness)	FFMQ (Non-judgmental)	FFMQ (non-reactivity)	RRS	PPFI Avoidance	PPFI Acceptance	PPFI Harnessing
PWB	0.39	–	–	–	–	–	–	–	–	–	0.09	0.14	0.07	–
RRS	0.17	0.08	0.06	–	0.13	–	–	–	0.08	–	NA	0.23	–	0.05
State Depression	0.08	–	–	–	–	–	–	–	–	–	0.56	–	–	–
Trait Depression	0.06	–	–	–	–	–	–	–	–	–	0.64	–	–	–
State Anxiety	0.12	–	–	–	0.14	–	–	–	0.06	–	0.33	–	–	–
PPFI Avoidance	0.08	0.07	0.07	0.06	0.06	–	–	–	–	–	0.33	NA	0.06	0.08
PPFI Acceptance	0.07	0.06	0.06	0.07	0.16	–	0.07	–	–	0.06	0.06	0.09	NA–	0.18
PPFI Harnessing	0.08	0.07	0.08	0.07	0.08	–	0.06	–	–	–	0.11	0.12	0.16	NA
Trait Anxiety	0.14	–	–	–	0.12	–	–	–	0.05	–	0.48	–	–	–

Note. S-T = Self-Transcendence; SA = Self-Awareness; SR = Self-Regulation; RA = Reflectiveness Awareness; CSOSIM = Controlled Sense-of-Self in the Moment; SP = Self-Preoccupation; SC = self-compassion; PWB =Psychological Well-being; RRS = Ruminative Response Scale; PPFI = Personalized Psychological Flexibility Index.
NA: not applicable as the predictor variable and response variables can't be the same.
Variable did not reach 0.05 threshold to be classified as not an important predictor variable.

implementing two machine learning techniques (random forest and neural network analysis) as a more theory-free tool to examine the relationships among the large set of variables (i.e., two sets of mindfulness variables, flexibility, rumination, mental health, and well-being). This approach is particularly useful because some of these variables, especially the S-ART variables, cannot be easily consolidated into latent variables due to their internal manifold structure. Unlike linear regression models, machine learning approaches accommodate complexity and nonlinearity, leading to higher predictive capacity for outcomes by effectively handling complex relationships between mindfulness and mental health/well-being, which traditional linear methods may overlook (Karanika-Murray & Cox, 2010). These models avoid overfitting and typically generalize well to new data, while traditional statistical methods remain essential for detailed predictor-outcome analysis, highlighting the need for synergy between the two approaches (Karanika-Murray & Cox, 2010), as done here. The random forest analysis revealed that rumination and self-transcendence were the only variables with good feature importance scores across all response variables. Self-transcendence consistently had high predictive value, particularly for well-being, compared to other factors in both the S-ART and FFMQ models. Other S-ART factors, while relevant to mental health and well-being, primarily predicted psychological flexibility. This suggests, as hypothesized, that mindfulness factors may not directly predict mental health and well-being but instead exert their influence indirectly through mechanisms such as psychological flexibility and rumination. Furthermore, the FFMQ demonstrated lower predictive power than the S-ART for well-being, mental health, psychological flexibility, and rumination.

The subsequent deep neural network analysis confirmed that the model that excluded the FFMQ variables fit better than the model that excluded the S-ART manifold; the networks including only the FFMQ were among the worst performing. Thus, compared to the S-ART, the FFMQ exhibits low predictive power, not only for well-being and mental health but also for psychological flexibility and rumination. This aligns with the random forest results, as the S-ART model was explicitly designed to capture the neurological mechanisms of mindfulness as an integration of mindfulness processes (Vago & Silbersweig, 2012) rather than just its awareness aspect (which is essentially what the FFMQ taps into). Consequently, the SEM models were built from the S-ART manifold rather than the FFMQ. Additionally, the results indicate several key prediction patterns that align with the hypotheses. Specifically, mindfulness was a strong predictor of psychological flexibility, mindfulness and psychological flexibility collectively predicted rumination, and the model that excluded the FFMQ was a strong predictor of mental health/well-being. These findings indirectly support the hypothesis that mindfulness influences mental health and well-being indirectly through its effects on the psychological flexibility and rumination.

The second data-analytic step–the SEM analysis–revealed a multifaceted relationship between mindfulness, psychological flexibility, rumination, mental health, and well-being. The first finding was that the S-ART model, as presented in Miller and Verhaeghen (2022), Verhaeghen (2019), Verhaeghen and Aikman (2020, 2022), showed that the self-awareness variables (reflective awareness and controlled sense-of-self in the moment) predicted self-regulation (self-preoccupation and self-compassion), which in turn predicted self-transcendence, with an additional direct path from reflective awareness to self-transcendence. This manifold explained a large amount of variance in rumination, as also seen in Caswell et al. (2022) ($R^2 = 0.37$, after removing the influence of flexibility on rumination), suggesting that mindfulness is, as hypothesized, an important predictor of rumination. Additionally, although the concept of rumination appears to have the largest conceptual overlap with the self-preoccupation aspect of mindfulness, the largest correlations were, in fact, with self-compassion and self-transcendence ($r > 0.4$).

The main question concerned the role of flexibility as a potential mediator between mindfulness and mental health/well-being. Two

Table 2
Deep Neural Network RMSE Results.

Response Variable	All 13 Variables	Only SART Variables	Only FFMQ Variables	Excluding SART	Excluding FFMQ	RF Feature Extracted Variables
PWB	8.65	9.97	12.26	9.88	**8.01**	8.34
RRS	**11.76**	12.65	12.87	12.22	12.37	11.98
State Depression	9.30	11.44	11.76	9.25	9.44	**8.88**
Trait Depression	10.08	11.86	11.90	10.22	**9.85**	9.88
State Anxiety	9.62	10.35	10.45	9.57	9.47	**8.93**
Trait Anxiety	7.17	7.74	9.30	8.42	7.98	**6.70**
PPFI Avoidance	6.14	**5.80**	6.00	6.08	6.10	5.99
PPFI Acceptance	**4.96**	5.40	5.12	5.23	5.10	5.09
PPFI Harnessing	5.61	5.65	5.51	**5.49**	5.71	5.57

Note. Models that performed the best for the response variable are bolded.
PWB = Psychological Well-Being; RRS = Ruminative Response Scale; PPFI = Personalized Psychological Flexibility Index; FFMQ = Five Facet Mindfulness Questionnaire; SART = Self-Awareness, Self-Regulation, and Self-Transcendence.

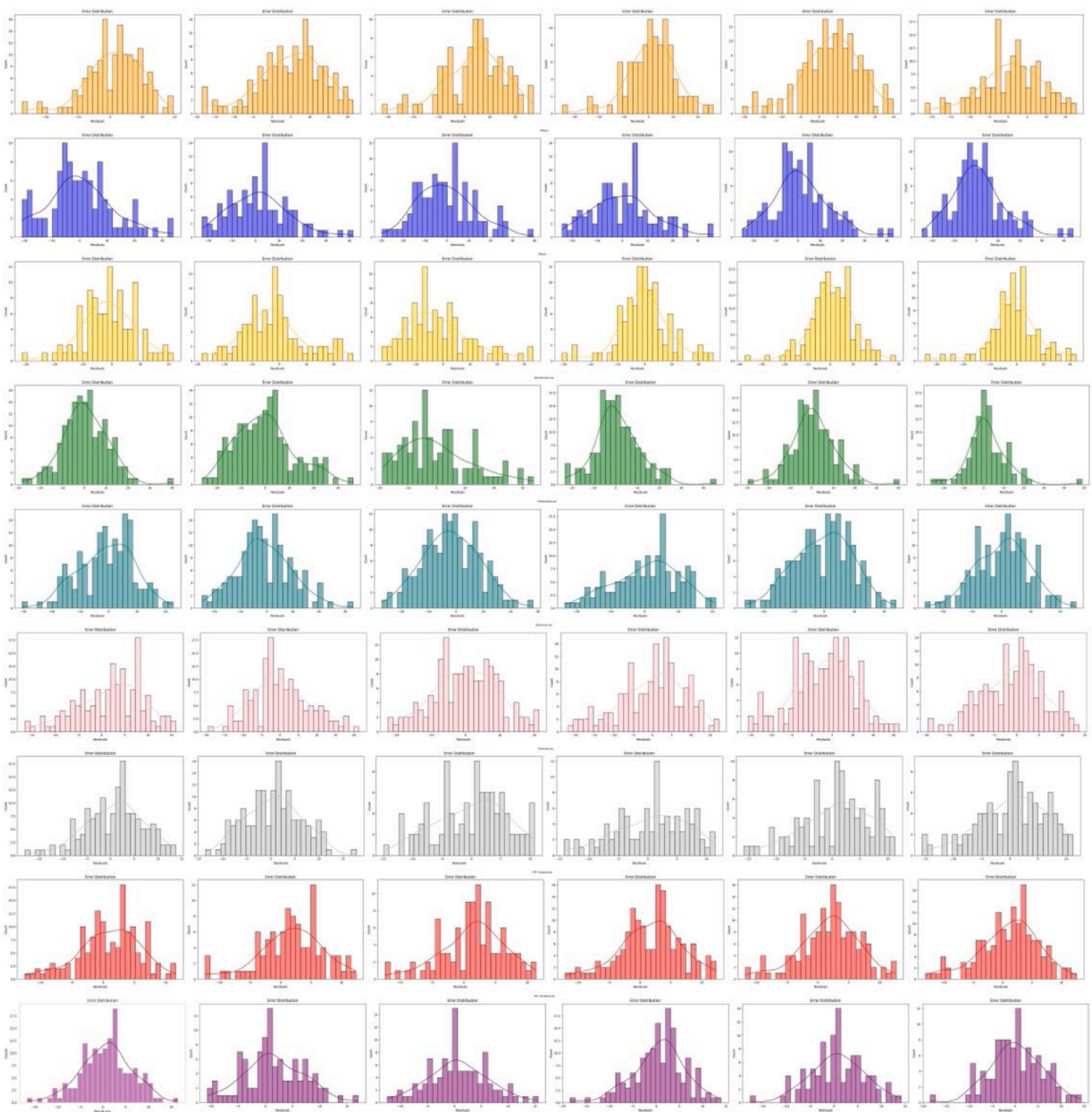

Fig. 4. Error Distribution Curves for each Neural Network Model. Order of response variable from top row to bottom row: PWB, RRS, State Depression, Trait Depression, State Anxiety, Trait Anxiety, PPFI Avoidance, PPFI Acceptance, and PPFI Harnessing. Order of different testing conditions from left to right: all 13 variables, only SART variables, only FFMQ variables, excluding SART variables, excluding FFMQ variables, and Random-Forest feature extracted variables.

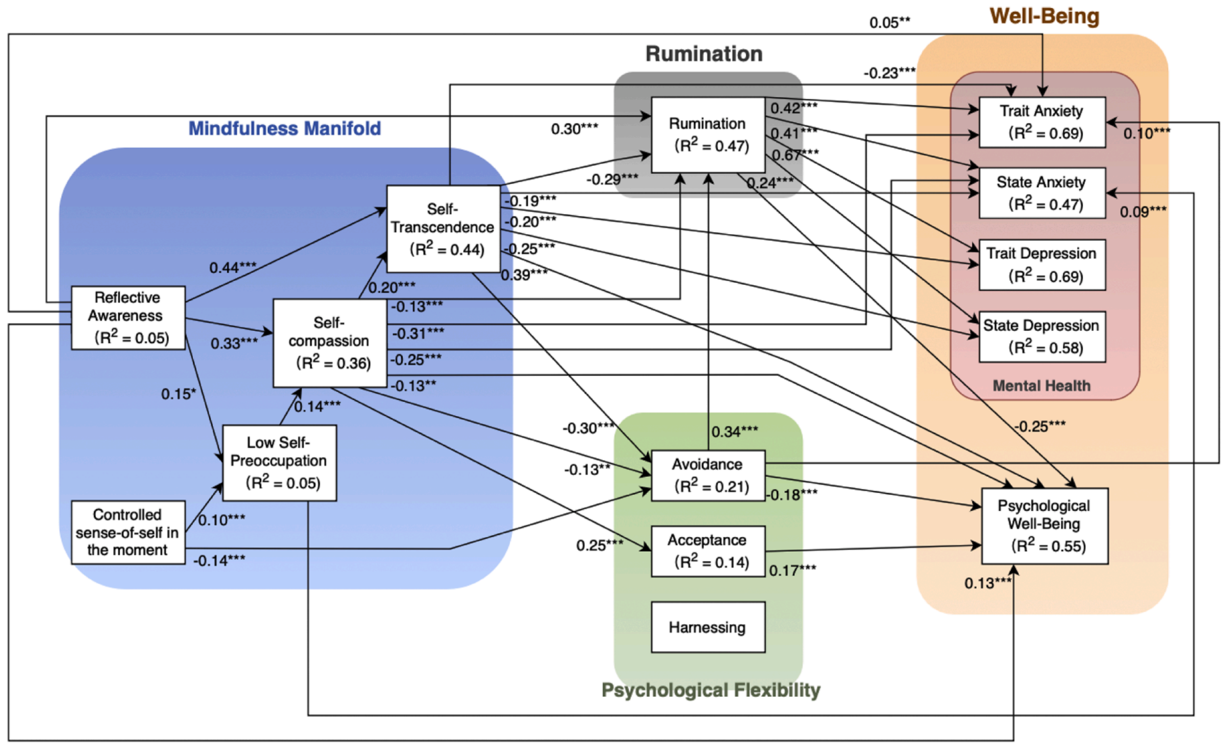

Fig. 5. Results from path analysis, describing the relationship between mindfulness, psychological flexibility, rumination and well-being; all path coefficients are standardized, chi-square (df = 79) = 178.68; CFI = 0.98; TLI = 0
Note. n = 500; Self-preoccupation subscale is forward scored. $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. χ^2 (df = 79) = 178.68; CFI = 0.98; TLI = 0.95; RMSEA = 0.02; SRMR = 0.04.

Table 3
Standardized paths from antecedent variables (the Big-Five personality factors, meditator/non meditator and gender) to the mindfulness manifold, psychological flexibility, Trait/State Anxiety, Trait/State depression and psychological well-being, as estimated in the final linear structural equation model.

	Extraversion	Agreeableness	Conscientiousness	Neuroticism	Intellect/ imagination	Gender	Meditator/ non-meditator
Reflective awareness		0.22					
Self-preoccupation					−0.10	0.11	
Self-compassion	0.12		0.12	−0.43		−0.11	
Self-transcendence	0.13		0.13	−0.14	−0.11		
Controlled sense-of-self in the moment							
PPFI-avoidance			−0.14				
PPFI-acceptance	−0.16	0.17		−0.12	0.11		
Rumination			−0.10	0.15		0.11	
State-anxiety		−0.04	−0.06	0.15			
Trait-anxiety			−0.12	0.17			
State-depression							
Trait-depression			−0.05			−0.07	−0.04
PWB		0.13	0.16				

N = 500. All paths indicated are significant at $p < 0.05$; all paths not indicated were fixed at zero, Gender: 0 = male; 1 = female; Meditator: 0 = non-meditator; 1 = meditator.

aspects of psychological flexibility, specifically avoidance and acceptance, were associated with the S-ART manifold. However, the third aspect, harnessing, did not show a significant association. Experiential harnessing is defined as leveraging challenges to motivate and support the pursuit of meaningful goals (Kashdan et al., 2020). The finding that it is not related to mental health and well-being contrasts with previous studies (Kashdan et al., 2020; Kimya et al., 2024), indicating the need for further investigation.

Experiential avoidance and acceptance of psychological flexibility related to mental health and well-being via different routes. Avoidance significantly predicted rumination, with individuals reporting higher levels of avoidance also exhibiting higher levels of rumination. Consequently, avoidance acted as a mediator for the influence of mindfulness on various aspects of mental health and well-being through its relationship with rumination. Furthermore, avoidance had additional direct effects on trait anxiety and well-being, serving as a direct mediator between mindfulness and these specific aspects of mental health and well-being. The results confirm the hypothesized serial mediation pathways posited in Fig. 1, suggesting that enhancing mindfulness and decreasing experiential avoidance significantly might reduce rumination, which in turn might improve overall mental health and well-being, following a pathway from mindfulness to psychological flexibility, then to rumination, and ultimately to mental health and well-being. The influence of acceptance was only direct, and it was only on well-being (individuals who were more accepting reported higher well-being), this variable mediated effects from the self-awareness and self-regulation components of the mindfulness manifold. These findings are consistent with previous studies, which have shown that psychological flexibility mediates the relationship between mindfulness and psychological well-being (Yousefi Afrashteh & Hasani, 2022) and mental health (Wielgus et al., 2020). The current study provides a more comprehensive analysis of the mediating role of each factor of psychological flexibility between mindfulness and well-being.

In addition to the effects mediated though flexibility and/or rumination, some aspects of the S-ART manifold still showed direct effects on mental health (a positive [not negative] effect of reflective awareness on trait anxiety, negative effects of self-compassion on state and trait anxiety, and negative effects of self-transcendence on state anxiety and on state and trait depression) and well-being (positive effects of reflective awareness and self-transcendence and a negative [not positive] effect of self-compassion). The few (i.e., three out of nine) effects in the direction opposite expectation could potentially be suppressor effects. The direct effects of self-transcendence (and, to a lesser degree, reflective awareness and self-compassion) suggest that the mechanisms associated with this variable are less well captured by rumination and psychological flexibility than those of the other variables. This is important to highlight because self-transcendence is not often considered in either clinical or positive psychology, although it is empirically connected to a large number of positive outcomes, such as well-being (Caswell et al., 2022; Verhaeghen, 2019, 2021; Verhaeghen & Aikman, 2022), positive self-view (Verhaeghen & aikman, 2022), compassion (Miller & Verhaeghen, 2022), ethical sensitivities (Miller & Verhaeghen, 2022), wisdom (Verhaeghen, 2021), and virtue (Verhaeghen, 2021).

4.1. Limitations and future directions

The current study has certain limitations: (1) the sample was comprised of college students, who may not be representative of the general population (e.g., a higher incidence of dysphoria and anxiety than the general population). It remains to be seen in future studies if these data patterns generalize to other populations, notably those of different ages and different educational and cultural backgrounds. (2) The final analysis in this paper was performed using path analysis. Such analyses allow for the examination of a potential flow of influence within a set of variables but are not definitive. The cross-sectional nature of the data is an obvious limitation and only allows us to state that the data are compatible with this presumed flow. Longitudinal data, either of an observational nature or gathered from a controlled mindfulness intervention, would be necessary to fully test the direction of flow. (3) In this study, we did not compare different machine learning methods with traditional statistical approaches, as our research focus was on the application of machine learning algorithms in testing the theoretical hypotheses within a psychological context. However, future studies could incorporate a broader comparison of various machine learning techniques alongside traditional methods to evaluate their predictive power and appropriateness for testing the theoretical hypotheses. Thus, there is a clear need for continued exploration and refinement of ML applications in this field. Such efforts have the potential to uncover complex patterns, improve predictive accuracy, and ultimately enhance psychological assessments and interventions.

5. Conclusions

This study explored how mindfulness impacts psychological well-being and mental health among university students, focusing on the roles of psychological flexibility and rumination. Machine learning techniques revealed that self-transcendence and rumination were key predictors of well-being, and neural network analysis confirmed that models excluding FFMQ performed better, leading us to base the SEM analysis on the S-ART variables. SEM analysis suggested that the avoidance and acceptance aspects of flexibility, as well as rumination mediate the relationship between mindfulness and mental health/well-being. Specifically, avoidance mediated the relationship between mindfulness and rumination, supporting the hypothesized serial mediation pathway. The self-transcendence aspect of mindfulness seemed an especially powerful predictor for student mental health and well-being. In summary, the findings emphasize the complex interplay between mindfulness, psychological flexibility, rumination, mental health and well-being, suggesting a multifaceted approach to mental health enhancement through mindfulness practices.

In addition to these theoretical contributions, our findings hold practical implications for clinical practice and mindfulness interventions. Incorporating mindfulness practices, particularly those that enhance self-transcendence, may offer a multifaceted approach to improving mental health and well-being. The serial mediation pathway from mindfulness to psychological flexibility, then to rumination, and ultimately to well-being has important implications for both practice and research. This order suggests that interventions aimed at improving psychological flexibility—by teaching individuals how to navigate stressors with greater openness and resilience—can create a ripple effect, reducing harmful thought patterns such as rumination, and consequently enhancing well-being. Further exploration of the cognitive mechanisms underlying psychological flexibility may reveal how it increases individuals' ability to switch focus from current events, helping them avoid becoming stuck in ruminative thinking. Moreover, future research should continue to explore these relationships in more diverse populations and investigate the use of machine learning across different research designs to enhance predictive accuracy and intervention outcomes.

Compliance with ethical standards

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. This study was approved by the Institutional Review Board of Georgia Institute of Technology (Reference No H23363).

Ethics statement

All procedures were in accordance with the ethical standards of the IRB and with the Helsinki Declaration of 1964 and its later amendments. This study was approved by the Institutional Review Board (Reference No H23363).

Use of artificial intelligence statement

AI was not used.

Preregistration

This study is not preregistered.

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CRediT authorship contribution statement

Ruohan Feng: Conceptualization, Investigation, Methodology, Software, Formal analysis, Writing – original draft, Project administration. **Vaibhav Mishra:** Investigation, Software, Formal analysis, Methodology. **Xin Hao:** Conceptualization, Investigation, Methodology. **Paul Verhaeghen:** Conceptualization, Formal analysis, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare no competing interests.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.mlwa.2024.100614.

Data availability

We will be glad to answer any questions about the data collected in this study and to share unpublished information on this dataset and code for data analysis.

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