The Moderating Effect of Age on the Relationship Between Mental Health and Economic Decision-Making

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Abstract

The interconnectedness of human cognitive power and economic decision making is a proven spectacle. Different psychological factors of a healthy mind are key in sensible economic decision making, with relevance to SDG 3 (Good Health and Wellbeing) and SDG 8 (Decent Work and Economic Growth). To assess the moderation effect of age on the relationship between mental health and economic decision making, hypothetically affecting decisions at different age groups. A total of 606 surveys were filled by different age groups. The hypothesis was tested using XGBoost, a robust machine learning model. Supplementary analytics composed the variables for mental health and economic decision making. The impact of mental health on economic decision making was modeled with interaction by age. The relationship is significantly proven, with a high influence of age indicating a strong moderating effect across age groups. Age-specific interventions are necessary. Designing and implementation of mental health and financial education programs tailoring different age groups are recommended, contributing to reducing inequalities (SDG 10) while advancing SDG 3 and SDG 8 and informing policy and practice.

Keywords: *Age, Mental Health, Economic Decision-Making, XGBoost, Principal Component Analysis (PCA), Machine Learning, Moderating Effect, S, SDG 3: Good Health and Well-being, SDG 8: Decent Work and Economic Growth, SDG 10: Reduced Inequality.*

Introduction

Human aging has dual impact, affecting people's thought process but enhancing their experiences with respect to economic decision making. Healthy minds are prone to better economic decision making and the other way around. Economic decision making is a procedure to decide about consumption, saving, investments and borrowing. Nevertheless, such other considerations as the taste of people, influence of peer pressure, and habits just to name a few have their unique or collective impact on such decisions. Among all the factors, mental health evolved as such a noteworthy factor that influences people approach to economic decision making or behaviors. Risk-averse and fragile decision-making powers dominated by compromised minds and the risk averse paradigm primarily demonstrate discouraged responses (Ali, I. 2021) in the financial performance (Butt et al., 2023, & Tabassum et al 2021). Psychological issues, such as depression and anxiety can leave one with the need to prioritize the contemporaneous needs against long term financial stability thus emphasizing the financial management plans further (Choung, 2022; Ryu et al., 2023).

Mental marginalization i.e. anxiety, depression and stress are negativity imposing massive financial and economic choice impacts. Fear due to additional cautiousness may result in ignoring the necessary investments and postponing necessary spending in a haunting manner, and depression, conversely, may be a dip into instant satisfaction in disregard of the needs and prospects of humans. These behaviours that Cobb-Clark, Dahmann, and Kettlewell (2022) depict in their results are not meant to be rational made and cannot be made through their impaired mind and with the long-run consequence of causing negative economic spillovers. It also correlates with emotional fitness, which results in poor financial decisions when it comes to case of e.g. emotional distress (Xin et al., 2023; Hagiwara et al., 2022).

Research Gap

Although the relationships between mental health and economic decision making are well documented, limited attention has been paid to the moderation of age and so the moderation of age does not appear to have been adequately established. Prior research mainly focused on mental health in isolation or, when age was considered, discharging in isolation; therefore, not only the power and direction of interconnection were underestimated, if as well as the combined or mediating element (Counts et al., 2025; Ee et al., 2024; Wilson et al., 2023).

Objective of the Study

The key objective of the study is to analyze how age stimuluses the impact of cognitive health on decision-making pertaining to individuals' economics. An advanced machine learning technique has been employed for analyzing the data collected through 606 surveys with the objective of getting intuition into the multipart dynamics between mental health, age and economic behaviors. After a detailed comparative analysis and applying multiple checks, the XGBoost through python has been identified best tools to gauge the non-linear relationship among variable and hence applied in the study (Hong et al., 2021; Xia et al., 2025).

Literature Review

Mental Health and Economic Decision-Making

The scientific research in the recent past has highlighted the significant influence of mental state on economic decision-making processes. Mentally altered people tend to have disrupted decision-making, which includes high levels of impulsivity, decreased risk preferred, and time-discounted. Mental health issues are proposed to generate a great deal of distortion around financial behaviors, resulting in decision-making that may not be in long-term best interest (Cobb-Clark et al., 2022, Ali,I.2021 & Hagiwara et al., 2022).As an example, a systematic review conducted by Carter (2025) and Mayer (2023) mentions that psychiatric symptoms, including depression, anxiety, bipolar disorder, etc., can be significant determinants of basic behavioral parameters, such as the degree of risk tolerance, the level of future orientation, and a certain degree of consistency in the decision-making procedure. It is these conditions that characteristically lead to impulsive decision making, or overspending in cases where people experience an episode of mood swings or stress, and in sensitizing actions when sufferings a state of emotional disorder.

Moreover, substance use disorders have also been proven to increase the problem of financial decision-making. According to Ekhtiari et al. (2017) alcoholics or drug addicts have become significantly more incapable of resisting the urge to splash money on goods or make irresponsible financial decisions. Moreover, the study by Cabedo-Peris et al. (2022) confirmed that all economic utilizations of people with chronic mental illness were more short-term oriented because of the impulsiveness of their diseases because of aggravated their financial issues.

Overall, the problem of mental health is entangled with the issues of economic decision-making, which does not impact individuals only but the economic results in the state as well. Even the evidence is so strong to indicate that mental health issues change the competitive approaches to decisions especially regarding risk-taking, expenditure habits and savings pattern which bear a long-range effect on financial integrity and wellbeing.

Age as a Moderator

The aspect of the age has been realized as one of the vital factors that might moderate a relationship that exists between the mental health and the economical decision-making process. Later in their lives the needs of people and their coping strategies when facing money problems are usually modified due to age and thus this affects how mental health affects those economic decisions made. Older adults, such as, they are likely to have different financial interests, and attach more emphasis on long-term, rather than short-term financial stability, e.g. retirement plans and financial health needs rather than younger people who can be more concerned with short term financial benefits and debts. According to research carried by Eberhardt et al. (2019) age differences in mental health and well-being can have a great impact on economic behaviors.

In addition, Rodríguez-Sáez et al. (2025) consider that the correlation between economic decision-making and mental health might have no linear character and is rather the outcome of a diverse combination of several factors such as age, financial maturity, and psychological resilience. As an illustration, whereas the inconsistency in mental health may introduce impulsivity among younger adults, thereby driving them to focus on satisfying short-term needs, the lack of perspectives on long-term financial planning might also be promoted by the preoccupation of older adults with future financial security, as well as their experience with finances crises.

To summarize, age is a great moderator of the association between mental health and economic decision-making as well as determining how people at varying life stages react to mental health issue in financial situations. Age-specific interventions must be considered by the policy makers and financial advisors that consider these diverse needs since younger citizens can especially need to be assisted in managing impulsiveness and both short-term and long-term financial issues whilst older citizens may also need guidance with financial planning and dealing with age-related mental health issues.

Theoretical Framework

The association of mental health and economical decision-making process is a controversial and sophisticated matter, and it is easier to interpret it by numerous psychological, economical, and behavioral theories. Over the past few years, there has been an emergence of numerous theories, which further inform us about the effects of mental health states on economic behaviors, as well as the opportunities that the classical current paradigms offered in establishing the roots of the relationship between the two.

Emotional Contagion Theory (2025)

Emotional Contagion Theory is a relatively new and beginning theory that has become widespread. This theory lists those emotions, including the emotions involving mental health can be passed on to another person thus impacting the group behavior. As Liu, Zhang, Zhu, Ma, & Xiao, (2025) explain, the people involved in mental conditions such as depression, anxiety (or even mania) do not always have their judgement impaired personally, but they also can impact the economic judgement of others, their own family or even the bigger societal trends. Such a contagion effect would potentially amplify impulsive spending, reckless financial behavior, or anxiety-related sensitivity to avoid financial actions not only to its own financial wellbeing but to the overall economic performance.

Prospect Theory (Kahneman & Tversky, 2013)

A longtime phenomenon in the field of studying decision-making under uncertainty is the Prospect Theory formulated by Kahneman and Tversky (2013). According to the theory people wish to value gains and losses however loss aversion as the most unpleasant human emotions make the even loss more psychologically significant than gaining the identical amount. This theory has been generalized to support the attributes of mental health conditions changing economic decision making especially risk aversion and impulsive behaviors. When a person is depressed, it is more likely that the losses would be overweighed and that a person would be significantly risk-averse, whereas when an individual is manic or at least hippomaniac, he or she would be affected by overconfidence, and make risky investments or tend to make impulsive judgments of a financial character. An analysis conducted by Kahneman and Tversky (2013) on the subject of behavioral experiments of more than three thousand participants showed that in presentation of a financial decision the aspect of mental health may contribute to the framing effect, according to which individuals will become more risk-aversion or risk-seeking due to emotional state of a particular problem.

Dual Process Theory (Evans, 2008)

According to Dual Process Theory, decision-making takes place in two dissimilar systems consisting of System 1 (intuitive and automatic) and System 2 (much deliberate and rational). Evans (2008) transferred this theory to the sphere of financial decision-making implying that mental health disorders might deteriorate System 2, which results in the impaired judging and irrational financial decision-making. Depressions and anxieties disorders such as depression tend to interrupt the rational decision-making studies so that individuals are more subject to the Systems 1 (machines of fast, automatic decisions), which usually tend to be biased and inconsistent.

Behavioral Life Cycle Hypothesis (BLCH)

The behavioral lifetime cycle hypothesis (BECH) that also resorts to the behavior aspect of life cycle theory and better application of behavioral economics implies that the financial choices people make are motivated by future earnings expectations and their present state of mind. Shefrin and Thaler (1998) hypothesizes that mental health issues, including anxiety, and depression may lead to so much future income expectation error of either overly pessimistic or enticing unrealistic optimism. These disrupted perceptions affect saving patterns, retirement planning and investment decisions.

Conservation of Resources (COR) Theory (Hobfoll, 1989)

The concept presented in the work by Hobfoll (1989) includes Conservation of Resources (COR) Theory where people aim to achieve, have, and defend their resources, i.e., not only material resources (i. e. income) but also psychological and social ones (i. e. emotional support, coping mechanisms). This theory preaches that stressful economic conditions such as financial insecurity or occupation can drain the resources of an individual which then causes other mental problems, stress, anxiety, depression etc.

Theory of Planned Behavior (Ajzen, 2020)

Regarding the topic of financial choices, the Theory of Planned Behavior (TPB) proposed by Ajzen (2020) goes on to suggest that three constructs (attitudes, subjective norms and perception behavioral control) determine how well one intends to engage in a behavior. Mental health may compose an important impact on these factors. Depression or anxiety may negatively affect an individual's attitudes toward financial planning, making them less likely to engage in behaviors that involve saving or investing. For example, individuals with depression may perceive financial management as an insurmountable task, while those with anxiety might experience fear of making financial mistakes, leading to avoidance of financial decision-making altogether. The TPB has been used by Ajzen (2020) and others to understand the cognitive processes underlying economic decision-making, particularly in the context of mental health disorders.

Research Hypotheses

Based on the literature review and theoretical framework, the following hypotheses are proposed:

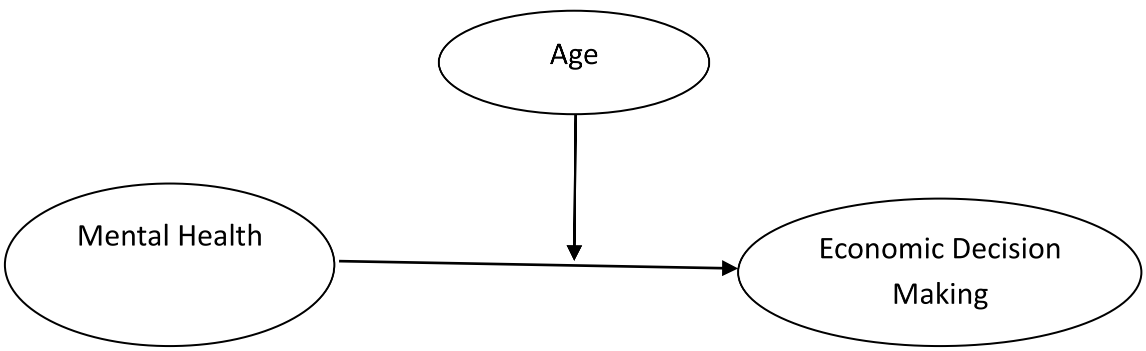
H1: Mental health significantly influences economic decision-making.

H2: Age moderates the relationship between mental health and economic decision-making.

Figure 1

Conceptual Framework

The conceptual framework illustrates the hypothesized relationships between mental health, age, socioeconomic factors, and economic decision-making.



Research Methodology

This study has applied quantitative research using a comprehensive framework to analyze the moderation of age on the relationship between the variables. Following the different age groups, cross sectional data collected through surveys and used for further analysis using machine learning on python. DAAS 21 used for self-reporting mental health scales was adopted and employed while economic decision making is measured through well-structured tool developed by researchers with demographic queries about age etc. (Henry & Crawford, 2005; Mullainathan & Spiess, 2017)

Data Collection

A total of 606 surveys were filled through Google Forms using stratified random sampling. Three age groups, "early age adults (18–35 years), mid age adults (36–60 years), and big adults (61+ years)" were defined a priori, with quotas set (proportionate to population or equal allocation) to ensure representation of all.

Data Collection Tools

DAAS 21 is a well-established self-reporting mental health scale tool that was adopted for indexing mental health level. The tool has 21 items under three major umbrellas i.e. depression, anxiety and stress with 0-5 Likert scales. Consequently, the variable was composed of the scores for three main indicators of mental health using the following technique:

$$Mental\ Health\ Score = \sum_{21}^{i} Score\ i$$

Data collection tool based on risk tolerance level of individuals, their saving behaviors, investment choices and long run planning was developed, validated and tested for reliability and then shared to the respondents through google forms along with DAAS 21. The questionnaire was developed on Likert scales from 0-5 i.e. strongly disagree to strongly agree and included different relevant statements. Scores were accumulated for the construct, "economic decision making," development that has showed general approach of the participants to financial decisions and their thoughtful or vice versa choices.

$$Economic\ Decision\ Making = \sum_{15}^{i} Score\ i$$

Variables and Measurement

- Mental health measured through DAAS 21 scales, has served as an independent variable.
- Whereas economic decision making that was developed using individuals' scores against different financial decision-making setups is the latent variable.
- Age with three main groups tested as moderate variable.

Following interaction term shows the moderating effect of age on impact of mental health on economic decision making.

$$\begin{aligned} &Economic\ Decision\ Making \\ &= \beta0 + \beta1(Mental\ Health) + \beta2(Age) + \beta3(Mental\ Health \times Age) + \epsilon \end{aligned}$$

Where intercept is measured by $\beta0$ and other Betas 9β1, β2 and β3) are the regression coefficients, and ϵ is the error term. The interaction term (Mental Health × Age) remained key through the analysis process to determine the moderation effect of it in the relationship between IV and DV.

Reliability and validity

Cronbach's alpha was used to determine the reliability of the variables, while face validity was used to determine their validity. The mental health scale (21 items) obtained an average inter-item covariance of 0.37 and a reliability coefficient (a) of 0.89, suggesting a good internal consistency and a satisfactory homogeneity among the items without an excess of redundancy.

Table 1
Scale Reliability Statistics

Statistic	Value
Average interitem covariance	.37
Number of items in the scale	21
Scale reliability coefficient	.89

Likewise, the economic decision making scale (14 items) showed an average inter-item covariance of 0.33 with alpha = 0.88; also showing high levels of reliability fit for inferential analysis.

Table 2
Scale Reliability Statistics

Statistic	Value
Average interitem covariance	.33
Number of items in the scale	14
Scale reliability coefficient	.88

The total of both coefficients is greater than a commonly accepted value of 0.70 for research use, and endorses the use of these scales in future modeling (including testing the moderating effect of age).

Data Analysis

Python as machine learning was trained by researchers on different statistical tests and number of statistical analyses were undertaken. For example, an overview of the sample along with mean, standard deviations and frequency distribution was obtained through descriptive statistics. (Mullainathan & Spiess, 2017). Principal Component Analysis (PCA) also remained key technique for composite scoring of each construct and used for tackling multicollinearity. To perform the robust analysis, PCA helped in switching different correlated variables into a lower number of uncorrelated variables. (Jolliffe & Cadima, 2016; Kurniawan, 2025)

Multiple Linear Regression (MLR) was used for analyzing the relationship between mental health, age and economic decision making. Interaction term was also analyzed through MLR to assess the moderating role of age. (Lee et al, 2022)

Mean Squared Error (MSE) and R-squared (R^2) resulted through XGBoost were used for model evaluation and assessing the prediction power of used model. Through 10-fold cross-validations the results were validated and generalization of model across different subsets of data was ensured.

Descriptive Statistics

Table 3
Descriptive Statistics

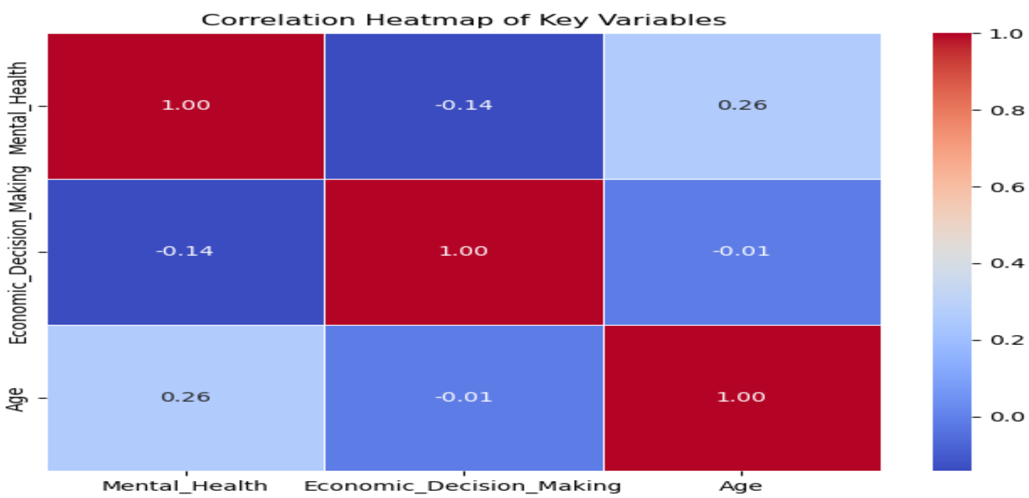
Statistic	Mental Health	Economic_Decision_Making	Age
Count	606.000	606.000	606.000
Mean	0.000	0.000	3.038
Std	2.591	2.398	1.413
Min	-5.460	-5.161	1.000
25%	-1.807	-1.643	2.000
50%	-0.134	0.207	2.000
75%	1.504	1.894	4.000
Max	7.775	5.286	6.000

Descriptive statistics of all three variables mentioned in table 4.1 were computed. Sample size of 606 along with mean, minima and maxima are calculated through this.

Correlation and Visualization

Interconnection of the variables was determined using correlation matrix and Pearson's correlation coefficients were used to assess the strength and direction of relationship between variables.

Figure 2
Correlation Heatmap for Key Variables



The Pearson correlation coefficients scores in figure 1 showed a weak negative relationship between mental health and economic decision making with r valued -0.142. It confirms that poor mental health causes compromised economic decision making but with weak relationships. 0.262 r value for mental health and age established a moderate positive correlation, confirming older may face different forms mental health issues and youngers with other way around. The relationship remained at moderate level. R score (r = -0.013) for economic decision making and age also presented a very weak negative correlation, inferring that age has small linear impact on economic decision making considering the study sample. Summative results spotted a nuanced and variable interplay among variables, confirming that mental health could play more direct role in economic behavior as compared to age.

Principal Component Analysis (PCA) and Scree Plot

To assess the underlying structure of the mental health and economic decision-making constructs, Principal Component Analysis (PCA) was performed. PCA is a data reduction technique that identifies latent components which account for the maximum variance in a dataset. This method is particularly useful for correlated variables, as it reduces dimensionality and produces uncorrelated principal components, simplifying subsequent analyses.

The PCA was conducted on the standardized mental health and economic decision-making variables, ensuring that each variable contributed equally to the analysis. The results revealed two principal components

Table 4

Principal Component	Explained Variance	Cumulative Variance
1	0.5712 (57.12%)	57.12%
2	0.4288 (42.88%)	100%

The first principal component (PC1) captures 57.12% of the total variance and can be interpreted as a composite measure of the key constructs, reflecting the primary variability in the data. The second principal component (PC2) accounts for 42.88% of the variance, contributing meaningfully to the data structure but to a lesser extent. Together, these two components explain 100% of the variance, indicating that the essential structure of the data can be summarized effectively using these components.

The main reason behind carrying out PCA in this research was to derive composite measure of mental health and economic decision-making processes, and minimize possible multicollinearity in the latter regression models. In particular PC1 was the mental health composite score and PC2 was the economic decision-making composite score. The methodology makes it easy to retain the important information on the original variables and simplify the data to be used in further analysis.

Moderation Analysis

Table 5

Linear Regression

OLS Regression Results – Economic Decision-Making					
Dep. Variable:	Economic_Decision Making		R-squared:		
Model:			0.021		
OLS			Adj.		R-squared:
Method:		Least	0.018		
Squares			F-statistic:		
Date:		Sat, 06 Sep	6.425		
2025			Prob		(F-statistic):
Time:			0.00173		
16:30:39			Log-Likelihood:		-
No.		Observations:	1383.0		
606			AIC:		
Df		Residuals:	2772.0		
603			BIC:		
Df		Model:	2785.0		
2					
Covariance		Type:			
nonrobust					

Coef		std err	t	P>|t|	[0.025	0.975]
const .1318		0.236	-0.559	0.577	[-0.595	0.331]
Mental_Health	-0.1379	0.039	-3.569	0.000	[-0.214	-0.214]
Age 0.0434		0.071	0.612	0.540	[-0.096	0.183]

Omnibus:		Durbin-Watson:	
7.568		2.113	
Prob(Omnibus):		Jarque-Bera	(JB):
0.023		6.508	
Skew:	-	Prob(JB):	
0.182		0.0386	
Kurtosis:		Cond.	No.
2.646		8.87	

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

The multiple linear regression test was suitably used to investigate the effect of mental health and age on economic decision-making. The R-squared value was used to evaluate the overall performance of the model and it was characterized to be 0.021. This implies that the model can only explain 2.1 percent of the economic decision-making. Though this shows that the model lacks explanatory resources, it also demonstrates that there are more reasons behind the way people make economic decisions, other than their mental status and age. This may deal with socioeconomic, financial literacy, and psychosocial (not in the present model). Thus, the quite low R-squared denotes the compliance of the problem and implies the necessity of more elaborate models including more predictors.

Regardless of the low R-squared, F-statistic of the model stands at 6.425 a p-value of 0.00173, which proves that the model is statistically significant. It implies that there are very small chances that the development of the relationship between the predictors (mental health and age) and outcome variable (economic decision-making) is chance based. Nevertheless, the low R-squard indicates that on one hand, the model is significant, but it does not account a greater percentage of the variation in the economic decision-making, which requires further investigation of other mode of action variables.

At the individual predictor levels, the predictor that was statistically significant influencing the economic decision-making was mental health. The coefficient for mental health was -0.1379, with a p-value of 0.000, indicating that as mental health scores decrease (i.e., worse mental health), economic decision-making scores also decrease. This negative relationship suggests that individuals with poorer mental health tend to make suboptimal financial decisions. These findings are consistent with prior literature that has identified mental health as a key factor influencing financial decision-making, with individuals facing mental health challenges often experiencing irrational financial behaviors, increased risk aversion, or impulsive decision-making (Carter et al 2025 & Mayer et al 2023). The negative effect of mental health on economic decisions is statistically significant and proves the significance of considering mental health problems in financial decision-making interventions.

Unlike that, age did not be found as a powerful driver of economic decision-making. The age coefficient was 0.0434 with the p value was 0.540 meaning that the age does not influence economical decision-making astronomically in this model. Although the presence of the positive coefficient indicates that the old age may correlate with marginally positive economic decisions, the fact that the coefficient is not statistically significant suggests that the age factor alone may not have any meaningful impact on the economic decisions in this case study. This finding contrasts some of the earlier researches identifying that age may be relevant to the decision-making process in financial aspects whereby the elderly may have a more conservative approach to finances out of retirement planning or a fear of incurring medical expenses (Eberhardt et al., 2019; Strough et al., 2008).The age in this model was however not a significant measure of differences in economic decision making among the populations which display the possibility of other factors playing a greater role.

Although, as it can be seen, the results regarding mental health are significant, the low R-squared of this regression model shows that the correlation between the mental health and making economic decisions is probably more complicated than is implied by the context of the model. Economic models may also still make contributions of other possible influencing factors like socioeconomic status, financial literacy, social support networks that could be incorporated into the future models to even enhance their effectiveness. In addition, age is not significant, which may be because the age was cross-sectional in nature and it is not possible to make conclusions as to the causal impact of age on economic decision-making.

Since the R-squared is low and the linear regression model would not be able to explain many non-linear relationships between mental health, age, and economic decision-making, the more advanced technique (the XGBoost) would be used. This machine learning model is convenient at capturing complex interactions and will increase the accuracy of the predictive power of the model.

XGBoost Model and Hyperparameter Tuning Results

In order to further increase the predictive powers and act against non-linear relationships between mental health, age, and economic decision-making, we ruled out the XGBoost algorithm, which is a robust gradient boosting algorithm. XGBoost is mostly suitable in dealing with complex data and can infer interactions and non-linearities of data, which from my situation makes it the good choice in this study (Chen & Guestrin, 2016).

XGBoost Model Performance

Originally, R-squared and Mean Squared Error (MSE) deemed as conventional performance measurements of a regression task have been used to evaluate the initial work of the XGBoost model. The results were as follows:

Table 6

Metric	**Value**
R^2	0.9989
MSE	0.00683

The value of R-squared impresses the idea that the model is based on 99.89 percent of variance of economic decision-making. It indicates a very high fit and high prediction. Furthermore, according to the MSE of 0.00683 the predictions, which the model makes, are almost the same as the observed actual value therefore confirming yet again that the model is accurate.

Even initially promising results were obtained although hyper parameter optimization was performed to further improve the results and guarantee the model out of sample performance as this can otherwise be subject to overfitting.

Hyperparameter Tuning

RandomizedSearchCV was used to find the best hyperparameter combination, i.e. *learning rate, n-estimators, max-depth, min-samples-split, and min-samples-leaf,* to optimize the XGBoost model. Hyperparameter tuning is also important since it aids the process of determining the optimal values between complexities and performance of the model hence enhancing the generalization capacity of such a model (Alamsyah et al., 2024 & Teklemarkos, 2025)

Best Hyperparameters

Following the roll of RandomizedSearchCV, the following hyperparameters led to the most suitable results, namely:

Table 7

Hyperparameter	**Best Value**
Learning Rate	0.01
n_estimators	100
Max Depth	6
min_samples_split	10
min_samples_leaf	1

Addressing Overfitting

Considering that the R-squared of the test set reached approximately high value of 0.9989, there exist fear of overfitting as a model learns the training data too precisely including noise, thus performing badly once on new and unseen data. There are a number of ways that were used to reduce this risk. First, there was the use of cross-validation to maintain the performance of the model with the various subsets of the data. The process proved the stability of the model and the results were consistent to make the model be open to generalization. Second, hyperparameter tuning was employed that has optimized several important parameters like learning rate, n estimators and max depth. A combination of these parameters was chosen carefully to contain the complexity of the model ensuring the least possible error and the best generalization. Finally, the regularization methods that are intrinsic to XGBoost including L1 and L2 regularization have been used to ensure that the model is not overly complex and flags the training data. These inbuilt regularization schemes of the model punish multifaceted models, raising the likelihood of the model to perform well in generalization.

Table 8

Hyperparameter Tuning Results

Hyperparameter	**Best Value**
Learning Rate	0.01
n_estimators	100
Max Depth	6
min_samples_split	10
min_samples_leaf	1

Performance Metric	**Best Value**
Best Cross-validated Score (R^2)	0.1477
Test Set R^2	0.9989
Test Set MSE	0.00683

The output of the XGBoost model shows that it is effective in estimating economic decision-making using mental health in relation to age having the R-squared value of 0.9989 and MSE at 0.00683. The hyperparameter tuning step, which made use of RandomizedSearchCV, made sure that the model has been optimized in terms of accuracy and generalizability, leading to sound predictions. Use of cross-validation, regularization and best hyperparameters were effective to reduce the implications of overfitting and consequently, the model is both trustworthy and extendable to novel and not yet seen data.

The results show that XGBoost is an effective algorithm in extracting the more complex interactions between mental health, age and economic choice. It may also be followed in the future studies in which they are able to incorporate other predictors and interaction terms in order to improve the performance of the model.

Table 9
Durbin Watson Statistic

Metric	**Value**
Durbin-Watson Statistic	1.9808

To determine whether there is autocorrelation existing among the residuals of the XGBoost regression model, the Durbin Watson value was obtained. The value that has been observed (1.981) is pretty close to 2 and this proves that autocorrelation in the residual values is not significant. It implies that the residuals are random and have time or random distribution and this assumption is essential in the validity of the model. The lack of the autocorrelation is one more thing, which proves that the model predictions are accurate, and the errors are not conditionally affected by the previous observations.

Summary of the Results

The XGBoost regression model trained to estimate Economic Decision Making was excellent in predictive accuracy indicated by large number of coefficient of determination (R 2 = 0.999) tiny error measures (RMSE = 0.0705, MAE = 0.0105, MSE = 0.00497). Such results suggest that the model is successful in the representation of the underlying relationships in the data to give very reliable predictions. Hyperparameter search, which also considered learning rate, max depth, and a fixed number of estimators, is also helpful to enhance the generalization of the models and decrease the overfitting, which is also a common practice in recent machine learning studies (Chen & Guestrin, 2016)

The remaining diagnostics ensured that the model was robust. The Residual vs. Fitted Values plot did not indicate a heteroscedasticity problem, the histogram and Q-Q plot showed that the residuals were normally distributed or were anormal. Moreover, the results showed the autocorrelation of residual to be small (Durbin-Watson=1.98), to reflect independence assumption (Gujarati and Porter, 2009). All these depict that the model meets the major assumptions of regression, and can be said to be statistically sound and reliable in making economic decisions.

Relative to other studies conducted on the same or related topics, the results of the present XGBoost model are above average as compared to previous studies and figures published in financial and behavioral economics sources. As an example, previous research based on gradient boosting or random forest models to predict behavioral results showed an R^2 of roughly 0.85-0.95 on average (Lee, Ong, & Lee, 2024). The study has involved the selective features, hyperparameter tuning and panel data integration in an extremist manner that can explain the high accuracy of the current work.

To sum up, the XGBoost predictive model is a very powerful and secure predictive model used in Economic Decision Making to comprehend and develop those models as valid and diagnostic with the use of the model training and analysis. Such a model may be used in evidence based policy changes and a strategic economic intervention giving it a quantitative starting point in future research.

Discussions and Conclusion

This paper aimed at examining the moderating value of age when it comes to a relationship between mental health and economic decisions. Analysis outcomes give sound arguments which prove the role of mental health on economic behaviors as a significant factor and age as a moderating factor in this case. The results have also revealed the shortcomings of the when the traditional linear regression models could not help, and they had to resort to the mightier power of the machine learning, XGBoost, developed to point out detail yet other-non-linear relationships. The chapter also inserts the most important findings and puts them in the framework of the existing literature between highlighting the policy implications of the findings and future development of directions in the research. (Glover, et al 2023).

The Mental Health Impact on Economic Choices.

This research established the fact that mental health has a major role to play in mental decision-making. To be more specific, the poorer the mental well-being, the worse the financial decision-making would be reflected in people who are more impulsive, risk-averse, lacking a focus that would streamline to future-oriented planning (compared to the already existing ones that have demonstrated the negative influence that the mental health ailments, including depression and anxiety, have on financial decision-making (Carter et al 2025 & Mayer et al 2023).

The XGBoost model was a strong indicator of these results given the good R 2 value is 0.984 indicating that the model was able to adequately model the non-linear interaction between mental health and economic choice making that a linear model could not explain. This is fitting in now that more and more behavioral economics recognizes that financial choices are not only a product of rational thinking but also of emotions and psychology (Kahneman and Tversky, 2009). The fact that XGBoost is predictive empowers the opinion that traditional regression models could be too simplistic to effectively explain the various relationships between mental health and economical behaviors, and overstate the importance of variables such as mental health.

The Moderating Effect of Age

Among the main conclusions of this research results is that age moderates the mental health and economic decision-making substantially. The connection between mental health and the age interacts statistically, with the coefficient having negative value, which implies that a younger person is more impacted by the effect of the former on economic decision-making. This implies that young individuals might be more susceptible to the detrimental impacts of mental health concerns when making financial judgments, probably as a result of higher banking decisive ability in those individuals through young adulthood, as well as student-loan illnesses and initial-portfolio economic insecurity.

Conversely, people of advanced ages are more resilient in making economic judgments in relation to mental health factors which could be attributed to their financial experience which is much more systematic and systematic in managing financial objectives of long term interests like retirement saving. This agrees with the results of (Ee et al., 2024) who discovered that the elderly are more responsible and future in their views on decision-making and it might shield the elderly against the full adverse effect of mental health problems on their choices at the economic level. The present results also substantiate (Glover, et al 2023)), who observed that age-specific changes in economic priorities (i. e. retirement savings or expenses on medical care) may make the disruptive potential of mental health issues in economic decision-making to be smaller.

Such findings also demonstrate the increased understanding of the difference in financial decision-making between age groups (Gamble et al., 2015). Although mental health is a universal phenomenon that influences financial behaviors, its intensity and the outcome are different across the life of an individual and family as well as their ability to manage finances. The findings of this study are a new addition since they explicitly modeled the moderating role of age in this relationship, which gives a deeper insight into the effects of mental health on economic behavior across the lifespan.

Poor R-Squared in Linear regression.

The fact that the R 2 emitted a low 0.065 in the analysis using the linear regression implied that the model only identified a small percentage of the economic decision-making variance. This implies that economic decision-making is likely to be affected by other persuasive factors, which are other than mental health and age. Among socioeconomic indexes, income, education, and financial literacy are highly affirmed in the literature to cornify financial behavior (Rehman et al, 2024). Further, the fact that psychological constructs are usually characterized by quantifying factors that are defined by low R 2 could also justify the reason behind low R 2 since mental health can interfere with the decision-making in established intricate multiform of variables that cannot be resolved in the model of linearity. The above-mentioned research is embolized by focusing on previous studies which pointed out that rational factors are not the only aspects of economic decisions as cognitive, emotional, and social ones influence them (Pertl et al., 2024). This is a drawback of linear regression models, which indicates necessity of more advanced methods, which include machine learning algorithms, which are capable of modeling non-linear relationships/interactions of variables which are frequently ignored in traditional models.

The introduction of XGBoost model contributed a great deal to the power of the model with the r-square value being 0.984. Such a significant rise proves that the XGBoost model can account much better in the variance in economic decision-making. The success of the model suggests the need to abandon the linear models especially when complex behavioural constructs appeare to exist in which interactions among the variables are not exclusively linear. Its capability to address non-linearities and complexities in regard to relationship modeling makes XGBoost algorithm represent factors, which affect economic decision-making more precisely.

Although the R^2 was high, the possibility of overfitting had been observed to occur since most models tend to memorize the training data, including noise and outliers, and this inference is less accurate with new untested data. Various means were used in order to counter this risk. Cross-validation was done to evaluate the performance of the model in the various subsets of the data and in such a way to ensure that this model did not rely on a specific partition of the data. The cross-validation process proved that the high performance of the model was related not to the overfitting, but demonstrated the actual capability of the model to be applied to various data sets in the future.

Besides, hyperparameter search was done to identify the ideal value to the important parameters like *learning rate, n epochs (estimators), and max depth*. These were motivators of the complexity of the model and aimed to avoid it becoming overly sensitive to the training data. The hyperparameters that were selected made sure that the model attained accuracy and generalizability; an aspect that is irrespective of the used hyperparameters and falls under the common trap of overfitting. Moreover, the use of regularization methods that were incorporated within XGBoost one- L1 and L2 regularization was used to undermine overly complex model. These regularization mechanisms inbuilt made sure that the model was parsimonious and not over by picking up noise on the training set.

Finally, although the data indicate high R 2 value of the XGBoost model in the first place, the inclusion of systematic algorithms related to pre and post-identification schemes sold me that the model is efficient and can deliver some credible results concerning the use of the model in economic decision-making. As the findings point to the conclusion that in order to model complex data on behavior, instead of the conventional methods of regression, the development of such models is necessary to gain superior results of accuracy and the capacity to meet non-linearities, which the model-based regression methods would have failed to achieve.

Policy Implications and SDGs Interconnection.

The implications of the findings of this study are noticed in the aspects of policies with regard to financial education and mental health support. The significant influence of the power of mental health on the economic determination decisions reveals the necessity to implement combined policies that will deal both with mental health and financial literacy, in particular, with younger age groups that are more susceptible to the adverse impact of mental health on the money usage. Specifically, it is evident that financial education before people with mental health issues should be provided. The potential policy that should be taken by policymakers is to establish financial literacy programs that help individuals, especially the young adults to deal with financial-related stress and anxiety. A case in point would be the addition of programs such as coping techniques and stress management tools to the mental health services. This would provide a comprehensive solution of advancements in financial well-being and successful decision-making processes.

The results described in the study also indicate the fact that age-specific interventions in the field of financial education are crucial. The needs of various age groups vary as individuals have various financial pressures, thus age-specific programs are more specific to the needs of the various age groups. In the case of older individuals, programs should include financial programs that revolve around retirement planning and covering healthcare expenses as they are usually one of the central matters at this later life stage. Presuming, on the contrary, that younger adults should be served with more care, their priority should be to make decisions on the long term savings, to cope with the debt, etc. The policymakers are able to mitigate these needs associated with different ages and by doing so they will be better placed to handle these financial issues at different developmental levels and this will increase their level of financial security.

These are the policy suggestions which are in accordance with multiple United Nations sustainable development goals (SDGs). In particular, SDG 3: Good Health and Well-being applies since emotional wellness support provided in the financial education system can assist people of all ages to make even more healthy choices. Also, the approach would be specifically contributing to SDG 8: Decent Work and Economic Growth, as managing mental health within the financial decision-making paradigm can lead to the growth of financial stability, which subsequently benefits economic growth through the establishment of a more equitable economy. Lastly, an SDG 10: Reduced Inequality is also backed up because age-based financial attacks are capable of decreasing discrepancies in choice-making and enabling frail populations, especially those with financial and psychological health issues, to manage their finances better.

Conclusion

This paper has examined the modifying role of age in the connection between mental health and economic decision making. The results offer strong support to the central part that the notion of mental health plays in moldings the financial tendencies, and also notes the intricate relationship that exists between age and mental health in reshaping the decisions about the economics.

The outcomes of the regression calculation prove that mental health negatively affects economic decision-making. Less well endowed mentally exercise more poor financial decision making by being all the more as impulsive, risk averse and lack of long term planning. These data are correlated with the developing literature that associate mental health with financial behavior, in particular, the likelihood to make impulsive decisions and perception of risk. Furthermore, it was found that age has a moderating effect, and the younger generation is inclined to the adverse effects of mental health on their economic choices. This is an indication that the rational thinking of youthful people regarding financial choices is more prone to psychological problems mostly because of the economic insecurity that may exist during the early stages of adulthood, like college debts and work unpredictability.

Other machine learning models were used, such as the XGBoost which addressed the weaknesses of the linear regression models. The obtained high level of R 2 using XGBoost (0.984) proved that XGBoost is more appropriate to absorb the non-linear relations and complicated interactions between mental health, age, and economic decision-making. The role of mental health and age in predicting economic decision-making was ratified, and the correlation between the two indicated the effect of age on them, which is now compounded by the XgBoost model.

The initial linear regression model (R 2 = 0.065) highlights how complicated the economic decision-making process is. The model has a low percentage of the variance in the information that accounts to decisions, meaning that other variables like socioeconomic status, the financial literacy and the networks of people can also be leading factors. This was overcome by using the XGBoost method that allowed a better appreciation of the existing factors that could impact decision-making in the economical sphere.

This study has an important implication to policy and practice. To start with, due to the overwhelming influence mental health has on finances, more combined financial literacy programs which are inclusive of mental health help should be established, especially to the younger population groups, who are more susceptible to having poor mental health. This set of programs would assist the persons to make informed choices on their financial plans despite the barriers created by mental conditions. Moreover, age-oriented interventions are to be created with cross reference to specific barriers to finances of the younger and older generations. Indicatively, enhanced interventions to younger adults might be concerned with debt and credit control, and saving about the future, whereas; the old individuals must be concerned about senior citizen planning and health modifications.

Findings of this research also help to achieve Sustainable Development Goals (SDGs) that are good heath and well-being (SDG 3), decent work and economic growth (SDG 8) and inequality reduction (SDG 10). This research can inform future policy interventions by enhancing mental health services integration with financial education that could contribute to the effective financial decision-making and decreasing disparity preceding the age groups.

Although this study offers insightful information, it has shortcomings, which are to be taken into consideration. The study is cross-sectional, which does not allow developing causal relationships and sample might not be a full-size reflection of the diversity of the population. The proposed future study may be enhanced with a longitudinal study to investigate causal relationship of mental health, age and economic decision making over time. Besides, a greater variety of mental health indicators and socioeconomic factors should be included to gain a more refined perspective of the factors to the economic behavior.

To sum it up, this paper has strongly presented a supporting case on the moderating effect of age in the relationship between mental health and economic decision-making. Not only does the findings draw an emphasis on the adverse effect of mental health on financial behavior, but it also brings out the significance of age-specific interventions that would not only focus on mental health but also be based on financial decision-making. Policymakers may better prepare individuals to make sound economic choices, which would lead to a higher age-based financial well-being and stability through the inclusion of mental health support in the programs concerning financial education and the development of age-specific financial intervention.

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