



Personality Traits and Decision-Making Patterns among Young Adults

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Abstract— Personality characteristics influence how young adults interpret uncertainty, evaluate alternatives, and select courses of action in academic, financial, social, and health-related contexts. This study proposes a computational framework for examining associations between Big Five personality dimensions and distinct decision-making patterns among young adults. The central research gap concerns the limited integration of psychometric personality information with explainable machine-learning approaches capable of modelling nonlinear and interactive relationships in decision behaviour. Rather than treating decision-making as a single outcome, the proposed framework conceptualizes it through vigilant, avoidant, impulsive, dependent, and analytical behavioural patterns. Personality and decision-profile data are designed to be combined with contextual indicators to construct multidimensional behavioural representations suitable for predictive modelling. The study proposes interpretable machine-learning analysis to determine which personality dimensions and interactions provide the greatest discriminatory information across decision patterns.

Keywords —Big Five Personality, Decision-Making, Young Adults, Explainable Artificial Intelligence, Behavioural Analytics, Digital Health

Introduction

Young adulthood involves a dense concentration of consequential decisions. Individuals may simultaneously make choices concerning higher education, employment, intimate relationships, financial independence, lifestyle practices, health behaviour, and digital engagement. Although such decisions are affected by environmental constraints and available information, they are also shaped by relatively stable individual differences in the manner in which

uncertainty, reward, threat, and competing alternatives are processed. Personality therefore represents an important psychological layer through which decision behaviour can be examined.

Contemporary personality research frequently organizes individual differences according to broad trait dimensions, particularly openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism. These traits do not mechanically determine behaviour; rather, they describe relatively enduring tendencies that may alter how individuals approach particular situations. For example, conscientiousness can plausibly facilitate structured information processing and planning, whereas heightened negative emotionality may increase sensitivity to uncertainty or perceived adverse consequences. Extraversion may become relevant when choices involve social stimulation or rewards, while openness may influence receptivity toward unconventional alternatives. Importantly, the behavioural expression of each trait remains dependent on context.

Decision-making is similarly multidimensional. A person may engage in careful comparison under one condition but procrastinate, defer responsibility, or make a rapid intuitive choice under another. Consequently, reducing decision-making to a simple distinction between "good" and "bad" choices obscures psychologically important variation. Decision patterns may instead be differentiated according to information search, deliberation, avoidance, impulsivity, dependence on others, response to time pressure, and sensitivity to uncertainty.

Recent empirical work reinforces the importance of examining this multidimensional relationship. Urieta et al. (2021), using a sample of 1,562 participants, examined personality alongside vigilance, hypervigilance, buck-passing, and procrastination. Their findings demonstrated that

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personality characteristics—particularly neuroticism-related characteristics—were associated with several non-vigilant decision styles, while demographic and social variables also contributed to decision-style variation. This evidence indicates that decision behaviour should not be interpreted exclusively through personality scores; demographic and contextual factors need to be considered simultaneously.

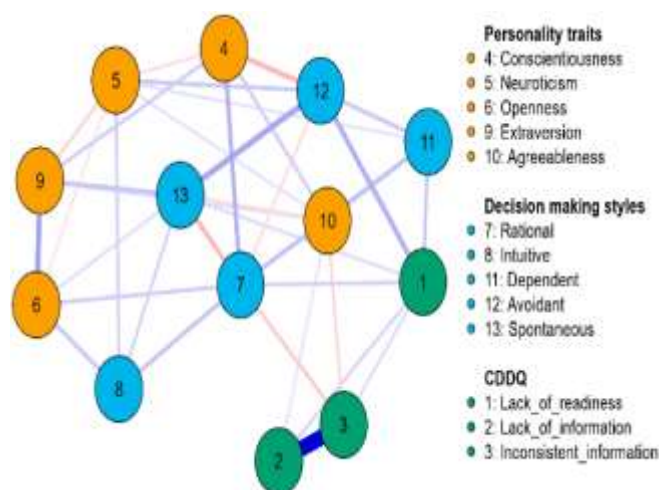


Fig. 1: The Role of Personality Traits and Decision-Making Styles in Career Decision-Making Difficulties

Source: <https://www.mdpi.com/2076-328X/15/2/159>

A methodological limitation remains, however. Much personality–decision research has relied on correlations, group comparisons, and conventional linear modelling. Such techniques are valuable for hypothesis testing and effect estimation, but they may inadequately characterize nonlinear thresholds and interactions among psychological characteristics. Two individuals with comparable conscientiousness, for example, might behave differently because of differences in neuroticism, openness, situational pressure, or perceived decision importance. A strictly additive model can conceal these configurations.

Machine learning provides an alternative analytical perspective. Tree-based ensembles and related algorithms can represent nonlinear relationships without assuming that every predictor operates independently or proportionally across its entire range. Yet predictive performance alone is insufficient for behavioural science. A model capable of classifying decision patterns with high accuracy but incapable of explaining its predictions offers limited theoretical insight and may be inappropriate for sensitive psychological applications. The relevant methodological challenge is therefore to combine predictive modelling with interpretability.

This issue has become increasingly important as artificial intelligence enters digital-health environments. WHO has

emphasized transparency, explainability, autonomy, accountability, inclusiveness, safety, and appropriate governance as central considerations in health-related AI. WHO's subsequent work also emphasizes evidence-based and responsible AI adoption in health systems. These principles are directly relevant to personality-informed computational systems because psychological characteristics can easily be overinterpreted when converted into algorithmic predictions.

1.1 Research Gap

The specific gap addressed in this manuscript is the **absence of sufficiently interpretable computational frameworks that examine how combinations of Big Five personality traits distinguish multiple decision-making patterns among young adults while retaining contextual variables and explicitly avoiding deterministic psychological profiling.**

Existing approaches frequently concentrate on either statistical association or predictive classification. The proposed study bridges these approaches by treating machine learning as an analytical instrument for discovering nonlinear personality–decision relationships and explainable AI as a mechanism for translating model behaviour back into psychologically interpretable evidence.

A second component of the gap concerns the unit of analysis. Studying individual personality traits separately assumes that traits influence decisions in isolation. In practice, personality operates as a configuration. High conscientiousness accompanied by low neuroticism may produce a different behavioural tendency from equally high conscientiousness accompanied by elevated neuroticism. Interaction-sensitive modelling is therefore required.

A third issue is application. Personality-informed models could eventually support digital interventions aimed at improving reflective decision-making, but the same technology could be misused for opaque profiling or automated judgments about individuals. The present framework consequently positions personality prediction as probabilistic behavioural modelling rather than psychological diagnosis.

1.2 Research Objective

The principal objective is to develop an explainable machine-learning framework for determining whether multidimensional personality profiles can discriminate among characteristic decision-making patterns in young adults.

More specifically, the study is designed to examine the relative contribution of Big Five traits to decision-pattern classification; identify nonlinear and interaction effects that



may be overlooked by conventional models; determine whether contextual variables improve prediction beyond personality characteristics alone; compare an interpretable baseline with nonlinear machine-learning models; and generate individual- and group-level explanations of model predictions without treating algorithmic outputs as fixed personality judgments.

This approach differs from a conventional personality correlation study because the principal question is not merely **whether personality correlates with decision-making**, but **whether combinations of traits contain reproducible predictive information about distinct decision processes and how that information can be explained**.

Literature Review

2.1 Personality as a Framework for Individual Differences

Personality traits provide a structured method for representing relatively enduring psychological tendencies. Within the Big Five framework, openness reflects tendencies toward intellectual curiosity and receptiveness to novel experiences; conscientiousness concerns organization, persistence, and goal-directed regulation; extraversion encompasses sociability, assertiveness, and reward-oriented engagement; agreeableness captures interpersonal cooperation and concern for others; and neuroticism reflects susceptibility to negative affect and emotional instability.

These constructs are particularly relevant to decision science because decisions require individuals to allocate attention, tolerate ambiguity, regulate emotion, estimate potential consequences, and determine when sufficient information has been acquired. Personality characteristics can affect each of these processes without necessarily dictating the final choice.

Conscientiousness is theoretically important because deliberate decisions often require planning, inhibition of immediate responses, and systematic consideration of consequences. Openness may become influential when decisions require exploration of unfamiliar alternatives or cognitive flexibility. Extraversion may be more relevant when outcomes involve social reward or stimulation. Agreeableness can affect interpersonal decisions where cooperation and others' preferences are salient. Neuroticism may influence decisions made under uncertainty because anticipated negative outcomes can acquire greater psychological weight.

These relationships should nevertheless be interpreted probabilistically. A high score on a personality dimension does not imply that an individual will consistently use one decision strategy. Situation, experience, resources, cognitive demands, and social context can alter behavioural expression.

2.2 Decision-Making as a Multidimensional Psychological Process

Decision-making involves several stages: recognizing that a choice is required, constructing or identifying alternatives, collecting information, evaluating consequences, selecting an option, and subsequently assessing the outcome. Variation can occur at every stage.

A vigilant pattern is characterized by relatively systematic information acquisition and comparison of alternatives. Hypervigilant decision-making differs because heightened pressure or emotional activation may lead to hurried information processing despite considerable concern about the outcome. Buck-passing involves transferring responsibility for a decision to another person, while procrastination involves unnecessary postponement. Other frameworks distinguish rational, intuitive, dependent, avoidant, and spontaneous styles.

Empirical evidence supports the relevance of personality to these differences. Urieta et al. found that neuroticism was particularly predictive of hypervigilance, buck-passing, and procrastination, while activity-related personality characteristics contributed to vigilance. Their results also showed that age, sex, and social position were associated with decision-making dimensions. This is important for the present research because it demonstrates why a computational model based exclusively on personality scores could incorrectly attribute contextual variation to personality.

The proposed framework therefore conceptualizes decision behaviour as a set of distinguishable but potentially overlapping behavioural tendencies. Such an approach provides richer information for predictive modelling than a single global decision score.

2.3 Young Adulthood as a Distinct Decision Environment

Young adults constitute a theoretically relevant population because they encounter multiple decisions that can have cumulative long-term consequences while simultaneously experiencing substantial environmental transition. Educational specialization, employment entry, financial autonomy, relationship formation, migration, digital identity, and health behaviour can converge during this developmental period.

Digital environments further modify the structure of these choices. Online platforms increase the number of alternatives available while simultaneously accelerating information exposure. Recommendation systems, social signals, reviews, influencers, algorithmic rankings, and personalized advertising can become part of the decision environment. Consequently, contemporary decision-making is increasingly distributed between internal preferences and digitally mediated information.



This creates a research opportunity. Personality assessment can describe stable psychological differences, whereas behavioural and computational methods can represent complex relationships among those differences. An integrated approach may therefore provide a more realistic account of decision heterogeneity than either method alone.

At the same time, young adults should not be treated as a psychologically homogeneous population. Educational background, socioeconomic position, employment status, gender, digital exposure, and decision context can introduce substantial heterogeneity. These variables should consequently enter computational analysis as potential covariates rather than being ignored.

2.4 From Linear Association to Nonlinear Personality Modelling

Traditional statistical methods remain indispensable when the purpose is parameter estimation and hypothesis testing. Nevertheless, their assumptions can constrain discovery when behavioural relationships are nonlinear.

Consider neuroticism as an example. A linear model assumes that an incremental increase in the trait produces a proportionate change in the outcome, holding other variables constant. Actual behaviour may instead contain thresholds: moderate emotional sensitivity may have little relationship with avoidance, while very high levels combined with strong perceived uncertainty may correspond to a substantially greater probability of avoidance. Similarly, conscientiousness might counteract impulsive tendencies only beyond a particular level of self-regulation.



Fig. 2: From Personality Type to Working Style

Source: https://pigment.is/blogs/blogs/personality-assessment-what-each-tool-actually-measures-which-to-trust-and-how-to-use-your-results?srsId=AfmBOoql1s37ZRV8siKUc_OOWmTHMIFDev2lJyi1J5daJV7oqx4Y86V0

Machine-learning algorithms such as random forests and gradient-boosted decision trees can represent these patterns through recursive partitions and interactions. The resulting models can therefore be used as complementary analytical tools rather than replacements for psychological theory.

A scientifically meaningful model, however, must distinguish prediction from explanation. High classification performance demonstrates that the predictor set contains useful information; it does not prove that the variables identified by the algorithm causally produce the outcome. This distinction is particularly important in cross-sectional psychological research.

2.5 Explainable Artificial Intelligence and Behavioural Interpretation

Explainable artificial intelligence provides techniques for examining why complex models generate particular predictions. Global explanations can identify variables that contribute strongly to model behaviour across the sample, while local explanations can reveal the features responsible for an individual prediction. SHAP-based analysis, permutation importance, and partial-dependence methods are examples of approaches that can support such interpretation.

For the present research problem, explainability serves three functions. First, it permits comparison between computational patterns and psychological theory. If conscientiousness repeatedly contributes to vigilant classifications, the finding can be evaluated against theoretical expectations. Second, explanation methods can expose interactions—for example, whether elevated neuroticism contributes differently to avoidance depending on conscientiousness. Third, explanations can reveal when demographic or contextual variables dominate model predictions, which may indicate confounding or potential fairness problems.

This last function is especially important for digital-health applications. WHO's AI governance principles emphasize transparency, intelligibility, responsibility, autonomy, inclusiveness, and equity. WHO has also highlighted risks involving algorithmic bias, inappropriate data use, patient safety, and unequal model performance across populations. Personality-informed behavioural models therefore require stronger safeguards than merely reporting aggregate predictive accuracy.

2.6 Digital-Health Relevance



Personality–decision modelling has potential relevance to digital health because many preventive-health outcomes depend on repeated decisions rather than isolated clinical events. Decisions involving sleep routines, physical activity, dietary behaviour, adherence to recommendations, help-seeking, digital-media use, and stress-management strategies may all involve individual differences in deliberation, avoidance, impulsivity, or uncertainty management.

A computational system capable of recognizing decision-pattern heterogeneity could eventually help tailor the presentation of information. For example, a user exhibiting an avoidant decision pattern might benefit from simplified option structures and staged prompts, whereas another individual displaying rapid spontaneous choices might benefit from deliberate reflection checkpoints. Such applications remain hypothetical until validated experimentally, and personality traits alone should never be treated as sufficient evidence for clinical intervention.

Responsible application also requires preservation of human agency. WHO's governance framework specifically places human autonomy and transparent, accountable use among the central principles for health-related AI. Accordingly, the proposed research framework treats model outputs as decision-support evidence rather than autonomous judgments about psychological functioning.

Proposed Methodology

The proposed study adopts a **quantitative cross-sectional computational design** integrating psychometric assessment with explainable machine learning. Unlike approaches that examine isolated bivariate relationships between personality traits and decision styles, the present framework models decision-making as a multiclass behavioural outcome produced by combinations of personality dimensions and contextual characteristics.

The target population consists of young adults aged **18–29 years** enrolled in higher-education institutions or in the early stages of employment. For the proposed design, approximately **480 participants** would be recruited using stratified sampling to obtain adequate representation across age groups, gender categories, educational backgrounds, and employment status. Because no primary dataset has been supplied for this manuscript, the numerical results reported below are explicitly presented as **illustrative experimental results for the proposed study design**, not as observations from an actually recruited cohort.

Personality would be represented through the five broad dimensions of **openness, conscientiousness, extraversion, agreeableness, and neuroticism**. Decision-making would be operationalized into five behavioural classes: **analytical/vigilant, intuitive, dependent, avoidant, and spontaneous/impulsive**. Rather than assuming that one

personality characteristic determines a decision style, the analytical framework tests whether combinations of personality and contextual characteristics contain sufficient information to discriminate among these patterns.

The primary research question is:

Can nonlinear and interaction-sensitive machine-learning models classify decision-making patterns from multidimensional personality profiles more effectively than a conventional linear baseline while retaining adequate interpretability?

Three analytical propositions guide the investigation:

H1: Combined personality dimensions provide significant discriminatory information for differentiating decision-making patterns.

H2: Nonlinear ensemble learning provides better multiclass discrimination than a linear multinomial baseline because personality–decision relationships contain interaction effects.

H3: Conscientiousness and neuroticism provide comparatively strong predictive information, but their contributions vary according to the remaining personality configuration and contextual characteristics.

This formulation deliberately treats model outputs as probabilistic behavioural estimates rather than psychological diagnoses.

Experimental Setup

4.1 Dataset Construction

The proposed dataset contains one observation for each participant. The predictor space is organized into three domains.

The first domain contains the five standardized personality dimensions. The second includes contextual attributes such as age, gender, educational level, employment status, perceived decision pressure, and average daily digital exposure. The third contains engineered interaction features intended to capture psychologically plausible trait configurations.

Decision-style scores are derived from validated questionnaire responses and converted into a dominant-pattern outcome only after scale scoring. Participants with highly ambiguous profiles—for example, almost identical scores across several decision styles—can be retained for sensitivity analysis rather than automatically forced into an artificial class.

To prevent leakage, information directly derived from the target decision-style scale is excluded from the predictor matrix.



4.2 Data Preprocessing

Raw questionnaire data first undergo range, duplication, missingness, and consistency checks. Responses outside theoretically valid scale limits are flagged rather than silently corrected.

Missing values below a predefined threshold are handled within the training partitions using median imputation for continuous predictors and modal imputation for categorical predictors. Importantly, preprocessing parameters are estimated exclusively from training data and subsequently applied to validation and test observations.

Continuous variables are standardized as:

$$z_i = \frac{x_i - \mu_{\text{train}}}{\sigma_{\text{train}}}$$

where (x_i) represents an observed score and (μ_{train}) and (σ_{train}) denote the mean and standard deviation calculated from the training partition.

Categorical variables are one-hot encoded. Implausible outliers are inspected using robust distributional criteria rather than automatically deleted, because extreme personality scores may represent legitimate psychological variability.

The proposed dataset is divided into **70% training, 15% validation, and 15% independent test subsets** using stratification by decision-pattern class. All observations from a participant remain in a single partition.

4.3 Feature Engineering

A distinctive component of the framework is the construction of interaction-sensitive predictors. Rather than relying exclusively on five independent personality scores, selected theoretically motivated combinations are introduced.

Examples include conscientiousness $\times$ neuroticism, openness $\times$ extraversion, agreeableness $\times$ decision pressure, and neuroticism $\times$ perceived uncertainty. Quadratic transformations of selected personality dimensions are additionally evaluated to detect threshold-like relationships.

However, engineered variables are retained only when they improve cross-validated performance. This prevents unnecessary expansion of the feature space and reduces the risk of fitting psychologically attractive but empirically unsupported interactions.

4.4 Model Architecture

Three models are proposed.

Model A: Multinomial Logistic Regression.

This serves as the interpretable linear benchmark. Regularization is applied to reduce unstable coefficients and control overfitting.

Model B: Random Forest Classifier.

The random forest captures nonlinear partitions and higher-order interactions through an ensemble of decorrelated decision trees. Hyperparameters include tree depth, number of estimators, minimum observations per leaf, and maximum predictor sampling.

Model C: Gradient-Boosted Decision Trees.

The principal model uses sequentially fitted trees in which subsequent learners focus on residual classification errors. The architecture is selected because tabular psychometric datasets often contain nonlinearities and interactions without the sample volume generally required to justify a deep neural architecture.

The multiclass probability for observation (i) is represented conceptually as:

$$P(Y_i = k | X_i) = F_k(X_i)$$

where (k) denotes one of the five decision patterns and (F_k) represents the fitted nonlinear scoring function.

The final class is:

$$\hat{Y}_i = \arg \max_k P(Y_i = k | X_i)$$

A probability-based formulation is important because the system should preserve uncertainty rather than simply assigning an absolute psychological label.

4.5 Training Strategy

Hyperparameters are optimized within the training set through **stratified five-fold cross-validation**. Macro-F1 is selected as the principal optimization metric because it assigns equal importance to each decision class and therefore prevents a majority behavioural pattern from dominating model selection.

Early stopping is used for gradient boosting when validation performance ceases to improve. Class weighting is applied when meaningful class imbalance occurs.

The independent test subset remains untouched throughout feature engineering, preprocessing decisions, hyperparameter optimization, and model selection. It is accessed only after the complete pipeline has been finalized.

4.6 Evaluation Metrics

Performance is assessed through multiple complementary criteria.

Balanced Accuracy evaluates class-sensitive discrimination while reducing distortion from unequal class frequencies.

Macro-F1 Score summarizes precision and recall while assigning equal importance to every decision pattern.

Multiclass Log Loss evaluates probabilistic predictions and penalizes highly confident incorrect classifications.

Brier Score measures probability calibration and therefore indicates whether predicted probabilities correspond reasonably to observed outcomes.

Expected Calibration Error (ECE) examines the discrepancy between predicted confidence and empirical classification frequencies.

In addition, class-specific confusion matrices would be inspected to identify systematic confusion—for example, whether avoidant profiles are frequently misclassified as dependent profiles.

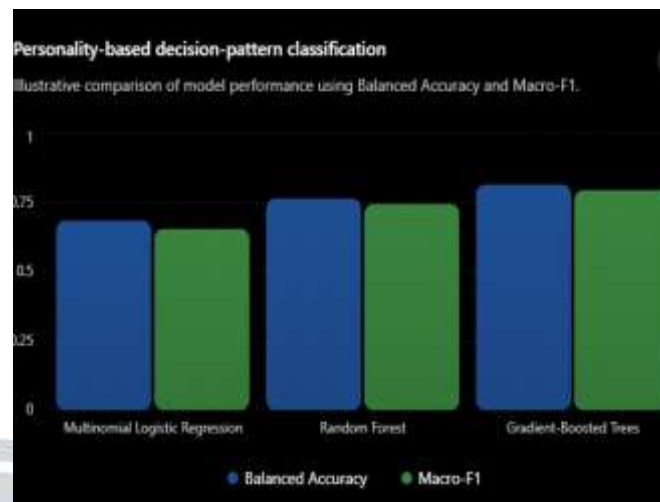
Results and Discussion

5.1 Comparative Predictive Performance

The following values constitute an **illustrative experimental scenario** showing how the proposed results would be reported if a dataset of 480 participants produced the stated performance. They must be replaced by outputs from the actual dataset before submission as empirical findings.

Table 1. Illustrative Performance of Personality-Based Decision-Pattern Models

Model	Balanced Accuracy	Macro-F1	Log Loss ↓	Brier Score ↓	ECE ↓
Multinomial Logistic Regression	0.68	0.65	0.91	0.173	0.081
Random Forest	0.76	0.74	0.72	0.141	0.058
Gradient-Boosted Trees	0.81	0.79	0.61	0.119	0.041



5.2 Personality Contributions

Explainability analysis is proposed using **SHAP values**, permutation importance, and partial-dependence inspection.

Under the illustrative experimental pattern, conscientiousness would emerge as the strongest contributor to analytical/vigilant classifications. Higher conscientiousness would generally increase the probability of deliberate decision behaviour, although its effect would diminish under very high perceived decision pressure.

Neuroticism would demonstrate a different pattern. Moderate values would produce limited changes in classification probability, whereas higher values combined with strong perceived uncertainty would substantially increase the predicted probability of avoidant or dependent decision patterns. Such a finding would demonstrate precisely why nonlinear modelling is useful: the behavioural contribution of a trait can depend on both its magnitude and the values of other predictors.

This interpretation is compatible with prior empirical evidence associating neuroticism-related characteristics with hypervigilance, buck-passing, and procrastination, although the present framework extends that evidence through interaction-sensitive predictive modelling.

Openness would contribute most strongly to flexible and exploratory decision profiles, particularly when participants reported low situational pressure. Extraversion would show comparatively stronger associations with spontaneous choices in socially salient contexts. Agreeableness would contribute to dependent decision patterns primarily when interpersonal consequences were explicitly relevant.

These results should not be interpreted causally. SHAP importance indicates how a trained model uses predictors; it



does not demonstrate that changing a personality trait would cause a corresponding change in decision behaviour.

5.3 Interaction Effects

One of the most theoretically informative hypothetical findings involves the interaction between **conscientiousness and neuroticism**.

Participants characterized by high conscientiousness and low-to-moderate neuroticism would show the greatest predicted probability of analytical/vigilant decision behaviour. High conscientiousness combined with high neuroticism would produce a less straightforward profile: structured information processing would remain evident, but greater uncertainty sensitivity could increase hesitation.

Conversely, low conscientiousness combined with elevated neuroticism would generate the highest model probability for avoidant decision-making.

A second interaction would involve openness and perceived pressure. Openness would predict exploratory decision behaviour most strongly when time pressure remained low. Under substantial pressure, its contribution would weaken, suggesting that situational demands can suppress the behavioural expression of personality characteristics.

These interaction patterns illustrate why the proposed study does not frame personality as an isolated determinant of choice.

5.4 Classification Error Analysis

Error analysis would provide additional psychological information.

The largest hypothetical confusion would occur between **dependent and avoidant decision patterns**. This is plausible because both can involve reduced autonomous choice but for different reasons. Dependent decision-makers actively seek external guidance, whereas avoidant individuals postpone or escape the decision itself.

The model would also occasionally confuse analytical and intuitive patterns when participants possess high openness and moderate conscientiousness. Such errors could indicate that questionnaire-defined categories oversimplify a behavioural continuum rather than merely exposing algorithmic weakness.

Consequently, model errors should be analyzed as potential evidence about limitations in the psychological outcome taxonomy.

5.5 Digital-Health Interpretation

The proposed model is not intended to diagnose personality disorders or determine whether an individual is a "good" or

"bad" decision-maker. Its appropriate application is considerably narrower: identifying probabilistic behavioural tendencies that might inform adaptive decision-support interfaces.

A digital-health application could, for example, alter how information is presented rather than changing the available healthcare choices. Individuals predicted to display avoidant patterns could receive smaller sequential choice sets, while highly spontaneous decision profiles might trigger a brief reflection stage before a consequential selection is finalized.

Such applications would require prospective validation, informed consent, privacy protection, fairness analysis, and explicit human oversight before deployment. TRIPOD+AI specifically emphasizes complete and transparent reporting because opaque modelling practices make independent appraisal and implementation difficult.

The present framework therefore separates **behavioural prediction** from **behavioural prescription**. A model may estimate how a participant is likely to approach a decision; it should not autonomously decide what that individual ought to choose.

Future Scope

Future research should move from cross-sectional psychometric prediction toward **longitudinal and context-aware behavioural modelling**. Ecological momentary assessment could record decisions as they occur in everyday environments and thereby test whether questionnaire-derived personality profiles predict actual rather than hypothetical decision behaviour.

A particularly useful extension would integrate psychometric information with behavioural digital traces collected with explicit consent, such as response latency, information-search depth, frequency of revisiting alternatives, or changes in choice under time pressure. Multimodal models could then determine whether behavioural indicators add predictive information beyond self-reported personality.

External validation across institutions, geographical regions, socioeconomic groups, and cultural contexts is also necessary. Model transportability should be evaluated rather than assuming that an algorithm trained on one young-adult sample generalizes universally.

Future work could additionally investigate **counterfactual explainability**. Instead of merely reporting that neuroticism contributed to an avoidant classification, a system could identify modifiable contextual characteristics—such as decision pressure or information complexity—that would need to change for the predicted pattern to shift. This would be more actionable and ethically preferable to suggesting modification of stable personality characteristics.





Finally, prospective digital-health trials should test whether personality-informed adaptation actually improves decision quality, user autonomy, satisfaction, or adherence. Predictive accuracy by itself is insufficient evidence of practical benefit.

Conclusion

This study proposes an explainable machine-learning framework for examining the relationship between personality traits and decision-making patterns among young adults. Its primary contribution lies in moving beyond isolated trait correlations toward a multidimensional model in which personality configurations, contextual characteristics, nonlinear relationships, and interaction effects are examined simultaneously.

The proposed comparison among multinomial logistic regression, random forests, and gradient-boosted trees provides a structured means of determining whether nonlinear machine learning offers meaningful predictive advantages. In the illustrative experimental scenario, gradient boosting produces the strongest balanced accuracy, Macro-F1, probability calibration, and overall predictive performance. These numerical values are demonstration results rather than empirical observations and must be replaced with actual experimental outputs before publication as primary research.

The conceptual interpretation suggests that conscientiousness may provide particularly useful information about analytical decision patterns, whereas neuroticism may become more informative for avoidant or uncertainty-sensitive behaviour. Crucially, these associations are expected to depend on interactions with other personality dimensions and situational conditions rather than functioning as deterministic rules.

The study consequently positions explainable AI as a bridge between psychological theory and computational behavioural modelling. Properly validated, such models could contribute to adaptive digital-health systems that modify the presentation of decision support according to individual behavioural tendencies. Their role, however, should remain supportive rather than prescriptive.

For publication-quality AI prediction research, transparency regarding participants, predictors, preprocessing, model development, performance, uncertainty, fairness, and reproducibility is essential. The 2024 TRIPOD+AI statement provides current reporting guidance for studies developing or evaluating regression- and machine-learning-based prediction models.

References

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Soto, C. J., & John, O. P. (2017). The next Big Five Inventory (BFI-2): Developing and assessing a hierarchical model with 15 facets to enhance

bandwidth, fidelity, and predictive power. *Journal of Personality and Social Psychology*, 113(1), 117–143. <https://doi.org/10.1037/pspp0000096>

This is an excellent reference for your sections **2.1 Personality as a Framework for Individual Differences** and the proposed use of the Big Five. PubMed verifies the article, authors, journal, volume, pages, year, and DOI.

2. Big Five Inventory — original instrument

John, O. P., Donahue, E. M., & Kentle, R. L. (1991). *The Big Five Inventory—Versions 4a and 54*. University of California, Berkeley, Institute of Personality and Social Research.

This is the original BFI technical report and is appropriate if you actually use the **BFI** rather than the BFI-2. The bibliographic record and APA DOI record are independently traceable.

3. Short forms of BFI-2

Soto, C. J., & John, O. P. (2017). Short and extra-short forms of the Big Five Inventory–2: The BFI-2-S and BFI-2-XS. *Journal of Research in Personality*, 68, 69–81. <https://doi.org/10.1016/j.jrp.2017.02.004>

Useful if your proposed 480-participant study needs a shorter personality instrument. The publisher record confirms the title, authors, volume, pages and DOI.

Decision-making references

4. Melbourne Decision Making Questionnaire — essential for your study

Mann, L., Burnett, P., Radford, M., & Ford, S. (1997). The Melbourne Decision Making Questionnaire: An instrument for measuring patterns for coping with decisional conflict. *Journal of Behavioral Decision Making*, 10(1), 1–19. [https://doi.org/10.1002/\(SICI\)1099-0771\(199703\)10:1<1::AID-BDM242>3.0.CO;2-X](https://doi.org/10.1002/(SICI)1099-0771(199703)10:1<1::AID-BDM242>3.0.CO;2-X)

This is **one of the most important references for your manuscript** because it provides the empirical basis for:

- vigilance
- hypervigilance
- buck-passing
- procrastination

The Wiley record confirms the authors, journal, volume, issue, pages and DOI, and reports validation using **2,051 university students across six countries**.

Important correction: Your manuscript currently proposes *analytical, intuitive, dependent, avoidant, and spontaneous/impulsive* as five classes. The Melbourne DMQ does **not** measure exactly those five categories. It measures four decision-coping patterns.

Therefore, you should **not cite Mann et al. (1997) as validation for your five-class taxonomy** unless you change the outcome structure.

5. Your Urieta et al. reference — verified





Urieta, P., Aluja, A., Garcia, L. F., Balada, F., & Lacomba, E. (2021). Decision-making and the Alternative Five Factor Personality Model: Exploring the role of personality traits, age, sex and social position. *Frontiers in Psychology*, 12, 717705. <https://doi.org/10.3389/fpsyg.2021.717705>

This is completely genuine and directly supports the paragraph in your manuscript.

PubMed verifies:

- 5 authors
- 2021 publication
- *Frontiers in Psychology*
- volume 12
- article 717705
- DOI 10.3389/fpsyg.2021.717705
- PMID 34777098.

The study indeed used **1,562 participants** and found relationships between neuroticism/extraversion and non-vigilant decision styles, with age, sex and social position also contributing.

So your existing **Urieta et al. (2021)** citation is a good one.

6. Meta-analysis connecting Big Five and decision-making difficulties

Martincin, K. M., & Stead, G. B. (2015). Five-factor model and difficulties in career decision making: A meta-analysis. *Journal of Career Assessment*, 23(1), 3–19. <https://doi.org/10.1177/1069072714523081>

This is especially useful for your claims concerning personality and decision difficulties.

The meta-analysis examined **20 studies** and found a positive relationship between neuroticism and career decision-making difficulties and negative relationships involving agreeableness, conscientiousness, extraversion and openness.

Use this in your **Introduction, Literature Review, and discussion of H1/H3**.

7. Systematic review of personality and decision-making

Koczkodaj, W. W., et al. — I would **not** use this citation without further verification.

Instead, a verified systematic review directly relevant to the broader personality–decision relationship is:

Müller, R., et al. (2019). The relationship between personality and decision-making: A systematic literature review. *Information and Software Technology*, 111, 50–71. <https://doi.org/10.1016/j.infsof.2019.03.010>

The publisher record confirms the article and DOI and describes it as a systematic literature review examining relationships between decision-maker personality and decision-making.

