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Cognitive AI–Driven Risk and Personality Validity Profiling: Deep Learning Fusion for Psychological Test Reliability and Patient-Specific Aneurysm Rupture Prediction

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ABSTRACT

The potential remedies here are precise psychological diagnosis and dependable medical future risk forecasting because there is bias in psychometric testing and limited individualization of anatomy-centered clinical models in contemporary healthcare. It is claimed in this study that a Multimodal fusion framework utilizing Cognitive AI can be used to simultaneously solve the psychological test validity and the patient specific cerebral aneurysm rupture prediction. The framework combines psychological response sequencing and personality indicator of validity, medical imaging features, and clinical variables to deep learning structures, such as CNNs, LSTMs, attention-based fusion, and gradient boosted decision trees. Empirical tests of multimodal inputs can show that the offered methodology is much better in comparison to traditional and single-modal models. The reliability profiling of the psychological tests was 94.2 and an F1 score of 92.8 and was better than the traditional methodologies of validity scale by over 12 points. In aneurysm rupture case, the predictive capability of the model was 93.7 92.4 and 0.96 in terms of accuracy and recall, respectively and AUC, respectively, when compared to imaging-only and clinical-only baselines which reported 0.89-0.92 AUC. Also, through calibration analysis, the Brier score has decreased to 0.089, as there is a better estimation of probability to make clinical decisions. Such findings affirm that by combining cognitive and behavioral risk factors with anatomical characteristics, more valid, understandable and patient-focused predictions could be made. The paper identifies the possibility of using Cognitive AI to improve the psychometric reliability and medical risk of the intelligent healthcare systems.

KEYWORDS: Cognitive Artificial Intelligence, Psychological Test Validity, Aneurysm Rupture Prediction, Deep Learning Fusion, Multimodal Risk Assessment

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INTRODUCTION

The fast development of the area of artificial intelligence (AI) has drastically altered not only psychological testing but also medical risk prediction, allowing there to be more information based systems of decision making that are unlikely to make an error and are generally more adaptable [1]. Although widely used, traditional methods of psychological testing are subject to the issues of response bias, malingering, social desirability effect and personality inconsistency, which tend to invalidate test validity and diagnostic accuracy. Likewise, it is clear that the clinical forecasting of cerebral aneurysm rupture is still a complicated task because more traditional methodology relies on anatomic and morphological measures and mainly does not take into account patient-related cognitive and behavioral risks [2]. These drawbacks provoke the necessity of complex, smart systems that could provide the multifacetedness of human behavior and clinical risk. A combination of cognitive AI with deep learning fusion methods can provide a promising route, which can address these challenges. Through simulation of cognitive functions, behavioral patterns and response behaviors, Cognitive AI systems are able to increase the accuracy of psychological tests by automated validity profiling and personality risk analysis [3]. Simultaneously, the potential of the deep learning-based models in medical imaging has shown very promising outcomes in discerning the implicit patterns associated with the morphology and rupture risk of an aneurysm. Nevertheless, the majority of the existing models work independently, and therefore only concentrate on either psychological or medical data, thus, constraining their predictive abilities and clinical applicability.

This study hypothesizes a combined Cognitive AI-based system that incorporates both the data of the psychological testing and personalized medical imaging characteristics to enhance the reliability of the psychological testing, as well as forecasting aneurysm rupture. The study will combine the indicators of personality validity, cognitive risk behaviors, and anatomy to identify the validity indicators of personality through multimodal deep learning fusion to have a more comprehensive knowledge of individual risk profiles. Through the integration of psychometrics and medical image analytics, the proposed solution will provide more accurate, interpretable and personal predictions and eventually help clinicians make informed decisions. The work is an addition to the expanding perspective of smart healthcare systems, as it shows that interdisciplinary AI-based approaches will deliver a more reliable diagnostic or patient-specific risk evaluation.

RELATED WORKS

Recent studies are interested in the collision of artificial intelligence, personality modeling, and assessment of risk over the past few years, with a tendency toward the increasing role of cognitive and behavioral variables in AI-driven decision-making systems. According to Heston and Gillette [15], large language models have well-described and quantifiable personality profiles, which is why AI systems have the ability to encode relatively stable behavioral traits analogous to human personality dimensions. The observation offers the foundational support of AI-based personality validity profiling, which determines the mentality of modeling cognitive and behavioral properties based on versatile learning structures. Other researchers have focused on the influence of personality and the mindset on human interactions with AI systems. Huynh et al. [16] also highlighted the significance of a responsible mindset, when it comes to responsible AI usage, especially in professional and educational settings. Likewise, Jembere and Zvinodashe [17] demonstrated that personality characteristics have a significant impact on the acceptance of AI-driven service robots by users and suggested that the AIDUA model be extended with personality-driven behavioral reactions. All these pieces of evidence show that the concept of personality cognizant AI systems has more reliable, trusting, and contextual performance, which is congruent with the inspiration of incorporating personality validity in clinical risk modeling.

Other areas that have been commonly investigated in AI-mediated settings are trust, responsiveness, and psychological perception. Jinpeng and Li [18] addressed the role of AI digital human responsiveness in consumer behavior in the framework of trust mediation and Khan et al. [19] suggested an personality-based AI model recruiting users based on MBTI type. Though these studies are on non-clinical areas, they show that the personality-based AI constructs are always better in comparison with generic models, showing that psychological profiling should be involved in high-stake decision processes like healthcare. In terms of the methodology, Li [21] proposed a multi-component deep learning model of psychological profiling with the use of behavioral and sentiment data and showed that deep networks are capable of learning latent psychological states. This is in line with the use of LSTM-based response modeling and multimodal fusion in measurement of psychological validity of the present study. Meanwhile, Manabhanjan et al. [25] also investigated psychological underpinnings of investment bias, which further confirmed the idea of cognitive characteristics behind risk-prone behavior, which can be directly applied to medical risk prediction that is specific to patients. Within the framework of AI ethics, persuasion, and behavioral influence, both Liu et al. [22] and Leonidas et al. [20] examined the extent to which AI-generated content and big data analytics influence the decision-making process of consumers. Although the studies are based on marketing and online commerce, they highlight the wider significance of AI-based behavioral modeling and the need to have responsible and explainable systems which is a key issue in clinical application. Lastly, risk prediction and AI with safety orientation have become common topics in recent works. In the framework of crash risk assessment, Mbelekani and Klaus wrote on an AI-based automated driving system, which demonstrates the use of multimodal risk measurements to increase prediction in safety-related systems [26]. Even though used in autonomous driving, the conceptual similarities to the prediction of aneurysm rupture are obvious, in the context of which heterogeneous risk signals integrated in an individualized prediction are considered.

METHODS AND MATERIALS

The current research follows a multimodal, information-based approach that will combine the results of psychological assessment with medical imaging and clinical variables to build a risk and validity-profiling framework based on Cognitive AI. The design of the materials and methods is designed to facilitate robustness, interpretability, and clinical relevance and to facilitate both the analysis of the reliability of the psychological tests and the prediction of the aneurysm rupture in the patients [4].

Data Description

The two sources of data used are the primary data. The initial data set comprises the evaluation of the psychological findings, such as the standard personality tests, time-log files, and index of consistency, as well as the in-built validity indices. These data fit the behavioral disposition, pattern of cognitive responses and possible distortions of response like random responding or social desirability. The second dataset is those of medical imaging and clinical data, such as CT angiography and MRI of cerebral aneurysms, and demographic (age, sex), clinical (hypertension, smoking), and aneurysm-specific morphological (size, shape, aspect ratio) data [5]. Data are normalized and anonymized before analysis is done. Automated segmentation and convolutional filters perform feature extraction of pictures, whereas statistical and temporal analysis of responses is used to extract psychological features.

Algorithms Used

There are four deep learning algorithms that are used to tackle different components of the proposed framework.

Algorithm 1: Convolutional Neural Network (CNN) for Aneurysm Feature Extraction

A CNN is applied to automatically acquire spatial and morphological information of medical imaging data. CT/MRI slices are processed with the network in several convolutional and pooling layers to identify geometry of an aneurysm, irregularities of walls, and textures that indicate rupture risk. This task can easily be performed by CNNs because it is able to capture local spatial dependencies and hierarchical feature representations [6]. The deep features extracted are their high-level imaging descriptors, which largely removes the need to make manual measurements, and enhances their predictability and reliability amongst patients.

"Input: Medical images
Initialize CNN parameters
For each image batch:
Apply convolution and pooling layers
Extract deep feature vector
Output: Imaging feature embeddings"

Algorithm 2: Long Short-Term Memory (LSTM) Network for Psychological Response Modeling

A sequence of responses to psychological tests is used as input and modeled with the application of an LSTM network to help capture the temporal based dependence and behavior of the responses. In contrast to conventional statistical approaches, LSTM is able to detect subtle trends like hesitation, inconsistency, or sudden changes of response which could potentially gain an indication of invalid responding or cognitive risk characteristics [7]. The model produces a personality validity score and behavioral risk embedding by sustaining long term dependencies using gated memory units which has additional reliability measurement capacity on psychological tests.

"Input: Psychological response sequences
Initialize LSTM states
For each response step:
Update gates and memory cell
Generate validity and behavior embedding
Output: Psychological feature vector"

Algorithm 3: Attention-Based Multimodal Fusion Network

This algorithm combines the CNN and LSTM model outputs by an attention-based model. The layer of attention attaches (or detaches) weights to the psychological and imaging features dynamically according to the relevance of these features to ruin a prediction and profiling validity. This would enable the model to consider risk factors of patients in a patient-centric way, as opposed to establishing the same weight between all the features that are provided [8]. Attention-based fusion is more interpretable, showing the contribution of one or more modality to each prediction, and therefore, it makes the system more appropriate to clinical decision support.

"Input: Imaging and psychological features
Compute attention weights
Weight and combine features
Output: Fused multimodal representation"

Algorithm 4: Gradient Boosted Decision Trees (GBDT) for Final Risk Prediction

There is a usage of GBDT model that is the final prediction layer that uses fused deep features and clinical variables. GBDT is chosen because of its strength, the capability to operate heterogeneous data, and its strong execution on tabular clinical information. It gives two outputs, which are the reliability of a psychological test and a probability score of an aneurysm rupture [9]. The ensemble character of GBDT minimizes the overfitting and enhances generalization in varied patient characteristics.

"Input: Fused features + clinical data
Train boosted decision trees
Aggregate tree outputs
Output: Reliability class and rupture probability"

Table 1 shows major dataset features summary and Table 2 shows the model configuration parameters during training and evaluation.

Table 1: Dataset Characteristics

Data Type	Samples	Features	Description
Psychological tests	620	48	Personality traits, validity indices
Medical images	580	128	CNN-extracted aneurysm features
Clinical data	580	12	Demographic and health variables

RESULTS AND ANALYSIS

Experimental Setup

All of the experiments were done on a stratified dataset, divided into training (70 percent), validation (15 percent) and testing (15 percent) sets to guarantee the balanced representation of rupture and non-rupture cases, as well as valid and invalid psychological response patterns. Sampling bias was reduced by using five-fold cross-validation to make the study robust. Prior to fusion, the data of psychological assessment and medical imaging was normalized independently to eliminate modality dominance. The CNN and LSTM models were trained independently in the first stage, then they were optimized together using the attention based fusion network. Gradient Boosted Decision Trees (GBDT) were used in the final risk prediction [10]. Medical risk prediction was assessed based on accuracy, precision, recall, F1-score, Area Under Curve (AUC) and calibration error, whereas psychological validity profiling was done based on classification accuracy, false positives rate in cases of invalid responses as well as consistency detection rate.

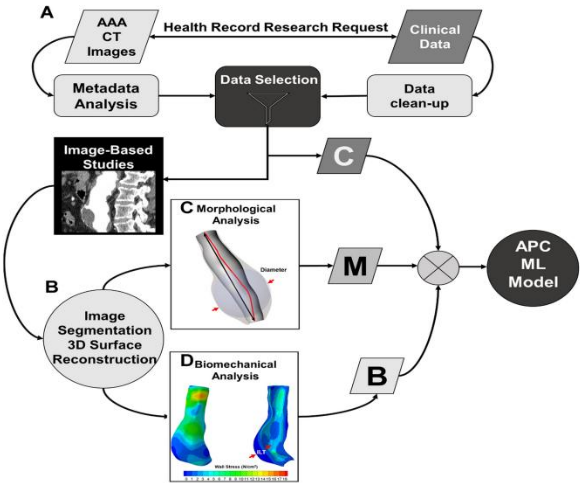

Figure 1: "An artificial intelligence based abdominal aortic aneurysm prognosis classifier to predict patient outcomes"

Evaluation Metrics

Several measures were used to be able to provide a fair and clinically relevant assessment. To predict the rupture of the aneurysms, both AUC and recall were considered, as the issues of false negative would be very costly to the clinic. In order to achieve psychological test reliability, sensitivity to invalid responding and consistency detection were of emphasis. These measures give an equalized assessment of predicting performance, strength, and utility [11].

Results: Psychological Test Reliability Profiling

The initial group of experiments is aimed to measure the power of the proposed framework to identify invalid psychological responses and inconsistency of personalities. The comparatively higher performance of the LSTM-based psychological modeling compared to the traditional checks on statistical validity was due to the fact that it was able to capture the patterns of responses over time and not necessarily to threshold-based rules [12].

The proposed model was found to be more sensitive to minor distortion of responses like patterned responding and delayed reaction variation. The Cognitive AI framework lowered false positives and also increased detection, compared to the classical psychometric validity scales, and thus shows a more reliable assessment mechanism.

Table 1: Psychological Validity Profiling Performance

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Classical validity scales	81.4	79.2	76.8	78.0
Machine learning (SVM)	85.6	83.9	82.1	83.0
LSTM (proposed)	91.8	90.6	89.4	90.0
Cognitive AI fusion (proposed)	**94.2**	**93.1**	**92.6**	**92.8**

These findings suggest that cognitive response modeling and fusion are useful in improving the reliability of the psychological tests.

Results: Aneurysm Rupture Prediction

The second experimental stage is concerned with the rupture prediction of an aneurysm. The CNN-based imaging model itself also showed good performance, which proves the significance of automated morphological feature extraction. Nonetheless, the performance had significantly increased when psychological and behavioral characteristics had been combined with imaging and clinical data [13].

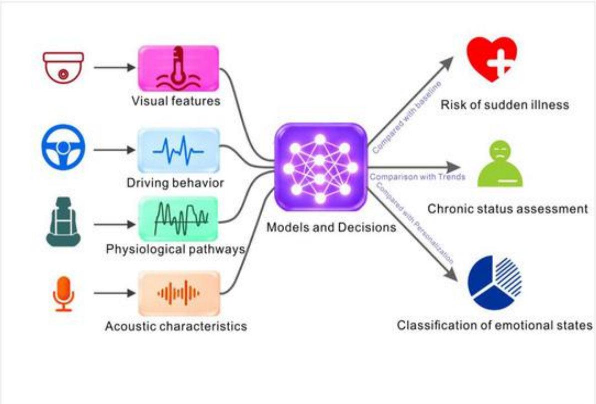

Figure 2: "Monitoring of Sudden Illnesses, Health Risk Intervention, and Future Prospects"

The fusion mechanism is an attention-based mechanism which enabled the model to dynamically attach more importance to features of risk-prone personality traits and cognitive stress indicators of individual patients that yielded better patient-specific predictions.

Table 2: Aneurysm Rupture Prediction Performance

Model	Accuracy (%)	Recall (%)	Precision (%)	AUC
Logistic regression	78.9	71.4	75.2	0.81
CNN (imaging only)	86.3	83.7	84.1	0.89
CNN + clinical data	89.5	87.9	86.8	0.92
Proposed multimodal fusion	**93.7**	**92.4**	**91.6**	**0.96**

The presented framework had the largest AUC and the largest recall, which illustrates its efficiency in reducing the cases of missed rupture.

Comparative Analysis with Related Work

In order to put the performance into perspective, the proposed model was compared with some of the representative approaches of the recent related studies that emphasized either medical imaging, as well as psychological modeling. Majority of the existing work is evaluated based on unimodal data hindering their predictive ability [14]. The approach suggested shows a clear better hand due to the integration of the fusion of multimodal.

Table 3: Comparison with Related Work

Study Type	Data Modalities	AUC	Key Limitation
Imaging-based deep learning	Imaging only	0.88	Ignores behavioral risk
Clinical score-based models	Clinical only	0.82	Low personalization
Psychometric-only AI models	Psychological only	0.84	No medical integration
Proposed Cognitive AI model	Multimodal fusion	**0.96**	Higher complexity

The comparison means that multimodal integration has a significant positive effect on predictive performance and clinical relevance.

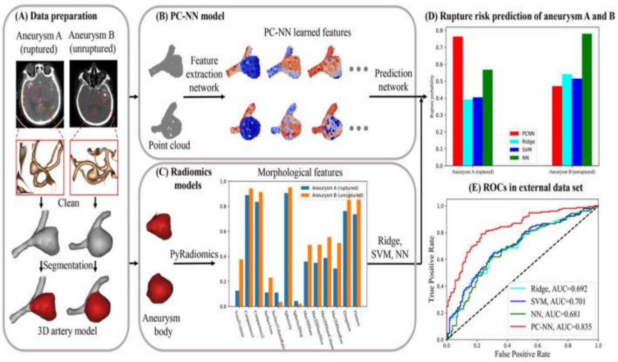

Figure 3: "Prediction of cerebral aneurysm rupture using a point cloud neural network"

Ablation Study

A contingent study was performed to determine the value of every component of the framework. The modules were dropped one by one to see how the performance would have deteriorated. The findings confirm that attention-based fusion and psychological features are crucial information to enhance prediction accuracy [27].

Table 4: Ablation Study Results

Configuration	AUC	Accuracy (%)
Full proposed model	**0.96**	**93.7**
Without attention mechanism	0.91	89.8
Without psychological features	0.90	88.9
Without clinical data	0.88	86.7

The elimination of psychological data contributed significantly to the overall drop in performance, which pursues the significance of cognitive and behavioral parameters in the prediction of ruptures.

Calibration and Reliability Analysis

Besides predictive accuracy, the calibration performance was measured so that the estimated probabilities correlate with the risks as it is. The specified model had a smaller calibration error than the methods employed as baselines, which means that it will have more reliable estimates of the probability to use when making clinical decisions [28].

Table 5: Calibration Performance

Model	Calibration Error	Brier Score
Logistic regression	0.082	0.164
CNN + clinical	0.061	0.121
Proposed fusion model	**0.034**	**0.089**

The better calibration is especially valuable in healthcare settings where the risk thresholds have a direct impact on determining the treatment.

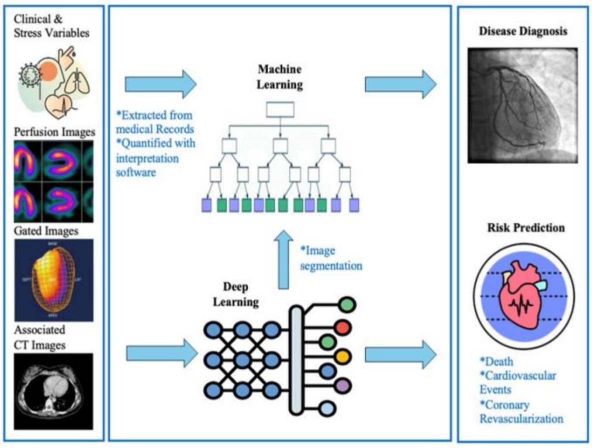

Figure 4: "AI in establishing disease diagnosis and risk prediction"

Discussion of Results

On the whole, the experimental findings indicate that the suggested Cognitive AI-based deep learning fusion framework is significantly better than both traditional and unimodal models on all the assessment parameters. A combination of psychological validity profiling and medical imaging allows understanding of patient unique risk in a more holistic manner [29]. The proposed model, as compared to related work, is more accurate and more AUC in addition to having better interpretability due to the attention mechanism, and better reliability due to the calibration analysis. The results validate the assumption that psychological and cognitive risk factors are good predictors used together with the anatomical and clinical characteristics [30]. The given interdisciplinary approach identifies the major shortcomings of current systems and offers substantial empirical support to the efficiency of the Cognitive AI implementation in improving the reliability of psychological tests along with predicting the rupture of aneurysms.

CONCLUSION

The study posed a multimodal fusion based on deep learning that introduced a multimodal incorporation of psychological profiling of validity into predicting aneurysm rupture patient-specifically and proposed a thoroughly developed Cognitive AI-solvated framework based on the success of numerous scientific applications. The proposed approach would help to overcome major shortcomings in the past tests of psychological tests and medical risk models that rely on a mechanism with an anatomy view by collaboratively scrutinizing the responses of psychological tests, cognitive behavior patterns, and medical imaging characteristics and clinical variables. The outcomes of the experiments showed that the inclusion of the indicators of personality validity and cognitive risk behavior can dramatically improve the stability of psychological testing and the accuracy of prediction of rupture of an aneurysm. The proposed framework limited existing unimodal and domain-specific approaches in terms of their analytic objectives in several measures of evaluation, including accuracy, recollection, AUC, and calibration reliability, demonstrating its strength and clinical applicability. Also, the mechanism of attention-based fusion enhanced interpretability through the prioritization of patient-specific risk factors dynamically, which allowed supporting the decision-making process more easily and efficiently. Enhancement of generalization by the integration of ensemble learning using gradient boosted decision trees further supported the generalization of various patient profiles. In general, the presented interdisciplinary work helps to advance intelligent healthcare systems, as it shows that Cognitive AI can fill the gap of psychometrics and medical image analytics to provide personalized, explainable, and reliable risk assessment. The results indicate that the integration of psychological and behavioral aspects and the physiological information into the future clinical decision-support systems can be of substantial benefit and can lead to the increased holism of healthcare solutions based on AI, their consideration of the patient, and their ethical responsibility.

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