A web based application for the collection and normative analysis of neuropsychological test data

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Abstract. Accurate analysis and interpretation of neuropsychological test scores are critical for clinical practice and research. However, the complexity and variability of these tests often make it difficult to collect consistent data and perform meaningful normative comparisons, particularly with culturally diverse populations. This work introduces a web-based application, currently under development, for collecting, storing, and analyzing neuropsychological test scores from diverse studies. The application allows the user to upload data from a study, conduct searches, and perform normative comparisons based on all submitted samples. For normative comparisons, the application classifies a patient's test scores against existing values in the database, allowing users to evaluate subject data against normative values and determine if they lie within typical ranges. A central aspect to the development is the database system, which requires a dynamic and scalable structure to accommodate a wide range of tests and parameters. This article also outlines the key design considerations for the database and addresses the challenges of structuring neuropsychological data for both flexibility and analytical accuracy. The web application aims to simplify the data management while offering robust tools for normative comparison and predictive capabilities.

Keywords: Neuropsychological Tests · Normative data comparison · Web Application · Database.

1 Introduction

Neuropsychological testing refers to a number of tests that healthcare providers use to get information about how your brain works and is a critical tool that can aid in assessing cognitive functions and understanding the impact of neurological, medical, psychological, and social conditions on the brain. By performing various tests, the healthcare providers can get a detailed profile of an individual's cognitive abilities. These tests can help clinicians determine a diagnosis, since test results can help understand the cause of some symptoms; identify strengths and weaknesses in the cognitive processes; provide plans for future treatment, like focusing on rehab, and to understand the risk of change upon a brain accident/surgery [6,33].

There are several types of neuropsychological tests, some of which are for memory, cognition, verbal communication, or motor skills, that typically involve writing, drawing, solving puzzles, answering questions, or responding to questions/images presented on a computer [6,33].

Therefore, the accurate analysis and interpretation of neuropsychological test results play a central role in both clinical assessment and research. However, the complex nature of neuropsychological tests poses significant challenges for consistent data collection and analysis. For instance, the Trail Making Test (TMT), an assessment of attention and executive function, includes two conditions: Trails A and Trails B. Trails A evaluates attention and executive function. Its parameters include time to completion, sequencing errors, and set loss errors. Trails B assesses attention, cognitive flexibility, and executive function, also measured by time to completion, sequencing errors, and set loss errors.

For some tests, especially those that check memory, we can't create different versions that are equally challenging. This means we can't re-test people often without them already knowing the answers, which limits the amount of information we can gather. A lack of data caused by the long duration of the tests and the large number of tests that fail for various reasons during their administration makes interpretation unclear and limits their validity or reliability, making normative comparison more difficult. The difference in languages and cultures also contributes to this lack of data, since some tests need to be translated and adapted to some cultures before being carried out [2].

The normative comparison is used to determine the subject's performance in a certain test, based on the performance of a reference group. These comparisons allow clinicians to verify if the subject's scores deviate significantly from what is expected. This comparison faces some challenges due to factors like differences in socioeconomic status, gender, age, education level, and cultural background, which can significantly impact the performance, making it difficult to establish culturally-specific norms [34]. Normative data often groups individuals into broad age ranges, which can lead to misrepresentation of individuals' cognitive abilities, since individuals in the same age group can perform very differently [3]. Also, normative data for some specific populations may not exist, making it challenging to interpret test results within a meaningful context [19].

To address these limitations, including the limited size or availability of existing normative datasets, this work presents the design and development of a web-based application for the collection, storage, and analysis of neuropsychological test scores across multiple studies. This application enables researchers to upload their neuropsychological study data, conduct targeted searches and normative comparisons using all data within the system. This tool is designed to support a growing and diverse group of tests, subjects, and test parameters.

The database architecture is a critical component of this application. It must be carefully designed to store diverse test data with varying tests, conditions, parameters, and score ranges, while ensuring data integrity and facilitating analytical processes. This paper details the design decisions for both the database and web interface, describing how the application supports normative comparisons.

This work aims to simplify the management of neuropsychological data and provide robust tools for their comparison and analysis, ultimately supporting more accurate and accessible neuropsychological assessment in both clinical and research settings.

From a software engineering perspective, the design of such a system poses meaningful challenges: test formats do vary widely, subject data must still remain flexible yet structured, and clinicians do require intuitive interfaces for complex analytical tasks. To go further, building a normative engine that updates dynamically with each new dataset demands a strong scalable backend architecture. This paper explores these challenges as it details our technical solutions. It also explains our designs to establish a flexible framework.

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2 Related Work

Neuropsychological assessment involves using performance-based tests to evaluate various cognitive skills, guided by established norms [12]. It's a multi-method, multi-informant, and multi-conceptual hypothesis-testing process that aims to quantify an individual's cognitive performance. While cognitive tracking tests can be used, a more extensive battery of neuropsychological tests provides the most reliable and valid assessment of an individual's cognitive status. Currently, neuropsychological test results are interpreted by statistically comparing an individual's age, education, and/or sex-adjusted standard score to a normal distribution, using normative data, to determine the probability of a cognitive deficit [18].

The neuropsychological evaluations in some cases, can even use standardized instruments to assess cognitive functions, behavior, and social-emotional functioning. The current method for evaluating a subject begins with the comprehensive assessment, that usually starts with a thorough medical record review, covering medical and psychiatric history, medications, lab results, and neuroimaging reports, along with in-depth clinical interviews. Next, a variety of neuropsychological tests are administered following their respective manuals. Finally, depending on the specific tests, scores are interpreted by comparing them to selected normative data that matches the patient's gender, age, education, and ethnicity [31].

Several software programs and databases already exist for managing neuropsychological test data. Benchmarks are also used to determine a person's normative score, derived from the mean and standard deviation of a healthy population group.

2.1 PsiNorm

PsiNorm is a free, open-source software which is available for researchers and clinicians who perform neuropsychological tests. It was designed to simplify cognitive evaluations for adults in Turkey. It incorporates commonly used standardized tests and is compatible with most operating systems. This tool significantly cuts down the time needed to calculate percentiles and norms, and also helps generate draft reports quickly. The tests included were specifically chosen from those commonly used for neuropsychological evaluation of adults in Turkey. The software calculates z-scores and their corresponding percentiles (when norms are available) or determines a score's relative position based on a threshold value [4].

2.2 ANAM

Automated Neuropsychological Assessment Metrics(ANAM) is a commercial software system designed for neurocognitive assessments and managing Traumatic Brain Injury (TBI) over time. Its cognitive performance modules evaluate speed, simple decision-making, and various memory components. ANAM's key feature is the ability to establish baseline assessment scores. This allows healthcare providers to compare subsequent ANAM test scores for individuals with suspected or confirmed TBI, helping to track recovery or identify ongoing impairment. These scores are also used to identify personnel whose performance may be impaired. This software possesses a SQL Server-based relational database and reporting system designed to store, index, and enable various reporting requirements [8].

2.3 NeurOn

Is an online platform that offers cognitive testing and data management, with a focus on clinician and researcher ownership of data. This platform allows: the use of standard existing neuropsychological and new cutting-edge cognitive tests, assessment of clients and participants cross-sectionally and over time, ensures that no identifiable information of your clients or participants is collected, and provides instant results and raw data access [23].

2.4 Databases

Although there is software for interpreting and storing neuropsychological test data, there are also databases that allow this data to be stored. For example: DANDI (Distributed Archives for Neurophysiology Data Integration) is an archive for publishing and sharing neurophysiology data; APA PsycTESTS is a database offering a vast collection of psychological tests and measures, primarily focusing on unpublished instruments and is designed to save researchers time by providing access to existing tests for previously studied constructs; Advanced Neuropsychological Diagnostics Infrastructure (ANDI) is a combination of data from multiple research groups to create a large collection of neuropsychological test scores from healthy individuals with advanced normative comparison methods that facilitate the comparison [7,1,35].

Systems for processing and storing neuropsychological test data are also being developed in Indonesia and the Netherlands [37]. Although existing software tools and databases such as PsiNorm, NeurOn, and ANAM provide useful functionalities for storing and interpreting neuropsychological test data, they are often constrained by rigid data schemas, limited test compatibility, and narrow cultural applicability. Many of these systems are designed around specific populations, which makes it difficult to incorporate new or culturally adapted tests. Inflexible structures further complicate or prevent the addition of new test data, reducing their long-term scalability and usefulness in diverse research contexts. Moreover, these tools typically lack support for real-time normative comparison using machine learning, limiting their capacity to deliver dynamic, personalized assessments. To overcome these limitations, the application presented in this work supports diverse data input, multi-study and multilingual data, and continuously trained normative modeling. This design promotes cultural diversity and analytical rigor, and it also makes managing and comparing neuropsychological tests easier and more scalable.

3 System Overview

The system presented in this work is a web-based application designed to facilitate the collection, storage, retrieval, and analysis of neuropsychological test data from multiple studies. The application's target is the researchers and clinicians that require a scalable solution for managing test score data and conducting normative comparisons across various populations. The system consists of three main components:

- **Data Upload Page -** This page enables authenticated users to upload neuropsychological test data in CSV format. The upload process requires completing essential information in both the study and researcher sections, including the study name, citation, language, publication date, researcher name, identifier, and affiliation. After the users select the tests that are going to be uploaded and their CSV file, the system requires the validation of the translated fields crucial for normative comparison, ensuring data consistency, clarity, standardization, and replicability. Users then map database fields to CSV columns, which guarantees data integrity, consistency, correct importation, and compatibility. The process also includes automated validation to ensure data consistency and proper alignment with the system's data model, giving users the choice to proceed with the upload after reviewing validation and error messages.
- **Search Interface -** The application has an interface for searching and filtering stored data. Users can perform searches based on several attributes, like: age gap, country, language, test, gender, and others. This feature en-

able researchers and clinicians to quickly access specific test data and create subsets of neuropsychological test scores for analysis or comparison.
– **Normative Comparison -** This is an important feature that allows a clinician to compare their patient's data with data from similar individuals in the system database. The result is the classification of that subject´s score, in other words, helps determine whether the subject's scores fall within expected normative ranges. The application allows users to choose attributes like the age, language, country, and educational level to be considerate in the normative comparison.

The application architecture separates the frontend, backend, and database, following a modular design that supports future scalability. The backend is developed using the Django web framework, which manages data processing, user authentication, and role-based access control through its built-in permission system. The frontend provides a simple, yet intuitive web interface for interacting with the application. All the information, such as test parameters, test, subject and researcher details, test scores, administration data, and study specifics, is stored in the PostgreSQL relational database. The data upload module includes dynamic field mapping and schema validation with user feedback, ensuring data consistency before insertion. This architecture supports an increasing volume of data from multiple studies over time. Clinicians, researchers, administrators are some of the roles presented, each one having their own set of permissions. For example, data uploads are restricted to researchers and administrators, while only administrators have the ability to create new accounts.

Overall, the application aims to improve the accessibility, organization, and interpretability of neuropsychological test data, all while supporting flexible and culturally sensitive normative analysis.

4 Database Design

The neuropsychological assessment of an individual involves a wide variety of tests, each designed with distinct objectives, structures, and execution methods. These tests differ significantly not only in the number of parameters they use but also in the type of data they measure, ranging from memory and attention to executive functions and emotional processing. Some tests may rely on just a few key indicators, while others generate large volumes of data across numerous variables. Furthermore, studies often combine multiple tests to capture a comprehensive profile of a patient's cognitive condition. Due to this high variability, rapid growth, and dynamic nature, a static database structure is insufficient. Instead, a flexible and scalable database design is essential to accommodate the diverse parameter sets and evolving requirements of neuropsychological data. There are many approaches to deal with these requirements, such as relational and NoSQL databases [37].

4.1 Relational Database

A relational database is a type of database that organizes data into tables, each with rows and columns, establishing relationships between them. The tables can be joined together via a primary key or a foreign key. These primary keys establish different relationships between the tables [13]. The system separates how data is organized logically from how it's physically stored. This means database administrators can manage the physical storage without affecting the way users see or access the data. Similarly, data manipulation operations are also distinct. To maintain accuracy and accessibility, databases enforce rules like preventing duplicate rows [25].

Advantages - This type of database has several benefits, including [13,11]:

- Creation of meaningful information by joining tables;
- Easier to use due to a vast community;
- Reduces redundancy via normalization and stored procedures;
- Easy backup in case of a disaster;
- Easier to add, change, update or delete tables, without altering the structure;
- Role-based security ensures that access to data is limited to specific users.

Disadvantages - Despite the advantages of relational databases, they also have some disadvantages, including [22,5]:

- Are designed for vertical scaling (more powerful servers) rather than horizontal scaling (more servers), which limits their effectiveness with massive datasets or high write volumes;
- Inflexibility due to their rigid schema;
- Complex joins and transactions can degrade performance in large datasets;
- Scaling relational databases can get expensive, mainly due to the cost of licenses and the need for powerful, high-end hardware to handle increased demands.

4.2 NoSQL Databases

NoSQL databases are non-relational systems built for large, diverse, unstructured data. They store all data in a single, schema-less structure, offering fast scalability and high availability through distributed, replicated storage across multiple servers. This enhances data availability and reliability, as the database remains operational even if some data sources are offline [14]. NoSQL databases are used for real-time web applications and big data due to their primary benefits: high scalability and high availability [26].

Advantages - This type of database has several benefits, like [14,26]:

- More flexible, since data can be stored in a more free-form without rigid schemes, allowing to easily handle any data format in a single data store;
- Thanks to commodity hardware, it's more scalable, capable of accommodating increased traffic to meet demand with no downtime;
- High performance, guaranteeing fast response times when traffic and data volumes increase;
- Better availability, since they automatically replicate data across multiple servers, data centers, or cloud resources. This feature also reduces the load of database management and minimizes latency for users;
- Are design to store extremely large data with minimal costs.

Disadvantages - The disadvantages of NoSQL Databases are listed below [5]:

- Lacks a universal query language like SQL, meaning each has its own, which complicates development, maintenance, and integration, and requires developers to learn new tools;
- Often prioritize availability over immediate data consistency by following the BASE model (Basically Available, Soft state, Eventual consistency). This means data might not be instantly consistent across all parts of the database, which can be a drawback for applications that require strict, real-time data accuracy.
- Some technologies are relatively new and lack the robust tooling, documentation, and community support;
- Handling complex transactions can be more challenging.

4.3 Relational Database vs NoSQL

The fundamental difference between relational and non-relational (NoSQL) databases lies in their data storage and organization methods. As previously mentioned, relational databases use a structured, rule-based approach. In contrast, NoSQL databases offer flexibility by storing data as individual units without a predefined schema. This allows them to handle frequently changing data and process diverse data types, defining the data model as needed [11] [25]. Ultimately, non-relational databases aim to solve the flexibility and scalability challenges that arise when relational models encounter unstructured data formats [13].

The choice between relational and NoSQL databases depends on the nature and scale of the data. Relational databases are suitable for applications managing fixed, manageable amounts of data. However, NoSQL databases are preferred for applications handling very large, complex data that require dynamic schema changes. They also offer faster response times for web applications and support large-scale statistical analysis [37].

Given the application's goals and the complexity, variability, and hierarchical structure of neuropsychological test data, we selected a relational database (PostgreSQL) to ensure data integrity, enforce relationships between entities, and support complex queries for normative comparisons. This decision aligns with project requirements for strong consistency, structured schema enforcement, and the need to validate and cross-reference diverse data types. The relational model also simplifies the implementation of role-based access control, the normative aggregation queries, and the validation rules, which are critical for maintaining data quality in a clinical research context.

4.4 Design

Given the vast number, diverse types, varying parameters, and inherent complexity of neuropsychological tests, we needed a specialized design that could structurally accommodate the continuous insertion of different tests. Tests are structured with one or more conditions, which then contain one or more parameters. Take the Rey-Osterrieth Complex Figure Test (RCFT), a visual memory and executive function assessment: it has four conditions: direct copy, immediate recall, delayed recall, and recognition. Within each condition, multiple parameters can exist, such as the time to completion and score for the direct copy.
To accommodate this, we created a model (as shown in the Fig. 1) where each test 'Test' is associated with multiple categories 'TestCategory' and may have several conditions 'Condition', with multiple categories 'ConditionCategory', which are linked to measurable parameters 'Parameter'. Sessions 'Session' represent timed subject assessments, and each session can involve multiple test administrations 'TestAdministration', each linked to specific tests. The results 'Result' store the outcomes of these test administrations, referencing both the administered test and the measured parameter, along with values like scores, validity indicators, and descriptive messages.
The database also includes other tables for metadata, such as 'Researcher', 'Subject', and 'Study'. This design makes our database more flexible (it handles different tests and parameters), scalable, consistent, easy to understand and implement, and includes more automated validations(thanks to the different types of relations and rules).

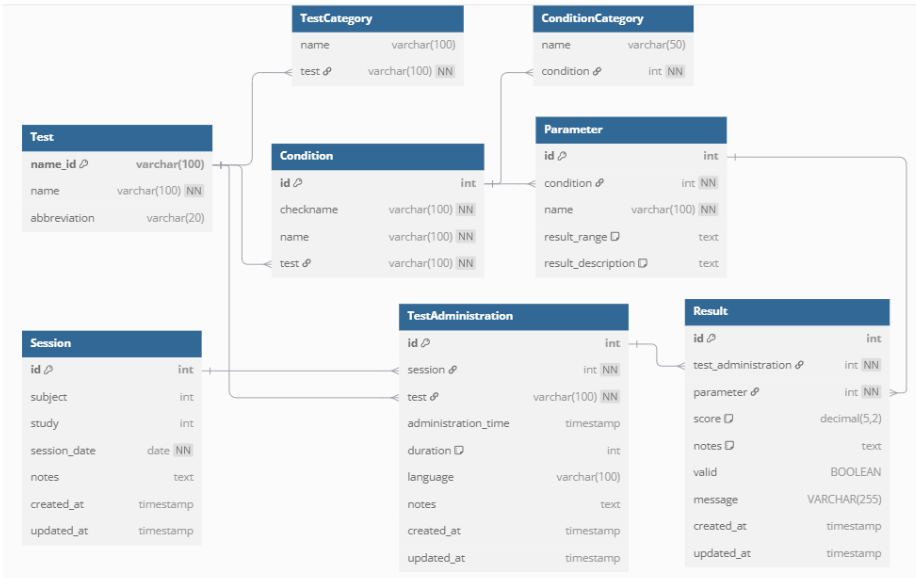

Fig. 1. Database schema design

5 Normative Comparison

As previously mentioned, normative comparison in neuropsychology involves comparing an individual's test performance to a pre-established "norm" group of healthy individuals. If an individual's performance deviates significantly from the norm group, we may then refer to it as abnormal [38]. Normative comparison helps clinicians and researchers determine if a subject's performance falls within the expected range for a defined reference group, taking into account relevant demographic and contextual factors.

Traditional normative datasets are often limited in size or diversity, making the comparison more difficult for some populations. This application performs multivariate normative comparisons, using age, language, country, gender, and education level to compare an individual's data with a population sharing those same characteristics in the existing available data. A supervised learning model within the application is continuously trained. It uses all existing subject variables in the database as input, updating each time new data is uploaded.

5.1 Solution Implementation Methodology

The comparative process begins by defining the normative sample based on selected characteristics and collecting their relevant scores. Next, we calculate descriptive statistics like the mean, standard deviation, and median. The supervised learning model then predicts test scores based on the input characteristics.

This predicted value helps calculate the standardized residual (z-score), indicating how much the subject deviates from their personal normative expectation. Finally, based on configurable thresholds, the system classifies the subject's score and presents this classification alongside various graphs.

Various regression algorithms can be used for these predictions depending on the complexity of the data and the desired interpretability. For simpler relationships, Multiple Linear Regression models linear associations between variables [28], while Polynomial Regression extends this by capturing curved trends [29]. More advanced methods can model complex, nonlinear patterns: Decision Tree Regressor splits data into branches based on feature values [9]; Random Forest Regressor combines multiple trees to improve accuracy and reduce overfitting [17]; Gradient Boosting Regressors, which build models sequentially to correct previous errors [27]. Among gradient boosting methods, CatBoost handles categorical features efficiently [24], XGBoost is optimized for speed and performance [16], and LightGBM is designed for high efficiency with large datasets [21]; and Support Vector Machines that can model complex relationships by maximizing the margin between data points and a regression line - [36] [15]. These models can be implemented using popular Python libraries such as scikit-learn, Statsmodels for statistical analysis [32], and PyMC for Bayesian approaches, offering flexibility and succinctness in statistical model implementation [30].

Considering the specifics of this problem, we plan to use LightGBM (Light Gradient Boosting Machine). We chose it because it's well-suited for large, complex datasets, offering high performance, low memory usage, and support for categorical features. Its faster training speed, higher efficiency, better accuracy, interpretability tools, and ability to handle missing data and multiple features [21] [10] [20] make it a practical and powerful choice for generating reliable normative comparisons.

In our implementation, the machine learning model receives inputs such as age, gender, country, education level, and test condition parameters. It then predicts the expected normative score using a regressor model trained on all matching records in the database. For each new subject, the standardized residual (z-score) is computed by subtracting the predicted value from the actual score and dividing by the standard deviation of the matched normative sample. The system then classifies the subject's score into categories such as "Below Norm", "Within Norm", or "Above Norm", based on configurable thresholds.

To begin evaluating the system's normative comparison functionality, we performed preliminary testing using a cleaned dataset of 269 subjects. These initial tests focused on validating the end-to-end workflow from model training to classification output, using a basic train/test split. Although the current dataset is limited in size and diversity, the implementation of the pipeline allows us to generate predicted scores and z-scores, and to classify subject performance based on configurable thresholds. While detailed performance analysis and comparison with clinician expectations are planned for future work, this early testing confirms that the core computational components are operational and ready for further validation.

6 Conclusion

This article presents the design and implementation of a web-based application destined to improve the collection, storage, and analysis of neuropsychological test data. This application addresses key challenges in neuropsychological testing, particularly the need for a flexible and scalable data structure. It also enhances normative comparisons, making them more culturally adaptable. By enabling users to securely upload study data, conduct targeted searches, and compare individual test scores against a dynamically expanding normative database, the application offers a practical and robust tool for both clinical and research purposes.

From a software engineering perspective, this project demonstrates the successful integration of dynamic data modeling, role-based secure workflows, and predictive analytics into a unified web application. Unlike existing neuropsychological tools, our system supports a modular schema capable of incorporating novel tests and parameters, while also performing multivariate normative comparisons in real time.

The database design demanded significant attention to handle a wide array of tests and parameters while maintaining consistency and analytical rigor. The application administrator can update existing tests and add new ones as needed. Due to our database choice, this also requires adding information about conditions, categories, and parameters for each test. The application's architecture supports future improvements and enhancements.

The primary development challenges revolved around database design, specifically crafting a structure that was scalable enough to manage the inherent complexity of the data.

This tool simplifies the management of complex neuropsychological data while offering meaningful normative comparisons. By facilitating broader and more inclusive data collection and analysis, the application has the potential to improve the accuracy and relevance of neuropsychological assessments across diverse populations.

Future work will focus on improving the application's web interface(frontend), in accordance with its specifications. We'll also implement the models for normative comparisons and thoroughly test their generated results. This includes validation against clinician-rated assessments to ensure the model's clinical relevance, and expanding the training dataset to improve predictive performance and generalizability. Finally, we'll thoroughly test the entire application in a real-world environment, using actual patient data and involving real users. This will simulate the normal flow of data uploads, searches, and normative comparisons. This is crucial for identifying and correcting any potential problems or bugs, ensuring a robust and error-free production.

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