AI-Rehab: A Framework for AI Driven Neurorehabilitation Training - The Profiling Challenge

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Abstract: One of the health clinic challenges is rehabilitation therapy cognitive impairment that can happen after brain injury, dementia and in normal cognitive decline due to aging. Current cognitive rehabilitation therapy has been shown to be the most effective way to address this problem. However, a) it is not adaptive for every patient, b) it has a high cost, and c) it is usually implemented in clinical environments. The Task Generator (TG) is a free tool for the generation of cognitive training tasks. However, TG is not designed to adapt and monitor the cognitive progress of the patient. Hence, we propose in the BRaNT project an enhancement of TG with belief revision and machine learning techniques, gamification and remote monitoring capabilities to enable health professionals to provide a long-term personalized cognitive rehabilitation therapy at home. The BRaNT is an interdisciplinary effort that addresses scientific limitations of current practices as well as provides solutions towards the sustainability of health systems and contributes towards the improvement of quality of life of patients. This paper proposes the AI-Rehab framework for the BRaNT, explains profiling challenge in the situation of insufficient data and presents an alternate AI solutions which might be applicable once enough data is available.

1 INTRODUCTION

Cognitive deficits are common after brain injury, dementia and normally due to aging. These impact the performance of activities of daily living and limit people's independence, with a high monetary and societal cost. Moreover, many cognitive rehabilitation tools lack flexibility to be adapted to each patient needs. Cognitive rehabilitation has been shown to be the most effective way to address this problem. However, current rehabilitation has some limitations:

- Rehabilitation tools are not adaptive and may not be adequate for every patient. Hence, a sub-optimal set of exercises limits the impact of rehabilitation and reduces engagement in rehabilitation;
- Interventions are time consuming and have a high cost, and are usually implemented in clinical environments. Thus, the lack of monetary and human resources prevent public health systems to implement ideal long-term rehabilitation.

Neuropsychological assessments (NPAs) are useful instruments to evaluate cognitive skills. However, current cognitive interventions are sub-optimal in terms of lack of adaptability according to the NPAs results (Williams and Sims, 2000; Parsons, 2015). Besides, the tools are not flexible enough to cover the needs of all patients and traditional therapy has a high cost both on human and monetary resources (Solana et al., 2014). Here we propose bridging NPAs and computational modelling to deliver a highly personalized tool that allows for the creation of interventions through Information and Communication Technologies (ICT). A tool that could generate validated cognitive training tasks, parameterized per patients needs, which intelligently adjusts difficulty over time, monitors changes and communicates with the patient's healthcare team. We start by creating an extension and enhancement of an existing tool, the Task Generator (TG[1]) (Faria and Bermúdez i Badia, 2015), to

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generate the appropriate cognitive training tasks using the patient profile as an input. The TG is a free web based tool for the procedural generation of cognitive training tasks. TG tasks are parametrized in terms of training difficulty and cognitive demands, but are not designed to monitor the evolution of the patient, which is essential to adjust training for the patient's evolution. In the BRaNT project, we are developing an extension of TG with extended and improved training content. This project uses two artificial intelligence modules (based on belief revision and machine learning techniques), gamification and remote monitoring capabilities to enable Health Professionals (HP) to provide long-term personalized cognitive rehabilitation therapy at home. AI-Rehab is the framework behind the personalization and adaptation of training, and relies on the results of validated NPA used to evaluate patient and create a computational Cognitive Profile (CP) of the patient. By comparing this profile with the Normative Data (ND) accordingly to the Socio-Demographic Information (SDI) of the patient, we infer the patient's Cognitive Status (CS). After this, the HP can decide on a set of training tasks for that patient. The patient trains at home and the performance is communicated to Belief Revision Engine (BR-E), which assesses evolution of the patient and manages task personalization over time. The proposed system will be able to contact the HP if something unexpected happens. This framework tackles three important Artificial Intelligence (AI) challenges: patient profiling, task selection and parameterization, and adaptive training. In this paper we propose a solution for the patient profiling challenge. In the Section 2, we review some literature about assessment of cognitive impairment and AI in cognitive rehabilitation field whereas, Section 3 gives detailed explanation on each step of proposed AI-Rehab framework. Section 4 describes the patient's profiling challenge and finally, its AI solution is reported in the Section 4.1, including task setting and iterative training.

2 STATE OF THE ART

Cognitive impairments following brain injury are common, and are present in approximately 70% of patients in the acute stages of recovery (Morris et al., 2012), causing problems in activities of daily life and social participation. Stroke commonly includes focal disorders such as aphasia and neglect, and more diffuse abnormalities such as slowed information processing and executive dysfunction (Cumming et al., 2013). Cognitive rehabilitation is designed to restore, substitute, or compensate for the lost of cognitive abilities, and is the treatment of choice for these deficits (Bott and Kramer, 2017). The American Congress of Rehabilitation Medicine conducted systematic reviews on a total of 370 cognitive rehabilitation studies for people with acquired brain injury, published from 1971-2008 (Cicerone et al., 2000; Cicerone et al., 2005; Cicerone et al., 2011). Cognitive rehabilitation was shown to be of greater benefit than conventional rehabilitation in 94.1% of the studies. Thus, cognitive rehabilitation is the best available form of treatment for people with neurocognitive impairment (Cicerone et al., 2011). Unfortunately, the efficacy of cognitive training highly depends on the intensity of treatment over an extended period of time. The traditional intervention model is very time consuming for teams to manage personalized rehabilitation programs; patients move to the clinical center, making the duration of the treatment conditional to patient's availability; interventions are subject to the availability of vacancies and transportation (Solana et al., 2014). This results in a very high cost, compromising sustainability, accessibility and scalability, resulting in a large economic burden to both the health system and families (Carod-Artal et al., 2000).

The ICT based solutions such as gaming, virtual reality or computer simulations have been shown to have an enormous potential for enhancing cognitive rehabilitation by supporting the ability to carry out controlled and highly adaptive valid tasks (Bermúdez i Badia et al., 2016). Over the past few years, several computer based solutions have been proposed to increase the availability and quality of cognitive training, flooding the marketplace with commercial brain exercise programs that claim to improve cognition and have diagnostic abilities (George and Whitehouse, 2011) such as the CogWeb and the Guttmann Neuro Personal Trainer. Through these platforms it is possible to deliver a training program to a patient, analyze results and transfer them to the Hospital Information System. Nevertheless, none of these tools addresses multiple domains of cognitive functioning in a systematic and quantitative manner relying on validated NPAs.

2.1 Assessment of Cognitive Impairment

The Montreal Cognitive Assessment (MoCA) (Nasreddine et al., 2005) is a well-known test which is the recommended instrument in Portugal for global cognitive screening measurement. It addresses (i) short-term memory, (ii) executive functions, (iii) visuospatial abilities, (iv) language, (v) attention,

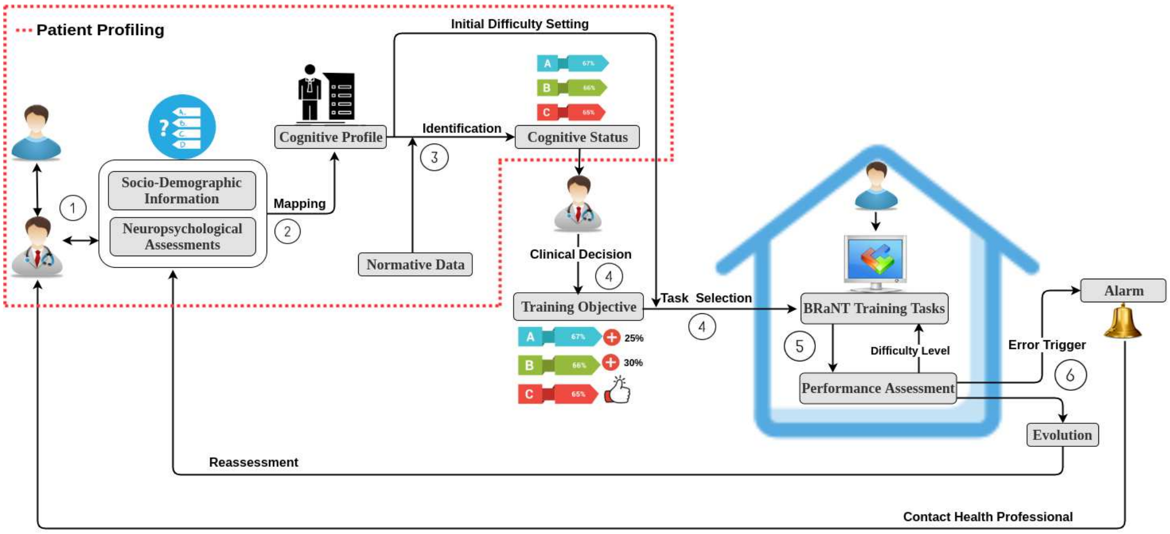

Figure 1: The AI-Rehab framework for the BRaNT project.

concentration and working memory and (vi) temporal and spatial orientation (Freitas et al., 2012c). MoCA has been the subject of systematic research within the Portuguese population and validation studies were conducted on specific clinical groups like Mild Cognitive Impairment and Alzheimer's Disease (Freitas et al., 2013), Frontotemporal Dementia (Freitas et al., 2012a), Vascular Dementia (Freitas et al., 2012b) and Multiple Sclerosis (Freitas et al., 2018). Many studies emphasize the psychometric characteristics of the test (e.g. (Freitas et al., 2012c; Freitas et al., 2015; Freitas et al., 2014), with norms for Portuguese population (Freitas et al., 2011). Unfortunately, as a screening instrument it can detect deficits but not quantify them accurately. That can only be achieved with domain specific NPAs. There are some NPAs such as Free and Cued Selective Reminding Test, Semantic and phonemic verbal fluency, Rey-Osterrieth Complex Figure Test, clinical evaluation of dementia, etc. The AI-Rehab is designed to receive information from any NPA.

2.2 Artificial Intelligence in Cognitive Rehabilitation

This section review the list of pilot studies of AI for cognitive impairment and rehab. AI aims to bring high precision in healthcare by employing computational intelligence in clinical tasks. Nowadays, the most popular ML algorithms for structured data are support vector machine, neural network (NN) and deep learning (DL) whereas for unstructured data is natural language processing (Jiang et al., 2017). Several statistical learning (Hastie et al., 2009), ML classification (Fernández-Delgado et al., 2014) and regression (Fernández-Delgado et al., 2018) and DL techniques (LeCun et al., 2015) are available, by using them a few AI models are developed and these really contribute for advancement of cognitive field. For instance, the study (Chi et al., 2017) developed personalized long-term and follow-up models to predict CS. First is sequential estimation of risk factors to predict how cognition will change over long time and second is observation of time-varying risk factors. Likewise, (Ko et al., 2019) developed adaptive Least Absolute Shrinkage and Selection Operator (LASSO) model to identify significant predictors of multivariate NPAs and demographic variables for prediction of cerebral amyloid beta abnormal level of status. Memory dysfunction is a crucial cognitive factor for early detection of disease and one of the instruments to calculate it is M-CRT. The binary classification (Bergeron et al., 2019) of cognitive health status (healthy or unhealthy) and health related question (yes or no) is modelled logistic regression using demographic data and M-CRT test score.

Belief revision systems are logical frameworks for modelling how agents modify their beliefs when they receive new information (sometimes inconsistent with the previous beliefs) [2]. To integrate the new information, the agent will have to give up some information while preserving as much of the old information as possible. The AGM-framework (Alchourrón et al., 1985) is the most popular framework to guide the change of belief. The AGM model has acquired the status of a standard model (for an overview,

[2]For the sake of simplicity, we will assume that beliefs, knowledge and data have the same status

see (Fermé and Hansson, 2011; Fermé and Hansson, 2018)). Several algorithms for the implementation of belief change operations were proposed. Most of them were constructed to recognize which beliefs are supported and how, and to perform changes while minimizing the number of sentences to be changed, thus preserving the maximum amount of the previous knowledge. Implementation also include proposals by (Katsuno and Mendelzon, 1991; Williams and Sims, 2000; Delgrande and Schaub, 2003; Peppas and Williams, 2016). Katsuno and Mendelzon (Katsuno and Mendelzon, 1991) also focused a lot of their paper on trying to define a notion of distance between Knowledge Bases. This will be useful later when comparing the CP at different stages. A core aspect in implementation is the space and time required for computation. Jin and Thielscher proposed Reinforcement Belief Revision that combines two desiderata for belief change implementations: It satisfies the standard rationality postulates, and the time and space required for its implementation can be assessed. Recently, new studies of implementation belief revision by Horn Clauses have been initiated (Booth et al., 2010; Delgrande, 2008; Delgrande and Wassermann, 2010). Pagnucco (Pagnucco, 2006) and (Zhuang et al., 2007) formalised a way of implementing AGM operations using a knowledge compilation technique involving prime implicates in order to improve computational efficiency. The study (Schwind et al., 2019) has proposed a change formula, that given two know bases (or the same knowledge base at different times) it is possible to determine what caused the change in the belief set. Belief Revision is still a relative new area of investigation and there are not many examples we can draw from, so we hope to contribute on this area.

3 FRAMEWORK

The BRaNT project is an interdisciplinary effort to create a new set of ICT for rehabilitation at home. For this project, we propose the AI-Rehab framework, which includes the steps shown in Figure 1. There are clearly three distinct challenges in the framework. First and foremost we need to find an optimal way to consolidate whole data from all the different NPAs into a consistent profile, that should be easily interpreted by HP. This is the Profiling Challenge. The second challenge refers to the task selection and settings definition. How will the system guarantee that the tasks are always optimally configured for a particular patient's profile? To achieve this, we will create a Belief Revision Engine (BR-E) to generate a predictable profile given a set of difficulty and follow the flow theory to keep the patient always engaged with the training task in hand (Nakamura and Csikszentmihalyi, 2009). Finally, the third challenge is the adaptive training at home. The goal of this challenge is to keep adapting the predicted profile and the game settings to keep the patient in flow, all at the comfort of his home, without updated NPAs data. The process of the AI-Rehab framework (Figure 1) can be explained as follows:

1. HPs use validated NPAs to assess the patient;
2. The result of NPAs data are then injected in a database and mapped to values by applying equation 1 from section 4.1, which creates a normalized patient's CP where each factor (or cognitive domain) is normalized from 0 to 100%;
3. Once the CP is created, it is compared with Normative Data (ND) to define the CS, so called $Identification$, and for that it is necessary to incorporate new information of the patient (SDI) along with ND;
4. The HP can then interpret the CS and specify training objectives (For instance, A, B and C with their percentages, shown in the Figure 1) for that particular profile, where the set of number of parameters of the training tasks are suggested. Simultaneously, the initial difficulty of the training is set based on the CP. At this time the BR-E tries to predict the expected results of the training task (ERTT);
5. The patient performs a gamified training task at home and performance is communicated to the BR-E. This compares the results of training with ERTT and identifies:
   (a) If patient performance is in the accordance to expectation,
   (b) Data shows patient evolution or involution, the patient profile is updated and a new difficulty is set,
   (c) Statistically unlikely change or inconsistent data is detected, and the HP is contacted to reassess the situation and train BR-E.
6. Finally, the HP will do a new NPA reassessment, after intervention is completed to quantify the impact of cognitive training with AI-Rehab and decide if more therapy is required.

Hence, we aim at combining the advantages of ICT with a participatory design approach involving health professionals (such as rehabilitation physicians, therapists and neuropsychologists) to develop a novel portable tool for the generation of cognitive rehabilitation training for the home use (Paulino et al., 2018;

Paulino et al., 2019). This tool will be a free and worldwide accessible for clinicians, able to generate patient's profile and personalized cognitive rehabilitation programs in digital form instead of paper-and-pencil format. It will be composed by a set of standardized rehabilitation tasks gathered from clinical settings and parameterized through a participatory design approach and will be able to procedurally generate a large number of tasks by specifying the values of their intrinsic parameters. It addresses the following task types as described below (Faria et al., 2018):

- Knowledge: Memory of Stories; Cancellation; Questions of General Knowledge; Find Locations; Image Pairs.
- Comprehension: Differences between Similar Scenarios; Categorization; Synonymous and Antonyms; Association.
- Application: Mazes; Problem Resolution; Tangram; Numeric Sequences; Navigation.
- Analysis: Action Sequencing; Visual Memory; Puzzles; Word Search.
- Evaluation: Differentiation between Coherent and Incoherent situations; Comprehension of Contexts.

These tasks will be implemented in an interactive digital environment, shaped as tasks through a gamification approach to deliver an immediate feedback and reinforcement on progress (Wilson and McDonagh, 2013), which is an important element to increase the motivation and avoid dropouts. Besides, adaptive training is the last challenge of the AI-Rehab framework. After each iteration of the task training, the BR-E will calculate a new temporary profile and cognitive situation. These will be compared with the ERTT calculated before to see if any adjustment needs to be done. The authors (Katsuno and Mendelzon, 1991) defined on their paper several operators that can be used to calculate the differences between knowledge bases. With this difference calculated, we can determine how that patient evolved during the previous iteration and we are able to use this information to adjust the parameters of the task. In this paper we will only focus on the computational patient profiling.

4 PATIENT PROFILING CHALLENGE

This step starts with the task of specification the relevant NPAs for a comprehensive evaluation of cognition. Screening tests are brief assessment triage tools to identify patients cognitively at-risk that require a fuller evaluation. Based on information from the clinical process, which includes medical data, interview data and scores on cognitive screening tests (such as MoCA), the patient examined may be referred for a more comprehensive NPA aimed at rehabilitation objectives. The NPA, instead, is a standard part of integrated medical and psychological care, and is a necessary step to implement and further evaluate rehabilitation procedures. The NPA has several objectives, namely: (i) to identify and characterize cognitive abilities and activities of daily life, personality, emotional functioning and behaviours of the person and to define changes in these domains in comparison to the level of premorbid functioning; (ii) to document and quantify the nature and severity of cognitive and functional deficits, symptoms and signs present, potentially associated with pathology, in the context of examining the structural and functional integrity of brain functioning, differentiating what is the associated decline to the normal aging and deficits associated with cerebral dysfunction / neurodegenerative pathology; (iii) to define a baseline in various domains of the cognitive, emotional and behavioural functioning, which can be examined in a longitudinal register, through repeated evaluations, thus enabling monitoring of the clinical evolution of the person, recovery of functions, response to the intervention (e.g., rehabilitation, psychotherapy, pharmacological) or the progression of the disease; (iv) to identify personal resources and preserved functions that are equally useful for planning and implementing rehabilitative / therapeutic and preventive intervention procedures, as well as evaluating their effectiveness, with the aim of promoting the person's well-being and quality of life. Further step is devoted to the factorization of the outcome of these assessments and translation to a formal language that allows creating automatically (by artificial intelligence techniques) a profile of the patient that can be used for defining a neurorehabilitation therapy. This will give us the CP, shown in the Figure 1. The $Identification$ part is more complicated. We need to create a CS using the ND and the SDI, in order to interpret how a particular patient CP compares to the ND. This will produce the CS in the Figure 1, which represents, in percentage, where the CP is located compared to the rest of the population with similar SDI. Hence, facilitating the interpretation of the data by the HP.

4.1 Proposed Solution

This section reports on the AI solutions for AI-Rehab framework. First and the most important challenge is patient profiling. Then we need to solve the task setting and iterative training challenge, which will not be tackled in this paper. Here, we propose some techniques without applying them on data which can be useful to automatize the neurorehabilitation system. The second step in AI-Rehab framework from Section 3 is to map NPAs values to a consolidated CP into the interval 0 to 100 and the equation 1 is used for the *Mapping*. Note that it is formulated owing to no data.

$$CP_k = \sum_{i=1}^{n}\sum_{j=1}^{m} Norm(NPA_iF_j).W_{kij} \tag{1}$$

Where,

$$W_{kij} = \begin{cases} 1/p, & \text{where } p \text{ is count of factors,} \\ & \text{contributing to } CP_k \\ 0, & \text{otherwise} \end{cases}$$

NPA_iF_j = factor from a neuropsychological assessment
CP_k= cognitive domain K from CP
Norm= normalization function, interval is 0 and 100
W_{kij}= weight function, interval is 0 to 1, which sums to 1
m= number of times a F appeared in NPAs
n= number of NPAs

The way this formula works is that we take every factor j from each NPA i (lets say, memory from MOCA for instance) and multiply by the weight that factor has on determining that specific cognitive domain (memory in this example). At the start, we will inquire HPs to provide us with weights for each factor, as it seems a better solution to follow the professionals intuition than to attribute arbitrary weights. Once we have enough data, we can start using AI algorithms to determine the weights which we have explained at the end of this section. The weight W should belong in the interval of 0 to 1. Given that, the '*Norm*' function will give us a value between 0 and 100 and the sum of the weights is 1, the output CP_k will be a value between 0 and 100, corresponding to the weighted factor of the CP (in this example, memory). This is the *Mapping* process from the Figure 1. Finally, the CP_k is the aggregated result of a battery of tests, instead of only one test, and CP is a set of cognitive domain k.

The final step is to contextualize this profile. If we interpret the CP using the ND from all the NPAs taking into account the patient SDI, we will get a standardized cognitive profile. This process will generate a profile that is compared to the population data. This is the step which is needed for the identification of deficits and the outcome of this is CS. Once again, these process will be improved as we get actual data from patients using the system.

$$SCP_k = \frac{\sum_{i=1}^{n} Norm(ND_i, SDI)}{n} \tag{2}$$

SDI= patient's socio-demographic information
ND= normative data of k for each NPA used to calculate *CP*
SCP_k= standardized cognitive profile K from ND and SDI
Norm= normalization function, interval is 0 and 100
n= number of NPAs

First, it is important to mention that we do not have access to the normative value for the factors of each NPA, we just have it for the result of the whole NPAs. Also, since it is normative data, there is no need to consider weights as it is already embedded in the ND value itself. The value represented by the ND and SDI pair is the average result of someone in the closest socio-demographic group as the patient, since the SDI is relative to her/him. This can be observed for MoCA in (Freitas et al., 2018) for the Portuguese population. For simplicity, lets consider only MoCA and memory for an example. The result of this formula would be the average of someone with a similar SDI as the patient. By doing a simple cross multiplication between the CP memory score and the result of this function, we can get a relative value of the patient when compared with the ND. This value would be, in this example, the memory domain in the CS of the patient, where 50% means that you are as good as it is expected for you group, 75% means you are 25% above average or 100% means you are twice as good as expected. Eventually, we will have collected patient's CS with all the factors so HP can interpret them and take clinical decision with ease. Eventually, it gives solution for profiling challenge without data.

$$CP_k = \sum_{i=1}^{n}\sum_{j=1}^{m} Norm(NPA_iF_j).W_{kij} \tag{3}$$

Where, W_{kij} belongs to (0≤W≤1) and $\sum_{i=1}^{n} W_{kij} = 1$ which is being determined by some AI techniques.

Once we get enough data, we can have AI solution for the W problem, appeared in the equation 1. The equation 3 is a proposal solution for the weights computation. Some statistical learning, ML or DL techniques will apply on NPAs data to obtain highly optimal W in the *Mapping* process, such as Principal Component Analysis, random forest or neural network. Besides, if the number of F and *NPA* grow over time then the system performance may decline and the data will suffer with high dimentionality. To overcome such problem, feature selection techniques like Principal Component Analysis, LASSO, Ridge or t-Distributed Stochastic Neighbor Embedding can be used. These techniques generate highly influential parameters without loosing much information. Subsequently, the next step is to create the Belief Revision Engine (BR-E), a computational infrastructure based on the Believe Revision that will enable the accurate prediction of CPs for patients, over the iterative training process. The BR-E has three objectives:

1. At each iteration, register the difference between the ERTT and the real result;
2. At each iteration, check for inconsistencies;
3. End finally, once the who training is completed, after n iterations, it will compare the n^{th} predicted profile with the new real profile after the NPA reassessment.

The first point will allow us the tweak the difficulty of the settings, with the goal of keep the patient in flow (Nakamura and Csikszentmihalyi, 2009). It has been proven that people at this level of concentration and immersion are at their most effective, which will lead to better rehabilitation results. If after each iteration, the new predicted profile is inconsistent, by any reason, then an alarm must be risen and the HP must be contact to evaluate the situation. Finally, once the patient has completed the trained and has been re-evaluated, we can compare the n^{th} predicted result with the new real result. This will allow us the evaluate the performance of the system and to see if it is performing as we want. The study (Schwind et al., 2019) can help us to understand where the system predicted wrong, given the final result. Once all is done, the loop restart until the HP decides that no more therapy is necessary.

5 CONCLUSION

The BRaNT project goal is the development of a novel cognitive rehabilitation tool to allow the health professional the monitoring and adaptation of treatment at home. To do this, we propose the usage of Artificial Intelligence (AI) to improve the existing TG tool. BRaNT proposes the usage of machine learning, deep learning and believe revision framework is able to assess the patient's deficits through the usage of the results battery of validated NPAs, generate gamified cognitive training tasks adjusted to each patient profile, and support the continuum of healthcare from the clinic to the home with a distributed architecture with remote monitoring capabilities. Consequently, this paper proposes the AI-Rehab framework for AI driven neurorehabilitation training and identifies three challenges: patient's cognitive profile, task settings and iterative training. The present work only focuses on profiling challenge and proposes a solution for $Mapping$ and $Identification$ process. Once we have enough data, we will apply machine learning algorithms. As for the BR techniques, (Katsuno and Mendelzon, 1991) research will be crucial to measure the distance between the several profiles gathered during the process and (Schwind et al., 2019) work will help us understand what actually changed and what needs to be adapted for the next training loop. Presently, the framework targets only cognitive domains. However, in future, it can easily be extended to cognitive sub domains or to other domains such as fitness.

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REFERENCES

Alchourrón, C. E., Gärdenfors, P., and Makinson, D. (1985). On the logic of theory change: Partial meet contraction and revision functions. *The journal of symbolic logic*, 50(2):510–530.

Bergeron, M. F., Landset, S., Tarpin-Bernard, F., Ashford, C. B., Khoshgoftaar, T. M., and Ashford, J. W. (2019). Episodic-memory performance in machine learning modeling for predicting cognitive health status classification. *Journal of Alzheimer's Disease*, 70(1):277–286.

Bermúdez i Badia, S., Fluet, G. G., Llorens, R., and Deutsch, J. E. (2016). Virtual reality for sensorimotor rehabilitation post stroke: Design principles and evidence. In *Neurorehabilitation technology*, pages 573–603. Springer.

Booth, R., Meyer, T., Varzinczak, I., and Wassermann, R. (2010). Contraction core for horn belief change: preliminary report. Unpublished manuscript.

Bott, N. T. and Kramer, A. (2017). Cognitive rehabilitation. *Encyclopedia of Geropsychology*, pages 544–551.

Carod-Artal, J., Egido, J. A., González, J. L., and Varela de Seijas, E. (2000). Quality of life among stroke survivors evaluated 1 year after stroke: experience of a stroke unit. *Stroke*, 31(12):2995–3000.

Chi, C.-L., Zeng, W., Oh, W., Borson, S., Lenskaia, T., Shen, X., and Tonellato, P. J. (2017). Personalized long-term prediction of cognitive function: Using sequential assessments to improve model performance. *Journal of biomedical informatics*, 76:78–86.

Cicerone, K. D., Dahlberg, C., Kalmar, K., Langenbahn, D. M., Malec, J. F., Bergquist, T. F., Felicetti, T., Giacino, J. T., Harley, J. P., Harrington, D. E., et al. (2000). Evidence-based cognitive rehabilitation: recommendations for clinical practice. *Archives of physical medicine and rehabilitation*, 81(12):1596–1615.

Cicerone, K. D., Dahlberg, C., Malec, J. F., Langenbahn, D. M., Felicetti, T., Kneipp, S., Ellmo, W., Kalmar, K., Giacino, J. T., Harley, J. P., et al. (2005). Evidence-based cognitive rehabilitation: updated review of the literature from 1998 through 2002. *Archives of physical medicine and rehabilitation*, 86(8):1681–1692.

Cicerone, K. D., Langenbahn, D. M., Braden, C., Malec, J. F., Kalmar, K., Fraas, M., Felicetti, T., Laatsch, L., Harley, J. P., Bergquist, T., et al. (2011). Evidence-based cognitive rehabilitation: updated review of the literature from 2003 through 2008. *Archives of physical medicine and rehabilitation*, 92(4):519–530.

Cumming, T. B., Marshall, R. S., and Lazar, R. M. (2013). Stroke, cognitive deficits, and rehabilitation: still an incomplete picture. *International Journal of stroke*, 8(1):38–45.

Delgrande, J. and Wassermann, R. (2010). Horn clause contraction functions: Belief set and belief base approaches. In *Twelfth International Conference on the Principles of Knowledge Representation and Reasoning*.

Delgrande, J. P. (2008). Horn clause belief change: Contraction functions. In *KR*, pages 156–165.

Delgrande, J. P. and Schaub, T. (2003). A consistency-based approach for belief change. *Artificial Intelligence*, 151(1-2):1–41.

Faria, A. L. and Bermúdez i Badia, S. (2015). Development and evaluation of a web-based cognitive task generator for personalized cognitive training: a proof of concept study with stroke patients. In *Proceedings of the 3rd 2015 Workshop on ICTs for improving Patients Rehabilitation Research Techniques*, pages 1–4. ACM.

Faria, A. L., Pinho, M. S., and Bermúdez i Badia, S. (2018). Capturing expert knowledge for the personalization of cognitive rehabilitation: Study combining computational modeling and a participatory design strategy. *JMIR rehabilitation and assistive technologies*, 5(2):e10714.

Fermé, E. and Hansson, S. O. (2011). Agm 25 years. *Journal of Philosophical Logic*, 40(2):295–331.

Fermé, E. and Hansson, S. O. (2018). *Belief Change: Introduction and Overview*. Springer.

Fernández-Delgado, M., Cernadas, E., Barro, S., and Amorim, D. (2014). Do we need hundreds of classifiers to solve real world classification problems? *The Journal of Machine Learning Research*, 15(1):3133–3181.

Fernández-Delgado, M., Sirsat, M., Cernadas, E., Alawadi, S., Barro, S., and Febrero-Bande, M. (2018). An extensive experimental survey of regression methods. *Neural Networks*.

Freitas, S., Batista, S., Afonso, A. C., Simões, M. R., de Sousa, L., Cunha, L., and Santana, I. (2018). The montreal cognitive assessment (moca) as a screening test for cognitive dysfunction in multiple sclerosis. *Applied Neuropsychology: Adult*, 25(1):57–70.

Freitas, S., Prieto, G., Simões, M. R., and Santana, I. (2014). Psychometric properties of the montreal cognitive assessment (moca): an analysis using the rasch model. *The Clinical Neuropsychologist*, 28(1):65–83.

Freitas, S., Prieto, G., Simões, M. R., and Santana, I. (2015). Scaling cognitive domains of the montreal cognitive assessment: an analysis using the partial credit model. *Archives of Clinical Neuropsychology*, 30(5):435–447.

Freitas, S., Simões, M. R., Alves, L., Duro, D., and Santana, I. (2012a). Montreal cognitive assessment (moca): validation study for frontotemporal dementia. *Journal of Geriatric Psychiatry and Neurology*, 25(3):146–154.

Freitas, S., Simões, M. R., Alves, L., and Santana, I. (2011). Montreal cognitive assessment (moca): normative study for the portuguese population. *Journal of clinical and experimental neuropsychology*, 33(9):989–996.

Freitas, S., Simões, M. R., Alves, L., and Santana, I. (2013). Montreal cognitive assessment: validation study for mild cognitive impairment and alzheimer disease. *Alzheimer Disease & Associated Disorders*, 27(1):37–43.

Freitas, S., Simoes, M. R., Alves, L., Vicente, M., and Santana, I. (2012b). Montreal cognitive assessment (moca): validation study for vascular dementia. *Journal of the International Neuropsychological Society*, 18(6):1031–1040.

Freitas, S., Simoes, M. R., Marôco, J., Alves, L., and Santana, I. (2012c). Construct validity of the montreal cognitive assessment (moca). *Journal of the International Neuropsychological Society*, 18(2):242–250.

George, D. R. and Whitehouse, P. J. (2011). Marketplace of memory: what the brain fitness technology industry says about us and how we can do better. *The Gerontologist*, 51(5):590–596.

Hastie, T., Tibshirani, R., and Friedman, J. (2009). *The elements of statistical learning: data mining, inference, and prediction*. Springer Science & Business Media.

Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., Wang, Y., Dong, Q., Shen, H., and Wang, Y. (2017). Artificial intelligence in healthcare: past, present and future. *Stroke and vascular neurology*, 2(4):230–243.

Katsuno, H. and Mendelzon, A. O. (1991). Propositional knowledge base revision and minimal change. *Artificial Intelligence*, 52(3):263–294.

Ko, H., Ihm, J.-J., Kim, H.-G., Initiative, A. D. N., et al. (2019). Cognitive profiling related to cerebral amyloid beta burden using machine learning approaches. *Frontiers in aging neuroscience*, 11.

LeCun, Y., Bengio, Y., and Hinton, G. (2015). Deep learning. *nature*, 521(7553):436–444.

Morris, K., Hacker, V., and Lincoln, N. B. (2012). The validity of the addenbrooke's cognitive examination-revised (ace-r) in acute stroke. *Disability and rehabilitation*, 34(3):189–195.

Nakamura, J. and Csikszentmihalyi, M. (2009). Flow theory and research. *Handbook of positive psychology*, pages 195–206.

Nasreddine, Z. S., Phillips, N. A., Bédirian, V., Charbonneau, S., Whitehead, V., Collin, I., Cummings, J. L., and Chertkow, H. (2005). The montreal cognitive assessment, moca: a brief screening tool for mild cognitive impairment. *Journal of the American Geriatrics Society*, 53(4):695–699.

Pagnucco, M. (2006). Knowledge compilation for belief change. In *Australasian Joint Conference on Artificial Intelligence*, pages 90–99. Springer.

Parsons, T. D. (2015). Ecological validity in virtual reality-based neuropsychological assessment. In *Encyclopedia of Information Science and Technology, Third Edition*, pages 1006–1015. IGI Global.

Paulino, T., i Badia, S. B., and Cameirão, M. (2019). Usability evaluation of an integrative exergaming system for the senior population. In *2019 5th Experiment International Conference (exp. at'19)*, pages 286–291. IEEE.

Paulino, T., Muñoz, J., Bermúdez i Badia, S., and Cameirão, M. S. (2018). Design of an integrative system for configurable exergames targeting the senior population. In *International Conference on Human Systems Engineering and Design: Future Trends and Applications*, pages 287–292. Springer.

Peppas, P. and Williams, M.-A. (2016). Kinetic consistency and relevance in belief revision. In *European Conference on Logics in Artificial Intelligence*, pages 401–414. Springer.

Schwind, N., Inoue, K., Konieczny, S., Lagniez, J.-M., and Marquis, P. (2019). What has been said? identifying the change formula in a belief revision scenario. In *Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, IJCAI-19*, pages 1865–1871. International Joint Conferences on Artificial Intelligence Organization.

Solana, J., Cáceres, C., García-Molina, A., Opisso, E., Roig, T., Tormos, J. M., and Gómez, E. J. (2014). Improving brain injury cognitive rehabilitation by personalized telerehabilitation services: Guttmann neuropersonal trainer. *IEEE journal of biomedical and health informatics*, 19(1):124–131.

Williams, M.-A. and Sims, A. (2000). Saten: An object-oriented web-based revision and extraction engine. *arXiv preprint cs/0003059*.

Wilson, A. and McDonagh, J. (2013). Application of the principles of gamification to facilitate acquisition of self-management skills in young people with long-term medical conditions. In *European Conference on Games Based Learning*, page 579. Academic Conferences International Limited.

Zhuang, Z. Q., Pagnucco, M., and Meyer, T. (2007). Implementing iterated belief change via prime implicates. In *Australasian Joint Conference on Artificial Intelligence*, pages 507–518. Springer.