Towards Human-Centric Psychomotor Recommender Systems

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ABSTRACT

Recommender Systems have been developed for years to guide the interaction of the users with systems in very diverse domains where information overload exists aimed to help humans in decision making. In order to better support the humans, the more the system knows about the user, the more useful recommendations the user can receive. In this sense, there is a need to explore which are the intrinsic human aspects that should be taken into account in each case when building the user models that provide the personalization. Moreover, there is a need to define and apply methodologies, guidelines and frameworks to develop this kind of systems in order to tackle the challenges of current artificial intelligence applications including issues such as ethics, transparency, explainability and sustainability. For our research, we have chosen the psychomotor domain. To provide some insights into this problem, in this paper we present the research directions we are exploring to apply a human-centric approach when developing the iBAID (intelligent Basket AID) psychomotor system, which aims to recommend the physical activities and movements to perform when training in basketball, either to improve the technique, to recover from an injury or even to keep active when getting older.

CCS CONCEPTS

• **Human-centered computing**; • **Computing methodologies** → **Artificial intelligence**; **Machine learning**;

KEYWORDS

recommender systems, psychomotor intelligent systems, human-centric systems, hybrid artificial intelligence

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1 INTRODUCTION

Recommender systems have been developed for years to guide the interaction of the users with systems in very diverse domains where information overload exists [4] aimed to help in **decision making** [18]. Their approach consists in suggesting items or actions based on information collected from the users [24]. To provide the required personalization, user models are built which typically maintain information regarding characteristics such as experience, knowledge, interests, context, etc. However, there are other characteristics more intrinsic to the user that are usually not taken into account and which depend on the application domain of the recommender system. In order to better support the humans, the more the system knows about the user, the more useful recommendations the user can receive.

In this sense, there is a need to explore which are the intrinsic human aspects that should be taken into account in each case when building the user models that provide the personalization. To explore which other relevant human aspects might improve the user experience in recommender systems, we have focused our research on the **psychomotor domain**. This domain has several particularities of interest for our research. First, psychomotor learning deals with many dimensions that have a strong impact on the user such as physical rehabilitation, keeping active when getting older, improving the movement performance in varied situations (novice trying to learn the technique, amateur with experience aimed to improve it, professional looking for the excellence) at the same time that injuries are avoided. In particular, recommender systems have already been explored to select rehabilitation exercises to motivate, engage and increase patients' adherence to their treatment with a recommender system of exergames for rehabilitation [15]. In this context, we have also explored the requirements to build an exergame to prevent frailty in adults [26] which resulted in the FRAGILESS system [25].

In addition, recommendations provided in this domain are expected to support the **acquisition and improvement of motor skills**, thus, going beyond just taking into account user preferences as in other domains such as entertainment. In fact, recommender systems in the educational domain in general are expected to take into account the pedagogical needs and not simply recommend learning resources that other learners found of interest. Moreover, context is also of major relevance in recommender systems to support learning experience, for instance to take into account affective issues in the learning process. Both are challenges identified in previous review of the field [10]. In this sense, recommender systems in the psychomotor domain rely on **sensing technologies** to get information about the movements performed which adds additional challenges from the context to those already identified when developing educational recommender systems. In fact, wearable devices are widely used to provide real-time data to enrich recommender systems [19].

A critical issue when developing adaptive systems in general and recommender systems in particular, is the **lack of methodological support during the development process** [12]. In fact, the development of artificial intelligence (AI) applications, despite the numerous risks they pose, has been characterised to date by a lack of rigour in engineering practices (with the exception of the field of Expert Systems, where a great effort was made in the 90s in the definition of methodologies such as CommonKADS [31]). As recognized in [22], due to the idiosyncrasy and special complexity of AI applications, the usual methodologies and tools of software engineering are not perceived as very useful. Moreover, until the explosion of Big Data in recent years, AI development was mostly limited to academia, which is not very prone to the use of systematic engineering approaches, especially because only prototype developments, such as proofs of concept, are usually addressed. Only in recent years, as AI technologies have begun to be widely adopted in industry [5][21][23], has the need for AI engineering research begun to be recognized, particularly in the Data Science community where methodologies such as CRISPML [8] are now widely used.

The need for engineering tools is recognized as particularly urgent in the areas of testing, data management and software quality, following the intense debates that have arisen around the various ethical risks associated with artificial intelligence technologies. Along with the need for a rigorous approach to software engineering, in recent years the AI community has also begun to agree on the need to implement ethical requirements in educational contexts [16]. [13] considers that a consensus is emerging on a set of **ethical principles** that should govern AI systems: i) privacy, ii) accountability, iii) security, iv) transparency and explainability, v) fairness and non-discrimination, vi) human control of technology, professional, vii) responsibility, and viii) promotion of human values. But theoretical and empirical research on ethical AI lags far behind purely technological AI research. As disclosed in [14] it is urgent to ground the practice of AI engineering in ethical principles. The tools developed in research centers to support the application of ethical principles are generally at an early stage of research, so their usefulness and impact have yet to be demonstrated [27]. There is currently an endless proliferation of guidelines and recommendations at all levels for an ethical approach to AI development, but formal engineering approaches, tools and libraries of reusable software artifacts are scarce and poorly tested in practice.

In addition, principles of ethics and governance of AI are related to the emerging paradigm of **Hybrid Intelligence** (HI)[1], which refers to socio-technological ecosystems in which adaptive AI agents and humans interact cooperatively, synergistically, taking human expertise, intentionally and values, as well as ethical, legal, and societal considerations into account. The emphasis of HI is on the need for "human experts in the loop" with the aim of augmenting rather than replacing human intelligence. An HI architecture is very suitable for a psychomotor training system that responds to the needs of supervised physical activity in general and of the elderly in particular, respecting the values of the ethics of care and avoiding dehumanisation.

FRAGILESS was a novel contribution from the conceptual viewpoint and a human-centered process was adopted for its design as reported in this workshop [25]. However, at the time of its development (6 years ago) and in line with the development practice at the time, we could not and thus, did not consider, an integrated framework, encompassing methodologies, guidelines, tools and libraries of core software artifact components, that would rigorously, reliably and ethically guide the development of FRAGILESS. In the case of this kind of systems such as FRAGILESS, which focus on particularly vulnerable users such as the elderly, it is crucial to ensure safety, preserve autonomy and privacy, build trust, respect diversity, address psychological and cognitive aspects, and prevent dehumanisation in care. All the agreed ethical principles mentioned above are therefore essential and must be applied from the perspective of the ethics of care [32].

The structure of this paper is as follows. First, in Section 2 we present the background of our research. Next in Section 3 we outline our approach for the HUMANAID framework base on the HI paradigm and the system engineering support. Next, in Section 4 we present the IBAID system that we are developoing as case study. Finally, in Section 5 some conclusions are outlined and on-going work is presented.

2 BACKGROUND

The research reported here is framed in the context of the **HUMANAID project** where a framework for developing autonomous or semi-autonomous, adaptive, user-centred decision systems is being defined. To illustrate the usefulness of HUMANAID framework we are developing a psychomotor system that recommends physical activities and movements to perform, where we explore and exemplify how to integrate ethical principles throughout a rigorous engineering process (from the specification of requirements to the implementation and maintenance, including impact measurement) in the development of intelligent systems for personalised psychomotor training. HUMANAID framework for psychomotor systems will integrate the SMDD (Sensing Modelling Designing and Delivering) process model [28] and the participatory and user-centric requirement engineering methodology TORMES [29].

The **SMDD process model** consist of four phases: 1) Sensing the learner's corporal movement as specific skills are acquired, and the context in which this movement takes place, 2) Modelling the interactions to allow comparing the learner movement against the accurate movement (e.g., how an expert would carry the movement out), 3) Designing the feedback to be provided (i.e., what kind of support, and when and how to provide it) and 4) Delivering the feedback in an effective non-intrusive way to advice the learner on how the body and limbs should move to achieve the motor learning goal. Following it we have developed some psychomotor systems to support the learning of martial arts such as KSAS [6] and KUMITRON [11], as reported elsewhere [7].

In turn, **TORMES** is a participatory and user-centric requirement engineering methodology that combines data mining techniques with user centred design methods to support the identification of the personalization needs to be implemented in the system. The modelling of corresponding recommendations consists of the following 5 elements [30]: 1) type: specifies what to recommend; 2) content: defines how to convey the recommendation; 3) run time information: describes when to produce the recommendation; 4) justification: informs why a recommendation has been produced; and 5) recommendation features: additional semantic information that compiles features which characterize the recommendations themselves (category, relevance, appropriateness and origin).

3 HUMANAID FRAMEWORK FOR PSYCHOMOTOR SYSTEMS

Our proposal for the HUMANAID framework for psychomotor systems has been to start from a basic framework consisting of a process model (the SMDD), a very generic architectural pattern according to the HI paradigm and a compilation of methodological and technical tools that we considered a priori to be useful. Our aim is to enrich and mature the framework in parallel with the development of a human-centric psychomotor system case study (presented in the next section). Progressing through the different phases of development will provide us with feedback to evaluate the initial framework, refine the architectural pattern, identify guidelines, recommendations and additional useful tools (with appropriate adaptations where necessary), and compile generic software artefacts and instances of them at different levels of specificity into libraries for supporting the development of human-centric intelligent systems for personalized, inclusive, safe, respectful with human values psychomotor training. Our concept of human-centric involves considering a wide range of human factors from a holistic viewpoint of the practitioner, and the trainers and therapists supervising training, linked by caring relationships.

The SMDD process precede the development of the system itself as its function is to generate the required data science models (Phases 1 and 2) and to design the feedback and how it is provided (Phases 3 and 4). The last two phases partially cover requirements engineering. The reason for considering these processes together is that they involve intensive user experiences of a very particular nature, and that they require a significant involvement of experts.

3.1 Generic architectural pattern

Regarding the architectural pattern, the models generated in SMDD Phases 1 and 2 will result in connectionist system components essential for personalisation. In the context of a hybrid paradigm, these components will have to be integrated with symbolic components that will enable human-machine collaboration. It should be kept in mind that HI emphasises the need for “human experts in the loop” with the aim of augmenting rather than replacing human intelligence [1].

3.2 Methodological and technical engineering tools

Regarding system engineering support we consider methodological and technical tools that are consistent with the HI paradigm.

3.2.1 Methodological tools. Regarding the methodological tools, so far we have only addressed the requirements engineering phase and the preliminary SMDD processes, experimenting with an extended version of the TORMES requirements elicitation methodology and the SHERPA[1] data science project development methodology (an adaptation of the the CRISPML methodology to take account of ethical criteria). In particular, regarding **requirement engineering**, to be "ethical", an AI application must fulfil a number of ethical requirements, which must be identified and clearly specified as functional or non-functional requirements, as appropriate, and then added to the system specification in a way that ensures their correct implementation and validation. To this end, we are working on extending TORMES methodology to pay special attention to ethical requirements in order to use it to address requirements engineering tasks. In addition, TORMES has to be adapted to the idiosyncrasy of psychomotor systems, which involve peculiar, complex and laborious requirements elicitation processes (SMDD phases 3 and 4).

The ethical problems posed by AI applications may be due not only to a lack of consideration of certain ethical requirements, but also to implementation errors, undesired behaviour caused by poor choice or malfunction of the models themselves, noise in the training data of a model, unexpected behaviour of the environment, difficulty in defining the criteria for correcting the outputs of the system, etc. In fact, as stated in [22] the goal of developing ethical AI is mainly a problem of software and data quality. Therefore, in addition to the TORMES and SHERPA methodologies, the framework must consider complementary methodological proposals that guarantee a rigorous and integral engineering approach, with well-defined processes adapted to the specificities of human-centred psychomotor training systems, throughout the entire engineering process, covering the implementation, maintenance and impact measurement phases.

3.2.2 Technical tools . With respect to techniques for dealing with the HI properties of "collaborative" and "adaptive", [1] provides a brief summary of the state of the art. With respect to the "collaborative" property, [1] refers to advances in the implementation of negotiation, task planning, distribution, and monitoring, particularly in the context of multi-agent models and game theory. In addition, [1] highlights the relevance of the concept of "reciprocity" between human and computer agents, which has already been explored in computational theories of reciprocity. The already vast field of multimodal human-machine interaction is also very relevant to the collaborative property, and many of the techniques proposed in this field are good candidates for our framework.

Regarding the "adaptive" property, [1] refers to the need for HI system agents to use machine learning techniques to learn from data, experience, and dialogue with other agents (human or artificial), while maintaining a trade-off between adaptability and safety & reliability. In this context, [1] points out the so-called automated machine learning methods that select and optimise learning algorithms for specific tasks or data sets, the multi-objective optimisation or multi-attribute negotiation systems, and the automated procedures for selecting and configuring algorithms for a given supervised machine learning, to which increasing attention is being

[1] https://project-sherpa.eu/wp-content/uploads/2019/12/development-final.pdf

paid. These techniques are relevant for the development of components resulting from SMDD phases 1 and 2 and possibly for the development of other components.

Regarding ethical requirements, many techniques have been developed to address the ethical risks associated with IA applications. The most widespread of these tools are presented in [17]. There are tools to safeguard privacy and transparency (anonymisation or encryption techniques, "privacy by design" approach, contextual integrity, differential privacy, federated learning...), to avoid bias and discrimination (there are already several commercial tools that implement bias mitigation mechanisms: IBM Fairness, Google What-if...) and to measure them (metrics such as statistical parity or equal probabilities). There is the whole field of XAI (Explainable Artificial Intelligence) with a multitude of explainability methods, tools for non-interpretable models (LIME, SHAP...), commercial tools (IBM AI explainability, H2O...). There are other no less important issues, such as impact measurement by design to facilitate responsibility, accountability, auditability, continuous monitoring and validation.

The main ethical risks of human-centric psychomotor training systems, which are essentially those posed by medical and educational applications, can be addressed with the tools described above. Despite the increasing proliferation of tools, from a technological point of view there is still a clear need for better standard ways of implementing and verifying ethical requirements in AI applications. We will also intend to enrich this toolkit with other tools such as guidelines to good practice, recommendations and illustrative case-studies that will serve as examples to follow.

3.3 Reusable software artefacts

Finally, to be useful the framework has to compile in libraries software artefacts of different levels of abstraction that can be reused in the different phases of the development of the human-centric psychomotor training system, such as requirement specifications in semi-formal languages (including ethical requirements common to a family of applications and others specific to particular application domains), architectural patterns, collaborative patterns involving virtual AI agents and human agents according to the HI paradigm, and data models (e.g. ontologies described in formal languages).

In particular, we intend to develop comprehensive ontologies for user and context modelling (intra- and inter-subject approach), taking into account a wide range of human factors (interaction preferences, psychological and emotional states, pathologies, physical fitness, medical history, training progress, context of practice....), and for low-cost multimodal data modelling.

4 IBAID CASE STUDY

In the current research we aim to explore how to build a human centric psychomotor recommender system. We have selected the practice of basketball as test-bed, mainly due the improvement of psychomotor abilities are crucial in their learning [2], and because it is also part of a proven methodology to develop psychomotor abilities in the field of physical education [20]. Therefore, the practice of basketball serves as a basis for implementing recommender systems that support the development of psychomotor learning systems, this is valid to all ages [33] and to all levels, from beginners to advance users. To encompass these challenges, we are developing the iBAID (intelligent Basket AID) psychomotor system, which aims to recommend the physical activities and movements to perform when training in basketball, either to improve the technique, to recover from an injury or even to keep active when getting older.

In the same way that during the practice of basketball, we can aid the training decision process, recommending supporting activities to improve the learning or specific actions to properly execute the movements, we can also assist artificial intelligent motor rehabilitation systems [3], providing expertise decision making tools for physical readaptation [9], executing appropriately all motor exercises required for a proper and prompt recovery. Physical activities derived from basketball can also be seen as a pivotal element for guaranteeing a healthy and active ageing. Thanks to the popularity of basketball and its values, we can contribute with its practice to the active aging process, incorporating routines based on this sport but adapted to the age of the participants. Therefore, the basketball basis recommender systems can be applied to the training of this sport, to rehabilitation processes, but also to the promotion of the development of exercises based on basketball in the elderly population.

When developing the iBAID system architecture we will take into account the aforementioned principles of ethics and governance of AI according to the HI paradigm: i) privacy, ii) accountability, iii) security, iv) transparency and explainability, v) fairness and non-discrimination, vi) human control of technology, professional, vii) responsibility, and viii) promotion of human values. In addition, iBAID system will also consider the core characteristics of HI systems (according to [1]) which are consistent with our concept of human-centric intelligent systems for psychomotor training:

- *Collaborative*: An intelligent human-centric psychomotor training system should promote the synergistic work of trainees and trainers; in the case of our pilot case, basketball trainees, basketball trainers and therapists such as physiotherapists, psychologists and traumatologists whith expertise in basketball training, and geriatricians in the case of elderly users. A physiotherapist working with basketball players knows the keys to minimising injury risk and maximising performance. So would a psychologist if we were thinking about a professional-level athlete. The sociotechnological system enhances the cooperation between the experts involved in coaching.
- *Adaptive*: a human-centric intelligent psychomotor training system must learn and adapt to the trainees, the trainers and the training environment; in the case of our pilot case, it must adapt to the specific changing needs of basketball coaches, as well as to the pedagogical style of the trainers and to the different therapeutic criteria, the technology and other resources available in the training centres, the environment in which the practice takes place, whether it is carried out in a group or individually, etc.
- *Responsible*: a human-centric intelligent psychomotor training system must behave in an ethical and responsible manner; in the case of our pilot, in accordance with the deontological codes of sport and sports education, as well as the

deontological codes of the therapeutic field with a particular focus on caring ethics and the rights of the elderly.

- *Explainable*: a human-centric intelligent psychomotor training system must promote dialogue with and between its users, so that all agents (virtual AI agents and human) share and explain their perceptions, goals and strategies; in the case of our pilot, the intelligent basketball coaches must dialogue with basketball trainees, as well as with trainers and therapists, and also promote dialogue and encounters between all its users and with a group of basketball players. The human-centric, intelligent psychomotor training system thus contributes to building a community rather than promoting solitary basketball practice. It also promotes therapeutic compliance and motivation to practice; trust is lost when users cannot understand the system's behaviour or decisions.

Undoubtedly, the above characteristics raise many research questions, which we intend to respond to by developing our framework supported by iBAID system and other similar approaches.

5 CONCLUSIONS

Our final objective is to illustrate the practical application of HUMANAID framework in a real case by developing an intelligent basketball trainer and evaluating its potential impact in the provision of support services in the city of Madrid. Our aim is that this system will be a useful tool for the City Council's sports education programme, in promoting physical activity and sports practice, facilitating learning and technical improvement in a flexible way, and in particular serving the physical maintenance of the elderly within the City Council's programmes on "Active Ageing" and "Unwanted Loneliness". We are also in contact with the government of Valencia to provide to foster active aging and with L'Alqueria Basket School (Valencia) to do it through basketball activities. Our framework is well suited to support such projects, promoting the participation of multiple stakeholders and professionals from different disciplines throughout the development cycle, a prerequisite for an AI technology based on ethical principles.

In addition to validating the usefulness of our approach and learning lessons on how to improve it, our research will serve to advance the field of intelligent psychomotor trainers by addressing the technical, psychological, ethical and legal issues that arise from the peculiarities of basketball. As recognised in [1], there are many open research questions in the field of HI. Therefore, our experimentation with a framework that support the development and deployment of ethical technology is of great value. The resulting system could be part of a socio-technological ecosystem interacting, in addition to the users (elderly users or any other sports practitioners), with the trainers of the sport in question, and therapists from various disciplines (physiotherapists, traumatologists, geriatricians, etc.).

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