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PH.D. THESIS

Intelligent Tutoring Systems for Psychomotor Development in Open Environments

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Abstract

Information technology has produced incremental changes in nearly all industries, whereas recent research on technology applied in education has shown the potential to generate an inflection point in the way people learn. The current educational revolution is mainly driven by three components: Artificial Intelligence, Internet availability, and advancements in educational sciences. Intelligent Tutoring Systems (ITSs) are considered one of the most suitable candidates for educational transformation. An ITS is a computer-based system that produces personalized tutoring through individualized, pedagogically sound, and easy-to-access educational material. ITSs engage students independently or collaboratively to ensure effective learning. The AI in Education (AIED) research groups explored various methods and assumptions for building efficient tutors in the cognitive field, with notable results in disciplines like physics, mathematics, and informatics. In contrast, the psychomotor field is exhibiting only lately an intensive digitalization process, as more recent approaches are introducing intelligent tutors for this field.

The overarching objective of this thesis is to provide personalized sports training sessions in the psychomotor field in the form of an ITS – Selfit – an efficient and easy-to-use system that has the long-term goal to engage people in sports and improve the general health of the mass population.

This objective is three-fold. First, we introduce an ontology to model key concepts of the psychomotor field – representations, and relations between the concepts, data, and entities. The ontology for knowledge modeling in Selfit, called OntoStrength, was built using the Ontology Development 101 framework and employing a multi-disciplinary team, with sports, medical, and computer science specialists.

Second, we introduce a contextual multi-armed bandit algorithm for generating personalized training sessions. The decision-making process of a psychomotor tutor proves difficult. There are many unknown variables and uncertainty: the training time is limited, the trainee cannot test all the activities, and the personalization should happen in real-time while maintaining the user motivated and engaged. The Selfit approach for psychomotor tutoring has proven to surpass the fixed-rules training approach in our simulations.

Third, we evaluate the utility and effectiveness of our ITS prototype on a population of 42 users, with low and medium training experience, which were involved in an experiment, that included two adaptive strategies for tutoring – one narrow, and the other with a wide exploration space. Selfit has a user-friendly mobile interface, where the user can visualize the video training content to execute and is required to assess the effort implied by each training component. A usability and experience survey was filled out at the end of the experiment. The users generally perceived Selfit as practical, predictable, simple, connective, stylish, motivating, novel, and captivating. The results are also in line with our initial simulations, proving the potential of the proposed approach in personalized training.

Selfit evaluation showed promising results and highlighted the usefulness of the ITS architecture in the psychomotor field. The current thesis can be considered at the foundation of a new crossroad, between AIED and psychomotor training, opening new research directions aiming to improve the general health of the population through automated systems.

Future work aims to extend the knowledge base from strength training to other training types, such as flexibility and mobility, enrich the user experience by providing voice support while training, as well as integrate NLP techniques to enhance tutor-trainee interaction and computer vision algorithms for real-time assessment.

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1 Introduction

1.1 Goals and Interests

The rise of information technologies, mainly driven by computer innovation, has revolutionized the way we interact and learn (Woolf, 2010). The confluence of the Internet, Artificial Intelligence, and cognitive sciences has further created new tools in education, improving the way educational content is produced, and delivered, and increasing education efficiency overall. An important candidate in this field is the Intelligent Tutoring System, which is an Artificial Intelligence-based computer system that provides an adaptive educational experience (Fenza & Orciuoli, 2016).

An Intelligent Tutoring System (ITS) aims to enhance student learning experiences by creating immediate, customized instructions and feedback while collecting comprehensive information. Most ITSs are divided from an architectural point of view into four components (Nkambou, 2010), namely: *Domain Module* – defines rules, concepts, and problem-solving strategies (expert knowledge), *Student Module* – learner's cognitive and affective states, evolution while learning, *Tutoring Module* – selects the best tutoring strategies and actions to take, and *Interface Module* –responsible for student interaction.

The present work aims at contributing to the development of ITS in psychomotor field for large communities of users with a focus on strength and health improvement. Psychomotor skills development is a lifelong process of learning how to move accordingly to a dynamic environment. A movement competence is a transaction between an individual and a movement task within an environment. Essential movements, such as pushing, pulling, core, knee, or hip-dominant exercises are prerequisites for learning specialized, complex psychomotor tasks required by daily life, professional, or leisure activities. Learning to perform a movement safely and efficiently requires practicing an adequate volume of exercises for enhancing associated physical qualities, such as strength, flexibility, or endurance.

However, one of the main challenges for such a development is the high cost when creating a strong knowledge base from scratch. As stated by Zouaq and Nkambou (2010), an acute research issue is how the tutoring module of an ITS can be efficiently modeled, and what kind of knowledge representations are available, and what kind of knowledge acquisition techniques can be applied.

In the process of building an Intelligent Tutoring System, each component is well defined with roles and rules for implementation. ITS components work together to produce a uniform instructional system capable of recognizing patterns of learner behavior (Orey, 1993) and responding to those patterns with appropriate instructions. However, when it comes to applying it to an open environment (which reflects more realistically the usual training environment), e.g., more unpredictable, and poorly defined, it raises new questions on modeling and efficiency.

Another challenge when developing such a system is to define the right tools and frameworks to acquire accurate student knowledge competencies for predicting its progress while training. Recent ITSs built for military training are often limited to laboratory settings on standard PCs and laptops, which focus on training cognitive skills (such as decision-making and problem solving) and may potentially limit the learning and retention of mastering physical tasks (LaViola et al., 2015).

Another challenge is the optimization of the teaching sequences – generally, the Tutoring system uses an estimation of the student competence levels and progression to choose the activities that provide the best learning experience at a certain time. An ITS accessible to the vast majority of people, which addresses general health, should provide a personalized learning experience relying only on little domain knowledge.

The challenge that the tutor faces is to find what is the optimal sequence of activities that maximizes the average competence level over all the targeted skills (Clement, Roy, Oudeyer, & Lopes, 2015). This challenge, which was raised initially in the cognitive field and has the equivalent in psychomotor development, is driven by three main factors: limited time for practicing activities – the tutor cannot test all combinations of sequences, or all activities; managing motivation is hard – students will learn efficiently only if they are engaged in the activities; individual differences between students make an optimal sequence for a student inefficient for another one.

In addition, an ITS is deemed to replace the human coach and mediate abstract knowledge with real trainees. Thus, ITS performance is not only determined by the knowledge it carries, but also by the quality of the user experience.

Based on the challenges raised above, this thesis addresses the following major research objectives:

- RO1: Design an effective knowledge representation model for the psychomotor skills development in an Intelligent Tutoring System.
- RO2: Provide personalized sports exercise' recommendations for the mass population when training in open environments.
- RO3: Implement an intuitive and effective Communication Module that facilitates the assessment of the sport trainee's progress in open environments.

1.2 Thesis Outline

The thesis is structured into three main parts, *Theoretical Aspects*, *Experiments and Results*, and *Discussions and Conclusions*. The chapters described in the *Theoretical Aspects* part support the sections from the

Experiments and Results, as can be seen in Figure 1. The chapters in the *Experiments* part have a corresponding chapter in the *Theoretical Aspects*.

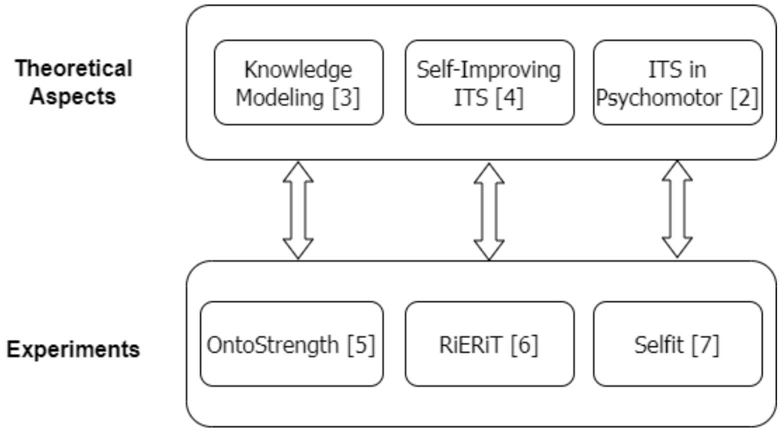

Figure 1 Thesis structure.

The *Theoretical Aspects* structure is the following – first, Intelligent Tutoring Systems are presented, together with their usages in the psychomotor field (Chapter 2), then we present how the knowledge is modelled in ITS (Chapter 3), and what are the methods commonly employed for tutoring in ITSs (Chapter 4).

Then, in the *Experiments and Results* part, we propose a new model for the psychomotor field, called OntoStrength (Chapter 5), which was built based on the findings presented in Chapter 3. Next, a method for personalizing learning sequences in psychomotor training is introduced, called RiERiT – Chapter 6, which was inspired by the findings in Chapter 4, where similar methods were proposed and used in the cognitive field. The *Selfit* system is introduced in the next chapter, as a prototype for psychomotor training ITS in open environments.

Here, the work presented in knowledge modeling and psychomotor tutors' experiments is merged to create a system that showcases the potential of our findings. The *Selfit* chapter also presents the Communication module and how this was integrated to exchange information with the other components. The last chapter in this part introduces the results of our experiments, conducted in two main directions - on one hand, the efficacy of the RiARiT algorithms – bandit learning, and on the other hand, the user's experience. The *Selfit* system was tested with real users, who trained between 1st January 2022 and 31st May 2022, the overall goal being to assess if the proposed prototype is valid for psychomotor training.

Next, the *Discussions and Conclusions* part describes the advantages of our approach, the problems faced and how they were overcome, and the limitations, along with a list of envisioned applications. The *Conclusions* Chapter presents the summary of the work, our contributions, and potential directions for future research.

2 Intelligent Tutoring Systems and Psychomotor Training

Intelligent Tutoring Systems (ITSs) are at the cross-road of education and technology (Paviotti, 2012). An ITS is a computer-based instructional system, aimed at supporting learning through different tutoring services that specify what to teach, how to teach, the teaching strategies, and makes inferences about a student's level of mastery on a set of topics for dynamical adaption of content or instructions (Murray, 1999). Development of such systems has been a co-disciplinary process, involving both didactics and knowledge technologies experts. Intelligent tutoring system development requires an understanding of how people learn and teach.

2.1 Intelligent Tutoring System Architecture and Features

The most common architectural pattern empowered when designing an ITS is the Four-Component Architecture, which is composed of a Domain module, a Tutoring module, a Student module, and the Graphical User Interface (Nkambou, 2010).

The *Domain module* handles knowledge relating to the subject matter and contains concepts, rules, and strategies. ITS uses the Domain knowledge to reason with, find solutions to problems or respond to students' questions. Another feature of the *Domain module* is that it can be used to detect students' errors and propose solutions to correct them. Alternative teaching strategies may be obtained by developing distinct knowledge representations of the same domain knowledge.

The *Tutoring module* provides the necessary knowledge to attain teaching goals. It receives information from both *Domain* and *Student modules*, and it is responsible for selecting the subject content the student will use, providing the response mechanisms for answering the student's questions and patterns to detect when learners need help by embracing different styles of delivery. The *Tutoring module* selects the teaching goals and decides what are the most suitable teaching strategies based on the Student model and the Student's objectives. A performant *Tutoring module* knows when it is the right time to update the learning process and how to do it. It interacts with the student through feedback and hints.

The *Student module* describes the learner's emerging knowledge and skills, and it is considered a critical component of an ITS. The teaching process should be adapted to every student's characteristics, and based on this, the system needs to collect as much information as it can about learners' preferences, cognitive and affective states, as well as their progression while learning. An ITS is more efficient the more it manages to collect data from and about the learner and use it to perform an analysis of the current state of its knowledge.

Intelligent Tutoring Systems and Psychomotor Training

The *Interface module*, also known as the Communication module, or Graphical User Interface module, facilitates the communication between the *Student* and the *Tutoring module*. Even with the best student and teaching knowledge, a tutor is of limited value without effective communicative strategies and so a large amount of work should go into developing this module (Woolf, 2010). In most of the cases, the graphical environment is responsible for providing lessons and help while learning, results, and pedagogical actions

2.2 Psychomotor Development in Intelligent Tutoring Systems

The psychomotor domain, also referred to as psycho-motor or psycho motor or physical, includes physical movement, coordination, and use of the motor-skill areas. The development of skills in this domain requires practice, and the corresponding measurements of performance consider speed, precision, distance, procedures, or techniques in execution.

A systematic literature review (Neagu, Rigaud, Travadel, Dascalu, & Rughinis, 2020) was conducted in November 2019 on the most reputable online data sources for assessing the amount and quality of research conducted to design and develop ITSs for training psychomotor abilities. This work was the foundation for the experiments presented further in this thesis.

The method to identify the existing digital tutors for psychomotor development implied three phases – Identification Phase, Inclusion/Exclusion Criteria Definition Phase, and Quality Assessment Phase, as can be seen in Figure 2.

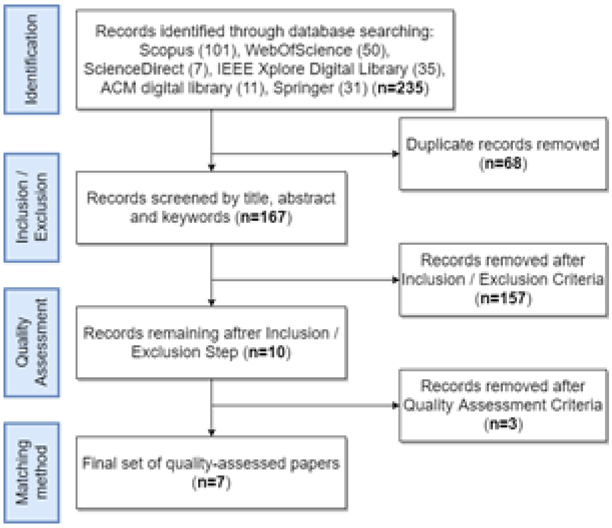

Figure 2. Systematic Literature Review - Method Overview

The search query applied for obtaining the list of articles in the online databases is the following:

Intelligent Tutoring Systems and Psychomotor Training

> ("Intelligent Tutoring System*" OR "Intelligent Computer-Aided Instruction*" OR "Intelligent Computer-Assisted Instruction*" OR "Knowledge-Based Tutoring System*" OR "Adaptive Tutoring System*" OR "Computer-based Tutoring System*") AND (psycho-motor OR psychomotor OR "psycho motor" OR physical)

Even though the above query was the targeted search query to be applied to all the data sources, different constraints were encountered while using each search engine, such as the length of the query provided was too large, or too many masks were applied (where the mask is considered "*" character), all presented further in detail.

The literature review was conducted in November 2019 using the following electronic international databases: Scopus, Web of Science, ScienceDirect, IEEE Explore Digital Library, Springer, ACM, and Journal of Education in Data Mining. These data sources are the most common online sets used in scientific research (Dieste, Grimán, & Juristo, 2009).

The literature review work was focused on finding adequate papers with original research on different areas where ITSs were used for training psychomotor abilities. Thus, the following inclusion criteria were developed: Full papers and peer-reviewed papers; Papers with empirical research (qualitative and quantitative); Papers describing ITS architectures or variations; and Papers clearly explain areas of the psychomotor domain, where ITS was applied.

The papers related to psychomotor training vary from very specific (e.g., training for marksmanship, training for ball-passing), to broader activities (e.g., improving human motor learning, training physical tasks). The papers matching the Inclusion / Exclusion criteria were published at several conferences in a timeframe of twelve years, while most papers were published in the past two years.

The next step implied reading the accepted papers after inclusion/exclusion filters and assessing if the solutions present any outcomes of the proposed architectures and if they are following any psychomotor taxonomies.

From this literature review, we conclude that, even though initially developed for training cognitive skills, ITSs have emerged also in psychomotor training, with usages in several sub-fields, such as Medicine (Laparoscopic Surgery Training, Radiology), Military (GIFT), Driving (Adaptive VR driving simulator), Sports (Football - Ball-Passing Training, dance, retraining for health), and Generic manual procedures (TUMA).

2.3 Challenges in Psychomotor Domain Digitalization

Knowledge Modeling. One of the most difficult challenges when building ITSs is creating a strong knowledge base from scratch (Zouaq & Nkambou, 2010). The tasks for representing the knowledge,

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the knowledge acquisition techniques, and efficient modeling of the tutoring require acute research in the field.

Sports training periodization is considered a young field. The first research work on describing the rules for training has been performed 5 years ago by Bompa (2017). Before there were no clear standards for performing sports training and periodization, and different sports coaches were using different terminologies when referring to specific topics.

Ontologies are becoming a strong candidate for building knowledge in Intelligent Tutoring Systems and adaptations of such systems. As stated by Neagu, Guarnieri, et al. (2020), no previous ontology has been developed in the psychomotor field; existing works focus on recognizing sports activities with technology or support decision-making based on data collected during sports competitions.

<u>Intelligent Tutoring Strategies</u>. The tutoring module of an ITS is responsible to choose the optimal learning sequences to provide a good learning experience based on the estimation of the student competence levels and progression, and little knowledge about the cognitive and student models (Clement et al., 2015). The same principles are applied in the psychomotor field too. The literature shows that for learning how to drive, Ropelato, Zund, Magnenat, Menozzi, and Sumner (2018) created a virtual reality environment where learners receive optimal sequences based on the Zone of Proximal Development and Empirical Success (ZPDES) algorithm..

The rifle marksmanship tutoring focuses on learning the basic functional elements for effectively operating the weapon, and the instructions are focused on consistently striking static targets at fixed distances (Goldberg, Amburn, Ragusa, & Chen, 2018). In the closed environment, the training components: stability, aiming, control, and movement, are tracked by the tutor using sensing technologies. The model for personalizing the learner training sequence tracked parameters such as body position, breathing, trigger squeeze, and muzzle wobble while training, but the algorithms implemented for adjusting the sequences were not clearly described.

A big challenge in tutoring in open environments is caused by the lack of accurate learner information while training. Also, time resources are limited for the learners, a learner cannot test all the training activities or all the existing sequences of training. A rule-based tutor may prove inefficient both in the cognitive and psychomotor fields. A learning sequence that is optimal for one trainee may be inefficient for another one (Clement et al., 2015). Building a psychomotor tutor in an open environment is a challenging task, as minimum learner data should be acquired while training, tutoring relies on the trainee's input, partially acquired data from the environment, and caution on learner's health– new sequences generated by the adaptive tutor should protect the learner from injuries, medical issues, or physical exhaustion. On the other side, the learner should be engaged in

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learning and maintain long-term motivation for training. Learning should be delivered in the trainee's zone of proximal development.

Interaction with the Trainee. A tutor may have the best student and teaching knowledge, but without an efficient interface component to interact with the learner, it will limit the value of the tutor (Woolf, 2010). The user interfaces should be clear and simple, attractive, and responsive. Based on these considerations, building a proper communication module usually involves a big amount of effort. A human tutor easily detects learner reactions in the classroom, he can easily detect problems and provides feedback and remediation. The traditional tutor can track learners' focus of attention during classes, level of fatigue, and motivation. The classification of the communication layers between tutors and learners inside an ITS includes graphics communication, social intelligence, component interfaces, and natural language techniques(Woolf, 2010).

In an open environment, the interaction with the learner proves to be more challenging than in closed, fully supervised environments. The learner training setup is unknown, and assessment is hard to perform. For learning psychomotor skills, the learner needs guidance for execution, which can be video, image, or written, and voice or visual feedback. Also, the assessment may prove critical for both tracking the learner's progress and avoiding the risk of injuries. The more data the system gathers, the better the assessment and personalization should be.

The data used to measure the training impact, such as heart rate, calories burnt, or quality of sleep, which can accurately be gathered through IoT devices (smartwatches, smart bands) should not be mandatory and just enhance the model, but it should not rely on them. The communication between the system and the trainee needs to be efficient and simple, the trainer should not be forced to be tied up with the system while training. Designing such a system is a challenge that, from our findings, was not addressed in the literature.

The literature review shown an increasing interest of the research communities in designing and developing intelligent tutors for psychomotor training. Researchers introduced in the past years systems in several psychomotor sub-fields, including ball-passing training, medical (for surgeries), car driving, or military (marksmanship training). Our goal is to build a psychomotor tutor for athletization, and to provide optimal training sessions for novice and intermediate trainees.

3 Models of Knowledge and Learning Process

3.1 Learning Theories

Every schoolteacher has an educational philosophy, a set of stated or unstated ideas and assumptions about how to best teach (Woolf, 2010). On one end, some teachers see their job's main responsibility to impart information to students and then identify who has learned. They are viewed as traditionalists in teaching philosophy (Becker, 2000), the instructor is the knowledgeable source, and the student is the novice, willing to listen and learn. On the other end, there are the modern teachers who are responsible for creating experiences for students.

ITSs are a particular type of intelligent system to support learning, whose components reflect the values regarding the nature of knowledge, learning, and teaching (Self & Akhras, 2002). The architecture focuses on representing the knowledge to be learned (domain model), inferring the learner's knowledge (student model), and planning instructional steps for the learner (tutoring model). ITS architecture is matching the traditional teaching philosophy. However, for the constructivist theory, Self and Akhras (2002) challenge the classic ITS architecture, the constructivist view emphasizes different values at its core and potentially requires a different architecture. Authors proposed a new approach to building ITSs where, at the core of the learning process, there are interactions between learners and tutors. They showcase their new architecture with two applications: SAMPLE – ITS to support the learning of salad-making concepts, and INCENSE – ITS for learning software engineering. Even though they briefly explain the design of the systems, no validation has been presented for any of them.

The field of Artificial Intelligent in Education aims to use intelligence to reason about teaching and learning. This is a challenging task, as knowing what, when, and how to teach involves multi-disciplinary teams, from several disciplines, such as psychology, education, and computer science.

3.2 Modeling Knowledge and Teaching

Common techniques for generating learner models include Bayesian networks, belief networks, case-based reasoning (CBR), and expectation-maximization. The learner models can be classified by their performing function (Sottilare, Graesser, Hu, & Holden, 2013). They are categorized as corrective, elaborative, strategic, diagnostic, predictive, or evaluative.

Models of Knowledge and Learning Process

Many ITSs developments consider the student model as an overlay or subset of the domain model (Ma, Adesope, Nesbit, & Liu, 2014). As the ITS aim to teach the domain or a part of the domain, initial work, before representing student knowledge, should be the definition of the domain model.

In a traditional ITS, the domain knowledge representation has been implemented through a) black-box models, where reasoning is not clearly explained, but the solutions are accurate; and b) glass-box models, where the reasoning is explained step by step (Polson & Richardson, 1988).

There are two types of knowledge in both models: a) declarative, which is conceptual information; and b) procedural, for action sequences and problem-solving procedures. The goal of these representations is to ensure that the tutor module has access to structured knowledge and proper learning sequences (Zouaq & Nkambou, 2010). Several representation formalisms have been proposed and used traditionally in ITS, such as simple rules, case-based reasoning, fuzzy logic, concept maps, topic maps, or conceptual graphs (Zouaq & Nkambou, 2010).

A domain ontology is a strong alternative for knowledge representation when building ITSs for their standard formalism, ease of reuse of other ontologies, and modularity. System designers must integrate different ontologies to enforce the reuse and interconnection of various relevant resources. An ontology is a shared vocabulary and representation of knowledge used to model a domain; ontologies define explicit descriptions of concepts and their relations and integrate computer-processable semantics for data on the Web (Fensel, 2001).

An acute research issue when developing an ITS is how the Tutoring module can be efficiently modelled (Zouaq & Nkambou, 2010), what kind of knowledge representations are available, and what kind of knowledge acquisition techniques can be applied. The tutor must have an explicit representation of the domain knowledge that is the subject of the learning goal.

The extensive literature review shows that the model-tracing / cognitive tutor approach has been used the most (21.21%), then example-tracing (18.18%), content and problem based (12.12%), dialog-based (9.09%), constraint-based (6.06%), machine and human-based (6.06%), while the remaining ones were not clearly described or non-specific (27.27%). The studies included presented ITSs either as an illustrative scenario (39.39%), controlled experiments (27.27%), case studies (15.15%), survey (3.03%), or others (15.15%).

The example-tracing tutors are responsible to interpret and assess the student's behavior regarding generalized examples of problem-solving behavior (Aleven, Mclaren, Sewall, & Koedinger, 2009). This paradigm has been proposed by Aleven 13 years ago and it has been adopted very fast; 18% of the selected studies in the literature review have been using example tracing as an authoring strategy.

This strategy allows domain experts and specialists to build a cognitive model by demonstration rather than by programming a rule model, reducing the development costs overall.

The apprenticeship teaching strategy implies the expert does not engage in explicit tutoring. It is the first strategy modelled on human tutoring, where the student acquires, develops, and uses authentic cognitive tools in learning, both outside and inside the school (Brown , Collins , & Duguid 1989). The apprenticeship tutor is responsible to monitor student performance, reflecting on students' approaches, can provide advice on demand, and the path to solutions should be modelled through multiple paths. Apprenticeship training is common in learning how to play an instrument, training for athletization, or learning how to drive. Based on the teaching strategies and the skills developed in the existing tutoring systems built using this approach, apprenticeship teaching is one of the strongest candidates for developing psychomotor tutors.

An intelligent tutor has limited value if the communication component does not implement efficient strategies. Communication modeling is a comprehensive process. Tutor-learner interaction should be simple, clear, and efficient. Several techniques have been implemented for communication modeling, including animated tutors, virtual reality, visual recognition of emotion, and natural language processing.

An efficient tutor communication module makes learners feel authentic, and social, involving the reciprocal exchange of information with the system. Intelligent tutors can compose explanations, either spoken or textual, to criticize or maintain a dialogue with the learner through natural language techniques. The classification of modeling communication made by Woolf et al (Woolf, 2010) includes 4 main categories: graphic communication, social intelligence, component interfaces, and natural language communication.

3.3 Principles of Models Evaluation

Evaluation is considered the process by which relevant data are collected and transformed into meaningful information used for decision-making, according to specific purposes (Mark & Greer, 1993). Evaluation is different in several fields. Intelligent tutoring systems evaluation involves both learning outcome effectiveness, and software usability, but also other evaluation parameters, such as user experience or learning theory contribution.

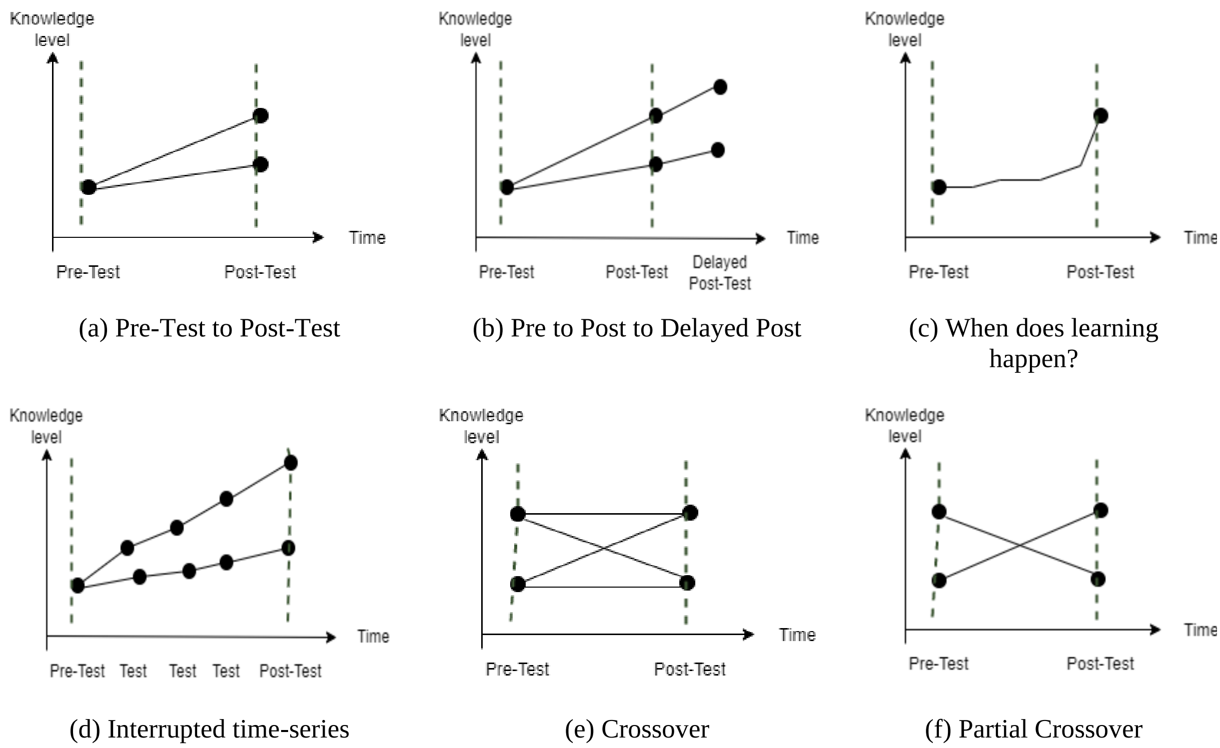
A recent systematic literature review on evaluation methods used in ITSs (Mousavinasab et al., 2018) shows that evaluation mainly involves the measurement of system performance, learner's performance, and experiences. Most of the studies were used in computer programming (55%), then health/medical (15.09%), followed by mathematics (15.09%). The focus on the health/medical ITSs is also in the cognitive field, for use-cases in theoretical education such as anatomy, childhood diseases, physiology, or clinical reasoning.

Evaluation in an ITS should also consider short-term and long-term issues. Woolf (Woolf, 2010) proposed six stages of tutor evaluation which include tutor goals, evaluation goals, evaluation design, tutor instantiation, tutor results, and evaluation discussion. In the next section, the evaluation principles will be described further, followed by a few recent ITS evaluation use-cases, in both the cognitive and psychomotor fields.

Evaluation designs include the following categories: pre-test, intervention, post-test, delayed post-test, interrupted time series, crossover, and partial crossover. Pre-test measure learners' knowledge level before starting the experiment. It might additionally assess student characteristics, such as learning style or motivation, to help allocate subjects to groups. This may be required for an even distribution across groups. Tutor intervention is involving the tutor in the learning process with specific teaching goals. Post-test is performed at the end of the experiment to measure acquired learners' knowledge. An example of an evaluation design with pre-test and post-test can be seen in Figure 3. a. Delayed Post-test is used in evaluation design to measure the long-term effects of learning. The evaluation setup with pre, post, and delayed tests can be visualized in Figure 3.b. The issue with these approaches is that they do not track the moments when learning happens, when learners improve their skills, and what are the roots of learning – see Figure 3.c.

Interrupted Time Series implies the measurement of learning outcome through repeated post-tests, which will enable the assessment of differences in learning – see Figure 3.d. Even though there are high benefits of this method, it is time highly time-consuming, and it involves more work to be enabled. The crossover method (Figure 3.e) implies a harder setup – four groups of students, two forms of intervention (which can be intelligent tutors and traditional classroom), and two versions of the same test (test A and test B). Groups first receive a type of intervention, and they perform first pre-test A, and then post-test A. Then, the group's intervention is switched, they perform pre-test B, and then post-test B. This method can assess the effects of different teaching methods in the population selected. The disadvantages of this method are the complicated setup and the complexity of the four experimental conditions. The partial crossover method (Figure 3.f) is a simplification of the crossover method, with only two groups, but following the same rules.

The evaluation design can be performed for real-world or laboratory setup. Real-world experiments are preferable to laboratory environments, as they increase the tutor efficiency argumentation. On the other hand, laboratory tests are useful in certain scenarios, as they permit experiment control, such as the number of subjects, prior knowledge, and learning profiles. When designing an evaluation, a critical factor is describing its validity, or what the experiment will measure to consider the evaluation success. If the hypothesis made is valid for a population and can then be extrapolated to the outside world, it means that the evaluation has external validity.



(a) Pre-Test to Post-Test
(b) Pre to Post to Delayed Post
(c) When does learning happen?
(d) Interrupted time-series
(e) Crossover
(f) Partial Crossover

Figure 3. Evaluation designs schemas

Evaluation efficiency needs to be performed using benchmarks. Woolf (Woolf, 2010) proposed six examples of evaluation comparisons, with their associated prototype designs, adapted from the theories of evaluation design, which are summarized in Table 1.

Table 1. Evaluation Comparisons Examples and Designs Used with Intelligent Tutors (Woolf, 2010)

Evaluation Comparisons	**Evaluation Designs**
Tutor alone	Intervention + Post-test
Tutor versus non-interventional control	Pre-test + Intervention + Post-test
Benchmark: Tutor versus traditional classroom	Pre-test + Intervention + Post-test + Delayed Post-test
Within system: Tutor 1 versus Tutor 2	Interrupted Time Series
Tutor versus ablated Tutor	Crossover
Between systems: Tutor A versus Tutor B	Partial Crossover

The fourth phase of tutor evaluation is the instantiation of evaluation design. The previous phases aimed to create the skeleton of the evaluation. This phase's goal is to describe experiment details, based on the decision made in the first three phases. Experiment details include defining dependent and independent variables, the number of participants, type of participants, detailed description and justification of control groups, and software usability.

4 Intelligent Tutoring Systems in Open Environments. Machine Learning in Practice

4.1 Overview of Teaching Techniques for Intelligent Tutors

In an intelligent tutoring system, the experience can be achieved through storing past tutoring data and using it as a training input for the machine learning model (Dlamini & Leung, 2018). Learning over time is called incremental machine learning and this can be achieved through several techniques, which will be briefly described further. The main benefits of adaptive tutors are the increase in tutor flexibility, reduced cost of building the tutor, and adaptation to new student populations (Woolf, 2010).

A recent literature review on intelligent tutoring systems which have implemented machine learning techniques for different goals has found 53 relevant studies between 2007 and 2017, all targeting cognitive development (Mousavinasab et al., 2018). The review included studies in education, training, or educational assistance tools, which have demonstrated the usage of the ITS architecture in their systems. The major educational field found in the review was computer programming, with 55% frequency, followed by medical and mathematics fields.

The review found several goals for using Machine Learning techniques in the system proposed, from adaptive tutor modeling (adaptive feedback, hints, learning path), adaptive student modeling (definition, classification of learner's characteristics), and adaptive domain modeling. The detailed list of machine learning techniques purposes with their associated frequency found in the review can be seen in Table 2.

Table 2. The purpose of applying Machine Learning Techniques in ITSs between 2007-2017 (Mousavinasab et al., 2018)

Machine Learning Techniques	**Frequency (%)**
Defining, classification, or updating the learner's characteristics	56.60 %
Adaptive feedback, hint, or recommendation generation	52.83 %
Learner's evaluation	45.28 %
Presenting adaptive learning material or content	41.50 %
Adaptive learning path navigation	28.30 %
Presenting adaptive tests and exercises	5.66 %

Computer programming ITSs found in the literature review used several machine learning algorithms to adapt tutoring: Fuzzy-based techniques (20%), condition-action rule-based reasoning (20%), case-based reasoning (13.33%), intelligent multi-agent (13.33%), and data mining (13.33%).

Intelligent Tutoring Systems in Open Environments. Machine Learning in Practice

Health ITSs found in the review used the following machine learning algorithms: Bayesian-based techniques (50%), NLP-based and intelligent multi-agent approaches. In mathematics, most ITSs implemented condition-action rule-based reasoning.

Recent advances in adaptive tutoring focus on finding the activities which provide the best learning experience to each learner, based on an estimation of student competence levels and progression, and with little knowledge about cognitive and student models (Clement et al., 2015). This design is based on the following principles:

- Weaker dependency on the cognitive and student model.
- Efficient optimization methods.
- More motivating experience

The development of such tutors relies on the use of multi-armed bandit algorithms in tutor modeling (Clement et al., 2015). Multi-armed bandit addresses a problem in which a fixed limited set of resources must be allocated between choices in a way that maximizes the expected gain. The choice's properties are only partially known at the time it is picked, and it becomes better understood as time passes. Multi-armed bandits' algorithm is a classic reinforcement learning problem that exemplifies the exploration-exploitation tradeoff problem. Next, common techniques for building intelligent tutors with reinforcement learning algorithms are listed.

Reinforcement Learning is one of the best machine learning approaches for decision-making in interactive environments and RL algorithms are designed to infer effective policies that determine the best action an agent can take in any given situation to maximize the cumulative reward (Ausin, Azizsoltani, Barnes, & Chi, 2019).

Four core elements characterize the definition of a reinforcement learning problem: the agent, the environment, the policy, and the reward function. The environment is defined as the external system where the agent, which in this case is the learner, exists, makes actions, and moves from one state to another. The agent can depict a long-term successful behavior through rewards, which are provided at the end of each action taken. In most cases, the reward is a scalar value that is maximized by the agent, and it might represent the degree to which an action or a state reached is desirable. The reward function defines the goal of a RL problem (Woolf, 2010). The function maps each pair's state-action of the environment to a number, positive or negative, called reward, which is indicating the desirability of that pair. The policy is defined as the agent's way of behaving at a given time. In some cases, it may be a simple function or a lookup table, which checks for previous states and actions taken in those states.

There are two major categories of RL algorithms – online and offline. Online RL methods learn the policy while the agent interacts with the environment. In the offline approach, the policy is learned from a pre-collected training dataset (Ausin et al., 2019). Online RL is more suitable for domains where the state representation is clear and the interaction with the simulated environment and real environment is computationally cheap and feasible. Offline RL is required for more complex domains, such as e-learning, where human learning problem is complex, and the process is not fully understood.

A specific class of problems in the reinforcement learning field, in a simplified setting, involving learning how to act in only one situation is the multi-armed bandit problem or the k-armed bandit problem. The multi-armed bandit problem is encountered when you are faced repeatedly with a choice among k different options, which can be defined as actions (Sutton & Barto, 2018). After each action, a numerical reward is given from a stationary probability distribution that depends on what was the choice selected. The goal is to maximize the cumulative reward across a period.

If the values per action are known, the problem is trivial – you would always select the action which has the highest reward. At a certain step, you will know the rewards for a set of actions that were previously selected. One possible future choice would be to choose the one with the highest value, from the known actions. This is called *greedy* action, and choosing an action you already know is called *exploiting* the current knowledge. Exploitation is the right thing to do to maximize the reward on one step, but exploration – of new choices, unknown yet – may produce a greater total reward in the long run.

ε-Greedy approach forces the non-greedy actions to be tried, within the ε - factor, but indiscriminately, with no preference for actions that are nearly greedy or particularly uncertain. This is where the Upper-Confidence-Bound approach may be more efficient. It is better to select among the non-greedy actions based on their potential for actually being optimal, based on how close their estimates are to being maximal, and the uncertainty in the estimates (Sutton & Barto, 2018). In simpler terms, the actions with a lower value estimate or the actions which have been selected many times will be less selected by the bandit. The more uncertain the bandit is about a specific arm, the bigger chances it will be selected. UCB is not suitable for nonstationary problems, or problems that have a large state space.

In a classic ITS architecture, the tutoring module uses an estimation of the trainee competence levels and progression to choose the activities that provide the best learning experience at a certain time. The challenge that the tutor faces is to find what is the optimal sequence of activities that maximizes the average competence level, across all targeted skills (Clement et al., 2015). This challenge is driven by three main factors, which were tackled by Clement et al. (Clement et al., 2015):

- Limited time for practicing activities – the tutor cannot test all combinations of sequences, nor all activities;
- Managing motivation is hard – the students will learn efficiently only if they are engaged in the activities;
- Individual differences between trainees make an optimal sequence for a given trainee inefficient for another one.

Clement et al. (Clement et al., 2015) proposed a multi-armed bandits approach used in conjunction with the Zone of Proximal Development. ZPD has been defined by an expert, knowledge components are in the mathematics field, more precisely numbers decomposition. ZPD will be adjusted based on the optimization algorithms, based on the answers, and the students learning progress. The results obtained using multi-armed bandit algorithms are comparable and even surpass, in certain conditions, the sequences created by expert teachers.

4.2 Machine Learning Techniques in Psychomotor Development

The literature and methods related to adaptive ITSs are vast and, in this section, the focus is on the implementations related to non-cognitive tasks, namely, psychomotor skills.

Training individualization is the main condition for its optimization. Sports training literature exposes the classical methods for individualization, used by coaches, such as the "model of the master" – a theoretical framework that is using the volume and intensity of training to compute the load, or by actual training – computing mean values of training means made in a given cycle by a group of athletes (Ryguła, 2005). The weak points of these approaches are the lack of individualization, by using tables of standards, and the impossibility to generate new training content, from the existing one.

In a recent literature review on intelligent data analysis methods for smart sports training (Rajšp & Fister, 2020), the authors challenge the way modern technology is revolutionizing the way athletes maximize their performance and compete on a higher level than ever before. They define sports training as a pedagogical process where the role of the trainer is one of the teacher and organizer, guiding athlete's activities, and organizing the training sessions. The exercises are defined as tasks that require physical effort, and should in some way improve the sports results of the trainee. They break down the sports planning process into four phases: planning (prescription of proper exercise units), realization (execution phase), control (comparison between exercises performed by the athlete versus the planned exercises), and evaluation (measurement of athlete's performance). The phases are interconnected and have a continuous transition, as can be seen in Figure 4.

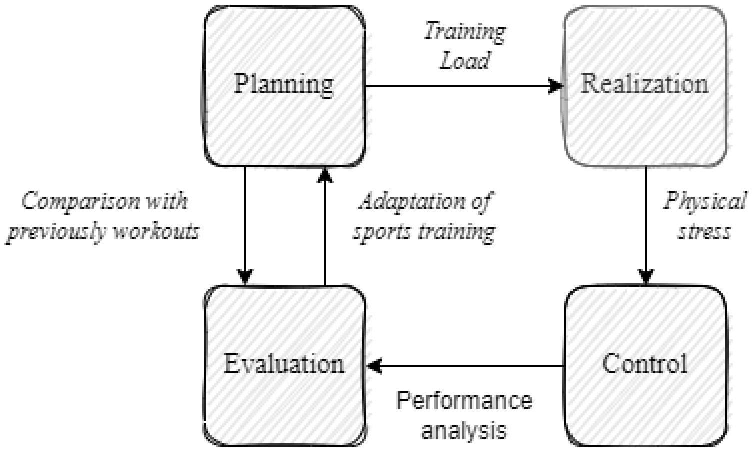


Figure 4. The four phases of sports planning.

The literature review shows that the smart sports training field has been rising in popularity in the last 5 years, since 2016, where the studies found were grouped into a taxonomy split into four main groups:

- Computational Intelligence methods (Evolutionary Algorithms, Swarm Intelligent Algorithms – Bat Algorithm (BA), and Particle Swarm Optimization, Fuzzy systems, and Simulated annealing)
- Data Mining (conventional Data Mining methods – i.e., Apriori, Machine Learning – Decision Tress, adaptive boosting, Random Forests, Gradient Boosting, K-Nearest Neighbors, Support Vector Machine, Artificial Neural Networks, hierarchical clustering, k-means clustering)
- Deep Learning (Recurrent Neural Networks, Long Short-Term Memory, Convolutional Neural Networks),
- Others (Case-Based Reasoning, Dynamic Time Warping, Bayesian Networks, Naïve Bayes, Markov chain, generalized additive models, Gaussian process, Linear Regression, regularized logistic regression, linear discriminant analysis, spline interpolation).

5 OntoStrength –A Framework to Represent and Inference Knowledge in Psychomotor Intelligent Tutoring System

5.1 OntoStrength's Design Methodology

The OntoStrength ontology aims to support the development of a psychomotor ITS dedicated to enhancing psychomotor skills and associated bio-motor abilities, such as strength. A multidisciplinary team composed of computer scientists and sports scientists developed OntoStrength. The Ontology 101 methodology, also known as OD101, (Noy & McGuinness, 2001) was used to develop the ontology.

We used the Protégé software to edit and refine classes, relationships, slots, and facets. GraphDB[1] was considered the semantic graph database for storing and querying the ontology, as well as for generating interactive data plots. The SPARQL query language (Prud'hommeaux & Seaborne, 2008) was used to test different training scenarios through queries.

Strength development is the domain covered by OntoStrength. Strength is defined as the maximal force or torque (rotational force) that a muscle or muscle group can generate or as the ability of the neuromuscular system to produce force against an external resistance (Bompa, 2017).

First, OntoStrength supports the ITS domain module by providing classes that describe the diversity of strength skills. Second, classes on strength development processes support the tutoring module. Finally, OntoStrength supports the ITS student module with knowledge about the different individual characteristics to consider for the personalization of strength program tasks. The first OntoStrength sub-domain aims to describe strength skills. The domain module uses strength skills to provide development objectives, the student module uses it to design a student strength fingerprint, while the tutoring module generates and monitors training workouts as an input.

Hence, a strength skill combines a movement skill and a strength type in the OntoStrength ontology. OntoStrength considers four movement types: Muscular, Functional, Fundamental, and Specialized. The first two movements support the general strength skills. *Muscular* describes the different types of possible contractions for each muscle involved in human body movement. OntoStrength describes twenty-four muscles and four contraction modes: eccentric, concentric, isometric, and plyometric. *Functional* is related to actions performed by the human body joints while moving.

[1] https://graphdb.ontotext.com/

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The OntoStrength strength skills sub-domain includes three hierarchies of classes that can be used to describe skills such as "Biceps Eccentric Maximum Strength," "Hip Flexion Strength Endurance," "Throwing Maximum Strength," or "Lunge Power." The classes used to represent the main concepts of this domain are the following: "Strength Skill", "Movement Skill," and "Strength Property".

The second OntoStrength sub-domain supports the description of a strength development program. The domain module for a psychomotor ITS can use this knowledge to provide relevant content to generate and schedule training workouts. The student module uses this knowledge to update student training components when performing workouts. Finally, the classes structure the behavior of the tutoring module. This sub-domain centered on strength skill development includes two hierarchies of classes: one to describe different periods and one to represent strength development modalities.

The third OntoStrength sub-domain supports the description of variables used when defining strength training development programs adjusted to students' characteristics. The student module from a psychomotor ITS uses this knowledge to provide the tutoring module with specific knowledge about each student. In addition, the tutoring module uses this knowledge when defining workout content and updates it based on the feedback received from the student. A typology of strength fingerprints structures these variables.

The "General Signature" class contains generic attributes such as the student's name, age, gender, size, or weight. One specific signature is associated with each bio-motor ability. The "Anthropometric Signature" refers to body sizes, weight, and body composition. The "Injury Signature" includes each student's history of relevant injuries to be considered when performing a strength development program. The "Motor Signature" associates specific levels to the student, for each movement skill. Moreover, the ontology includes the level of each strength movement type for strength development.

The "Strength Training Signature" describes the student training history for each workout performed, the content, success evaluation, and associated student feedback. Hence, the "Personalized Biomotor Development variables" organize all the different signatures in the OntoStrength ontology, as can be seen in Figure 5.

The previously described major class hierarchies support the instantiation of strength development programs, from the macro-cycle level to the exercise level. In addition, SPARQL queries were implemented to solve specific training tasks – for example, to obtain exercises associated with a specific body part (wide triceps push-up, side to side pull-up, feet elevated pike push-up), or to obtain generic training templates for a training objective, based on trainee characteristics. GraphDB was used to test the queries and interact with the ontology. Through SPARQL, new data can also be added to the ontology.

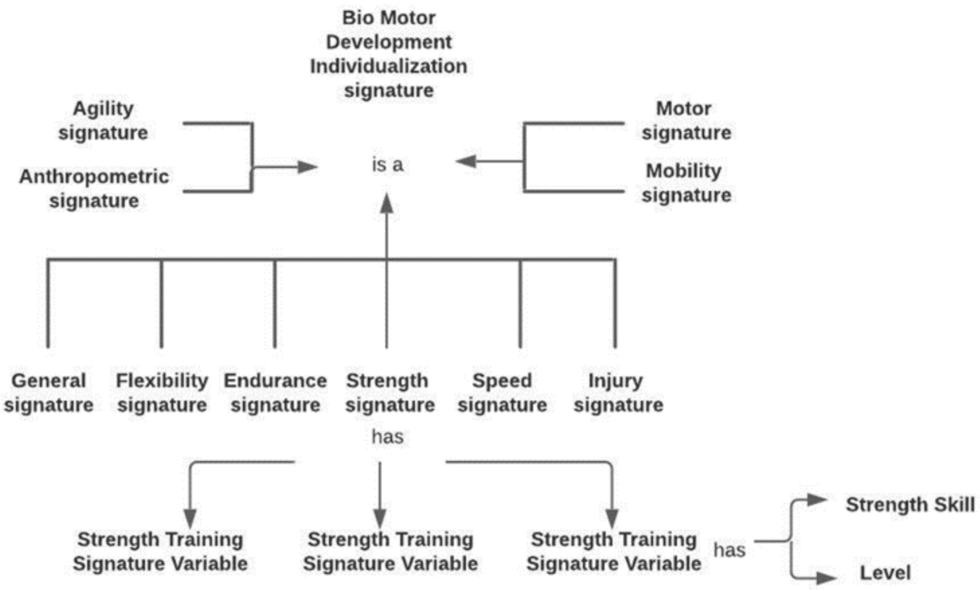


Figure 5. OntoStrength sub-domain for Personalized Development of Strength Skills

OntoStrength presents the instantiation of a Macrocycle entity, which has a Mesocycle entity as an object property, called hasMesoCycle. The Mesocycle entity has a Microcycle entity, as an object property, called hasMicroCycle. The Microcycle has two object properties (hasWorkout and hasObjective), whereas the Microcycle is defined as a Push Workout and a Full Body Workout.

The workouts are initialized with exercises following the rules defined by Bompa (Bompa, 2017), for a beginner-level load. Each exercise instance describes a list of functional and fundamental movements, together with the muscle contractions involved in the execution. The SPARQL query from Figure 6 retrieves all movements involved in a specific Microcycle defined in OntoStrength ("os" denotes the prefix specific to the OntoStrength ontology).

```
SELECT DISTINCT ?movement ?microCycle
WHERE
?microC os:hasMicroCycle ?microCycle.
?wkout os:hasWorkout ?workout.
?cntBlck os:hasContentBlock ?contentBlock.
?ex os:hasExercice ?exercise.
?ld os:hasLoad ?load.
?mvmnt os:hasMovement ?movement.
```

Figure 6. OntoStrength MicroCycle Movements query.

The inheritance hierarchy can be also visualized in GraphDB. OntoStrength relies on property inheritance between classes. Each exercise is represented as a class, which has specific base classes representing the type of movement involved, while the most generic one is the "Movement Skill" class. The "Exercise" class is inherited from the "Specialized Movement" class, which includes a list of "Functional Movements" to execute (such as "Elbow Extension," or "Shoulder Adduction"). Moreover, "Functional Movements" are composed of a list of "Muscle Contractions", such as "Hamstrings Concentric Contraction," "Quadriceps Eccentric Contraction," and "Teres Major Isometric Contraction".

An instantiation of an "Exercise" class is the exercise itself, with its specific level and description. "Feet Elevated Front Plank" from Figure 7 is an example of a named individual of the class with the same name, described as a Level 1 exercise, for the Anti-Extension Movement.

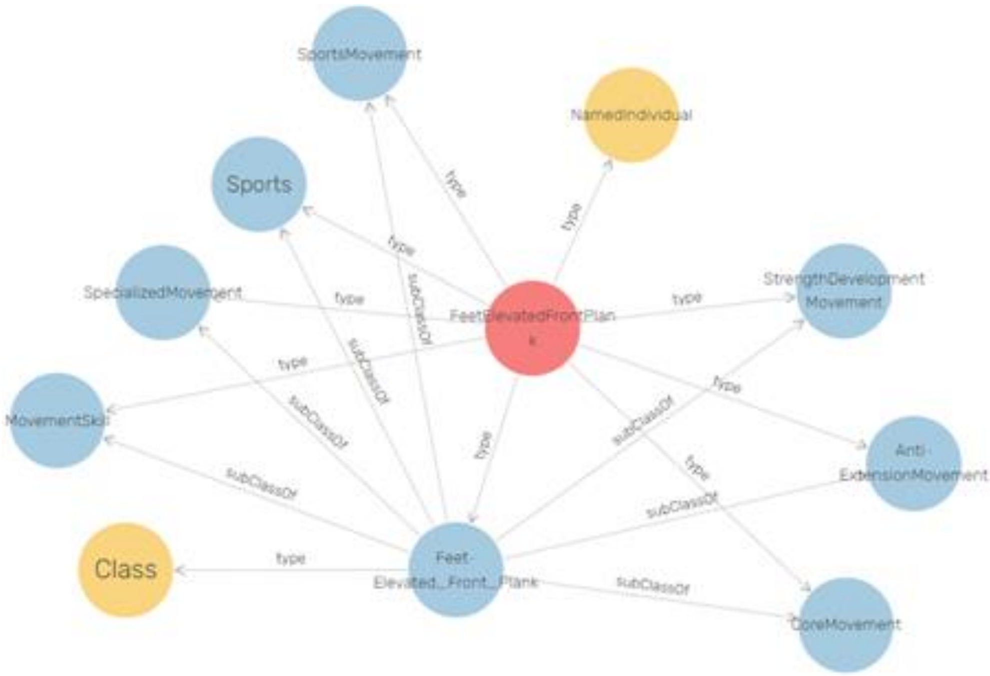


Figure 7. GraphDB View of Feet Elevated Front Plank instance and class

5.2 OntoStrength Usage

The OntoStrength ontology supports any psychomotor ITS by providing knowledge and relationships useful to different modules of the system. To this end, a RESTful API can interact with the ITS to provide microservices specific to the domain, student, and tutoring system functionalities. The following subsections illustrate the interactions of OntoStrength with a psychomotor ITS via the RESTful API.

The ITS Student profiling functionalities elaborate and refine student signature profiles used to personalize the definition of strength development workouts. The OntoStrength RESTful API provides queries to support the selection of signature variables used by the ITS, update signature variables, and obtain the values of signature variables.

OntoStrength –A Framework to Represent and Inference Knowledge in Psychomotor Intelligent Tutoring System

The strength individualization signature consists of a level ranging between 1-4 to match the level at which exercises can be safely performed, for all strength movement skills. The evaluation of these parameters is performed through an initial calibration workout session, which has an incremental complexity, until failure.

For example, "Side to Side Push Up" for upper body area level 1 complexity or "Self-Assisted One Arm Push Up" for level 2. This system calibration feature uses the RESTful API to obtain the exercises for a given strength movement skill and level, to get the actual student level for a selected strength movement skill, and update the student profile after each exercise. Once an initial student calibration is performed, a strength development training program is generated and is continuously updated after each workout.

We considered Ontology Development 101 (OD101) for building OntoStrength, a micro-level methodology that proposes a practical and explicit guide for developing ontologies. The process, based on interdisciplinary teamwork, implied a clear definition of the domain and the scope, the reuse of existing ontologies, the definition of classes, and properties, and finally instance creation to complete the knowledge base.

The ontology can be accessed using a microservices architecture, where specific endpoints are available to serve multiple queries for sports training purposes, such as exercises targeting a movement pattern, by difficulty, warm-up sessions generation, weekly training generic plans, based on objectives, and others. The microservices are ready to be integrated into any ITS for psychomotor development, where core components (i.e., student, domain, and tutoring models) may rely on the knowledge base for conceptualization and basic inferences.

The current section is the foundation to generate entire training chains, including workouts, micro cycles, mesocycles, and macrocycles. Improvements regarding the design of the ontology include additional gender dimensions and assessments of injuries while practicing training activities. OntoStrength will be published under an open-source license and will be further extended to include other psycho-motor abilities, such as Flexibility, Mobility, or Endurance skills.

6 Teaching Strategies in a Psychomotor Tutoring System

6.1 Accounting for Sexual Dimorphism in Psychomotor Intelligent Tutoring Systems

The morphological, cognitive, and physiological differences between males and females impact the content development of the training sessions, together with associated risks of injuries and psychological disorders. This section briefly describes these differences.

The difference between women's and men's skeleton size and body composition (i.e., density, relative fat mass, and lean body mass adjusted by height) varies at different age periods (Kirchengast, 2010) (Joyce & Lewindon, 2016) (Shephard, 2000). These differences increase at puberty due to hormonal differentiation. Adult human males are 7% taller than females, and there is a substantially higher amount of body fat and a substantially lower amount of lean body mass among women. Women have a smaller thorax, a larger abdomen, a broader and shallower pelvis, shorter legs, and a lower relative center of gravity than the male. The distribution of lower body muscle mass is quite similar between the sexes, whereas women have less muscle mass in the upper body than males.

Various theories (Baron-Cohen, Knickmeyer, & Belmonte, 2005) (Liutsko, Muiños, Tous Ral, & Contreras, 2020) (Li, 2014) enunciate the difference between women's and men's cognitive abilities impacting psychomotor skills. In general, women tend to adapt their behavior to their perception of another person's emotions and thoughts. For navigation, they favor an egocentric strategy while using street names and building shapes as landmarks. They outperform males in precision and fine hand abilities, object location and verbal memory, verbal recognition, and semantic fluency tasks.

In contrast, men tend to analyze and explore rules that govern a system. In general, they perform better on mental rotation and spatial navigation tasks than women. For navigation, they tend to favor an allocentric strategy that considers accurate judgments of distance. Men integrate speed and precision more quickly than women, and they tend to be better at sensorimotor tasks, including aiming, catching, and throwing.

Women's morphological differences and hormonal variability during the menstrual cycle induce a higher risk of injury and, in particular, Anterior Cruciate Ligament (ACL) injury. The prevalence of ACL injury for women is 2-10 times greater than in males, for the same psychomotor activities. This prevalence causes a lower rate of force development, hamstring activation deficits, and greater ankle dorsiflexion, combined with the valgus position of the knees and external rotation of the hip (Joyce & Lewindon, 2016) (Somerson, Isby, Hagen, Kweon, & Gee, 2019).

Traditionally, the schedule and the design of psychomotor skills training sessions rely on physiological temporal variables. The delay between two sessions must be long enough not to induce overfatigue and not too long not to induce detraining. The evolution of session load, which is computed using Equation 1, follows temporal patterns with progressive development from one week to another.

Equation 1. Session Load Formula

$$SessionLoad = \sum NoRepsEx\ k * IntensityEx\ k * RestTimeEx\ k * NoJointsEx\ k$$

The easiest week is set every three weeks to facilitate learning assimilation – for example, one week with easy sessions, one week with medium sessions, one week with heavy sessions, followed again by easy sessions.

Trainee's performance monitoring and feedback support load adjustment. When scheduling learning sessions for women, tutors must follow the same physiological temporal variables. However, when designing sessions, they must synchronize with the menstrual cycle to define session content. Table 3 describes the relationship between session load and the different phases of the menstrual cycle according to Pitchers (Pitchers & K., 2019).

Table 3. Training load adaptation to menstrual phase adapted from Pitchers

Menstrual Phase	Early follicular	Mid follicular	Late follicular	Early luteal	Mid luteal	Late luteal
Training Load	Light	Medium	Medium / Heavy	Very Heavy	Medium	Light

Trainee profiling before starting and during a psychomotor skill development program generally consists of assessing physical capacities and identifying areas of weakness or pain associated with performance (Joyce & Lewindon, 2016). The consideration of female-specific risks of injuries, particularly ACL and female athlete triad, requires integrating appropriate tests of assessing the injury susceptibility. Results from these tests are used afterward to provide dedicated prophylaxis sessions and adjust learning sessions accordingly.

6.2 Optimizing Teaching Sequences using Machine Learning. Right Exercise at the Right Time (RiERiT) Method

The tutoring process for a Psychomotor ITS was structured on a four-level maturity scale, which includes novice, intermediate, advanced, and expert trainers. Additional temporalities are considered in the adaptation process when moving from one level to another.

The Novice Trainer implements the Multi-Armed bandits' algorithm for personalizing the training sequences in a session. The Intermediate Trainer can personalize a session content; the Advanced Trainer personalizes the micro-cycle, while the Expert trainer can create customized mesocycle and macro-cycle content for each individual.

The underlying model relies on templates of training sequences for generating micro-cycles and sessions based on trainee input, including the number of sessions to train in the current week (associated micro-cycle), time to train for a session, and micro-cycle goals or focus. A sub-list of templates used for generating micro-cycles in anatomical adaptation is presented in Table 4.

Table 4. Micro-cycle Templates Examples for Anatomical Adaptation

Micro-cycle Template Name	# of pieces of Training	Recommended Trainee
Push / Pull / Lower / Upper / Lower	5	Men
Hip Dominant / Knee Dominant / Upper / Lower / Upper	5	Women
Upper / Lower / Full / Full / Full	5	Mixed

The charge level is represented by the number of repetitions (ranging from 8 to 15) and sets (ranging from 1 to 5). Targeted areas for exercises are represented by either fundamental or complementary movements, and the domain module maps real exercises with movement types and difficulty levels (from 1 to 5). Trainee level for each fundamental movement is estimated through calibration challenges, which were previously introduced. As such, the *Novice trainer's* challenge is to choose the right exercise from the list of available exercises (called the Right Exercise at the Right Time - *RiEaRiT*).

An efficient online method, namely contextual multi-armed bandits (Lu & Pal, 2010) was used to explore and optimize different exercises and estimate trainee progress. Such algorithms model a situation where a decision is taken in a sequence of independent trials based on a given context, which contains side information.

The context of *Selfit* is represented by the trainee shape-of-the-day, which is computed using a Borg scale (Spielholz, 2006), i.e., a CR-10 (Category Ration-10) scale to measure different body shape parameters. The selected algorithms ensure the creation of a personalized learning experience relying only on limited domain knowledge. The goal of the model is to maximize the total pay-off, or reward, of the chosen actions.

The reward of the Multi-Armed Bandit, after choosing an exercise, is computed as the difference between external load (EL) – considered exercise charge: number of repetitions and number of sets and internal load (IL) – computed from estimated user shape, subjective value. This difference is also defined as the number of Repetitions in Reserve (RiR) (Hackett, Johnson, Halaki, & Chow, 2012) and, for anatomical adaptation training, the best values are positive, as close as possible to 0.

RiR denotes how many more repetitions a trainee could have performed at the end of a set. 0 means the number of repetitions provided is the maximum number of repetitions the user could have performed. A positive value reflects the number of potential repetitions that could have been performed; nevertheless, this value is subjective. A negative value means the trainee has failed at that set; if, for example, the set had 12 reps and RiR was -2, the trainee was able to perform only 10 reps. While following a training program, there are specific sessions that require the trainee to reach failure (negative RiR).

The reward is computed based on the formula in Equation 2. Valid values of RiR are integer values in [-10,10] interval. If the reported RiR is either 0 or 1, the reward is 1, the highest value. This means the user was able to execute the number of repetitions of that exercise, and it was highly challenging also. If the reported RiR is greater than 1, the reward is positive, in the [0.1, 0.5] interval. The higher the RiR value is, the smaller the reward.

Equation 2. Contextual Multi-Armed Bandit’ Reward Formula

$$rew(RiR) = \begin{cases} 1 & , where\ RiR\ in\ \{0,1\} \\ \dfrac{1}{RiR} & , where\ RiR > 1 \\ \dfrac{1}{|RiR|} - 1 & , where\ RiR < 0 \end{cases}$$

If the reported RiR is less than 0, this means the user has failed the current exercise. The reward is proportional to the RiR variability. The higher the RiR value is, the higher the reward. For this branch, the reward is negative, with values within the [-0.9, 0] interval.

7 *Selfit* – A Psychomotor Tutoring System prototype in Open Environments

7.1 *Selfit* Architecture

The *Selfit Domain model* supports the learning process by providing answers to a) requests related to learning objectives definition, b) trainee evaluation, c) learning program definition, and d) adaptation by answering requests. OntoStrength ontology structures the *Selfit* domain model. Its core consists of the movement skill class, with associated psychomotor profile, movement patterns, and training program modalities. The ontology describes the relationships between body muscle chains, joint movements, agonist, antagonist, and synergist muscles for strength qualities development. It also describes different development modalities with associated load patterns.

The *Selfit Domain* encapsulates the logic for the calibration session, used to assess the trainee's level. 24 exercises were described, 4 for each movement area, with incremental difficulty and a protocol for execution. The domain also has a complete mapping of the movements with the body muscles. The trainee has the option to configure a session by specifying the desired muscles to train. The list of muscles selected is further mapped to the corresponding movements and based on trainee level and current session goal, the desired exercises are proposed.

The *Selfit Student Model* contains information about trainees' psychomotor capacities, especially the ones related to the super-compensation cycle status. Moreover, it includes usage statistics. The *Monitoring* module accesses information about how students are using the system and how they progress with their training. The module uses this information to modify the training parameters. The *Selfit Student Model* supports the generation of training sessions and the monitoring of trainee efficiency to optimize progression while ensuring motivation to practice and progress. More details on the student modeling imported from *OntoStrength* are presented in **Error! Reference source not found.**.

Selfit Student Module maps information about the trainee's mechanical status. This includes specific events reported by the user – pain, injury, surgery, or others, on one or more body regions: back, torso, upper extremity, lower extremity, and head and neck. This data, which can be updated at any type by the trainee, are reflected in the training planification. The reported events act as restrictions on specific movements and muscles to be used while training.

Selfit Student Module maps a list of physiological issues, with potential medical risks, which are also reported by the trainee. This includes a form the trainee can opt to fill in, which includes the following health risks – hypertension, diabetes, post-cancer, and obesity. The physiological status set a list of restrictions on the generation of the training program. Other data specific to the user is a list of favorite exercises, which are marked by the user while training and will increase the chances of being recommended further. Each user has a list of other trainees they follow, and who follow them in the *Selfit* application.

The *Selfit Tutoring model* supports the learning process by providing ML mechanisms to support the adaptation of the learning program to the trainee's characteristics. The tutoring module required integration with the psychomotor development domain. Sport training is a complex process, which supports adaptation and personalization while considering different temporalities (e.g., exercise, session, week, month).

A multi-armed bandit algorithm supports the definition of training workouts by adjusting the template content with inputs related to readiness to train, the effective realization of training tasks, and subjective assessment of task effects provided by the user. The sexual dimorphism dimension is also considered due to morphological, cognitive, and physiological differences between males and females. The design of training sessions relies on physiological temporal variables.

The delay between two sessions must be long enough to not induce overfatigue and not too long not to induce detraining. For men, the evolution of session loads follows temporal patterns with progressive development from one week to another. The easiest week is set every three weeks to facilitate learning assimilation – for example, one week with easy sessions, one week with medium sessions, one week with heavy sessions, followed again by easy sessions. For women, the evolution of session loads follows their menstrual cycles by using a specific template.

Selfit implemented the Right Exercise at the Right Time (*RiERiT*) method, which has proven efficient for adaptation in the psychomotor field, as shown in II.6. The tutor implements the multi-armed bandit algorithm for personalizing the training sequences in a session, based on session templates. A session template has a list of generic exercises, each of them with a targeted area, charge level, and rest time. *Selfit* proposes exercises most likely to increase the average competence level across all psychomotor components using previous trainee performance.

The *Selfit Graphical User Interface* supports exchanging information between the trainee and *Selfit* to facilitate the learning process. Students access the interface module through a Progressive Web App, available for cellphones, tablets, or personal computers. *Selfit* is accessible in the most popular mobile stores – Google Play[2] and App Store[3].

Progressive Web Application (PWA) development is a novel platform that combines the capabilities and experiences of native applications with the reach of the web (Biørn-Hansen, Majchrzak, & Grønli, 2017). PWAs are recognized for a set of key features, such as responsive, connectivity-independent, app-like, safe, or installable. The application acts as the User Interface Module and it is responsible for updating the Student Module, through continuous user feedback.

The interface module is composed of the authentication component, the calibration or assessment component, the feedback, and the training session. *Selfit* does not track and does not store any personal user data; user profiles consist of a nickname, password, and a security question managed by the *Authentication* subcomponent. The *Calibration* subcomponent supports the definition of each student's learning motivation by selecting physical qualities to develop.

For each physical quality, the component provides a testing protocol. For example, the evaluation for strength qualities development consists of a challenge aiming to perform four of the six essential movements categories (upper body push horizontal, upper body push vertical, upper body push horizontal, upper body pull vertical, lower body hip dominant, lower body knee dominant), one exercise for every four levels of difficulty. Calibration sessions should be performed regularly to adjust the user's progress while training.

Feedback is crucial to performing motor skills well (Bilodeau & Bilodeau, 1961). The *Dialogue* subcomponent supports students in providing information before and after training sessions to help adapt training sessions to students' shape and availability. Before starting a session, *Selfit* asks students to self-evaluate their fatigue level, motivation to train, sleep quality, and stress level on a scale from one to ten.

During training sessions, *Selfit* asks students to self-evaluate at the end of each content exercise and answer whether they could perform additional repetitions and, if yes, how many. After the training session, *Selfit* asks the users to input the session difficulty they perceived on a scale from one (very hard) to ten (very easy).

The *Training session* subcomponent provides learners with a training session description, which includes a summary of warmup, content, and cooldown exercises. Training sessions are easily configurable; trainees can select train location (home or gym), with many session templates available,

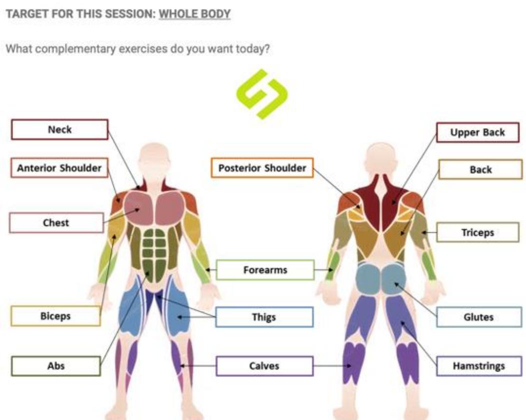
[2] https://play.google.com
[3] https://www.apple.com/app-store

the training materials available (barbell, elastic band, machine, etc.), and complementary muscles to target while training (anterior shoulder, biceps, forearms, thigs, etc.). While training, a video demonstrating the movement and details required to accomplish the correct load (i.e., number of sets, number of repetitions, rest between repetitions and between sets) is displayed for each exercise.

7.2 Workout Generation and Monitoring the Training Impact

The *Selfit* workout generation engine defines the content of the next workout session by using information about students' characteristics, past performances, and current fatigue levels. The tutoring module first identifies the workout target by predicting the most accurate template, based on the student's training history and actual fatigue signature. Once selected, the module generates appropriate content using training strategies and students' personalization signatures. The user can also customize training content by modifying his/her preferences about developing muscles, before starting a workout. At the end of each exercise, session phase, and workout, *Selfit* assesses success or failure and asks students about their perceptions of the effort.

The *Selfit* user interface module updates the ontology with training information updates submitted by users, such as the daily fatigue profile, or the perception of effort after achieving a training task. An example of the graphical interface inside the training session can be seen in Figure 8 (a), where the user subjectively assesses his physical shape before starting a training session; muscle development preferences are described in Figure 8 (b).



(a) Daily fatigue monitoring interface (b) Muscle development preferences interface

Figure 8. *Selfit* Interface – Parameters for Workout Generation

User feedback after each exercise is stored and the tutoring module improves recommendations based on the reported repetitions in reserve. Personalization is perceived at the session level. Before starting each training, the user configures the current session parameters' and then all the exercises are generated. Afterward, the session summary is shown to the user and then the training can be started.

7.3 Psychomotor Assessment using Computer Vision. A Study on Mitigating the Risk of Injuries

A women's ACL injury risk assessment module was developed to support student initial screening and injuries risks monitoring. The assessment process is structured into four phases, see Figure 9. The first phase consists of capturing one frontal and one sagittal video of the student performing a back squat. In the second phase, a human motion recognition module provides a discretization of each body joint's trajectory while performing the back squat. Then, the risk assessment module analyzes this model for calculating the ACL injury risk factor. Finally, if risks are detected, the module provides instructions to the ITS.

The two videos allow having a complete perspective of the performed movement and then provide information to assess knee valgus and ankle flexibility, two of the essential factors involved in the ACL injury risk.

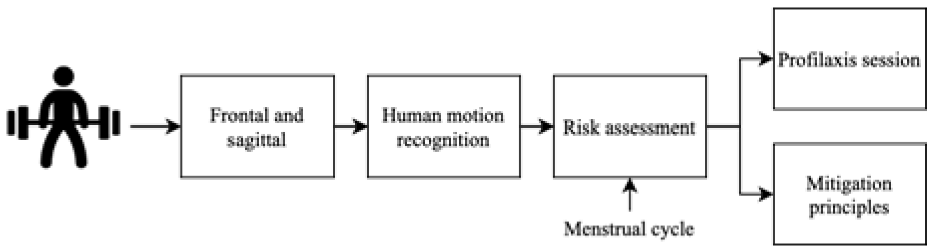


Figure 9. ACL injury risk assessment module process

In the second phase, a human motion recognition module provides a discretization of each body joints' trajectory performing the back squat. The OpenPose 2D pose estimation library (Cao, Simon, Wei, & Sheikh, 2018; Simon, Joo, Matthews, & Sheikh, 2017) allows obtaining videos with an added overlay containing the body key points and lines and a collection of JSON files, one for each frame, containing the position of the essential points, in pixels. A recent study (Ota et al., 2020) demonstrates the reliability and the validity of this library results by comparing them to results provided by a kinematic measurement by three-dimension motion analysis devices using VICON.

The risk assessment module analyzes this model for calculating the ACL injury risk factor. The monitoring of the medial aspect of either knee passing the medial malleolus from the anterior perspective during any phase of the squat supports identifying a valgus (Somerson et al., 2019). The module evaluates the distance between "R or L Knee" and "R or L Ankle" when the student performs the back squat.

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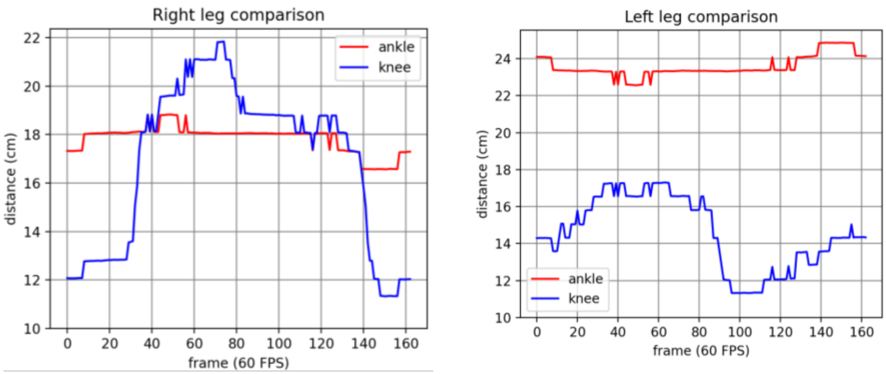
The squat movement starts in frame 30 and finishes in frame 150 in Figure 10. At the initial position, the distance between the knees and ankles is negative, and the distance between knees and ankles is superior to 5 cm, demonstrating the presence of a valgus position before the start of the movement. During the movement, the negative distance between the left knee and the left ankle increases, demonstrating the valgus position's increase.

The risk of ACL injury increases if both a valgus and flexible ankles are detected. During the ovulation period of the menstrual cycle, hormones maximize the risk. If the risk assessment module detects a risk of ACL, it communicates with the *Selfit* ITS by providing mitigation rules to redesign the planned and future learning sessions for considering low-risk tasks. Furthermore, *Selfit* provides additional prophylactic learning sessions to decrease the risk of ACL with specific strength, flexibility, and proprioceptive tasks.



a) a valgus on the right knee b) no valgus on the left knee

Figure 10. Illustration of the evolution of the distance between student's knees and ankles with variations between left-and right

The current chapter introduces a comprehensive description of *Selfit*, an ITS for psychomotor development, alongside encountered design and implementation challenges and architectural considerations for the sexual dimorphism dimension.

8 Results

8.1 Simulation-based Experiment

The efficiency of the Tutoring module was simulated with different contextual multi-armed bandits' implementations. The experiments were conducted in fully virtual environments, and the goal was to determine, based on the general sports training methodology, which algorithm converges first, and how many training sessions are required.

The experiment was conducted in an environment configured with 1800 exercises, 300 for each movement family, with 10 exercises per level of difficulty. Difficulty levels ranged from 1 to 5. The following strategies were implemented to assess performance: (a) random agent – picks a random exercise for that movement type and level; (b) multi-armed bandit upper confidence bound (MaB UCB1) – the principle of optimism in face of uncertainty, which means the more you are uncertain of an arm, the more important it is to explore; (c) multi-armed bandit ε-Greedy (0.1) –explore (choose a random action) with probability ε and exploit (choose an action with maximum value) with probability 1-ε; and (d) Bayesian multi-armed bandit UCB1 – use the same principles of UCB1, but incorporate prior information on the distribution of an arm's rewards to explore more efficiently.

For the ε-Greedy approach, the value of 0.1 for ε exhibited the best results for all the simulations. Initial competence levels were configured randomly for each movement type of the simulated trainees. The response of students after applying an exercise follows the standard Item Response Theory (Hambleton, Swaminathan, & Rogers, 1991), where the probability of being able to perform an exercise is given by Equation 3.

Equation 3. Item Response Theory (Hambleton et al., 1991)

$$p(success) = \frac{\gamma(a)}{1 + e^{-(\beta(c^{Q} - c(a) + \alpha))}}$$

Parameters β and α are constants to simulate different learning rates of the population; γ(a) was randomly generated for each competence level of the trainee between 0 and 1, where 0 means the trainee cannot perform the exercise. Also, it was considered that after every 30 exercises applied to a muscle family, the number of repetitions in reserve for all the exercises for the targeted muscle family will increase. The experiment goal was to understand how fast and efficiently the proposed algorithms estimate and provide training exercises, using the current state of the trainee. In the experiment, a population of 1000 trainees was generated, each with a specific competence level, generated randomly per exercise; RIR values were initially estimated per exercise and trainee.

Results

The previous population was trained for 2 years, including 384 sessions, using the four conditions given by the selected algorithms. The same exercises were applied to a trainee at a certain time, given the four strategies. Results can be seen in Figure 11. A data point on the Ox axis represents the current training session number, and the Oy axis encapsulates the cumulated training reward.

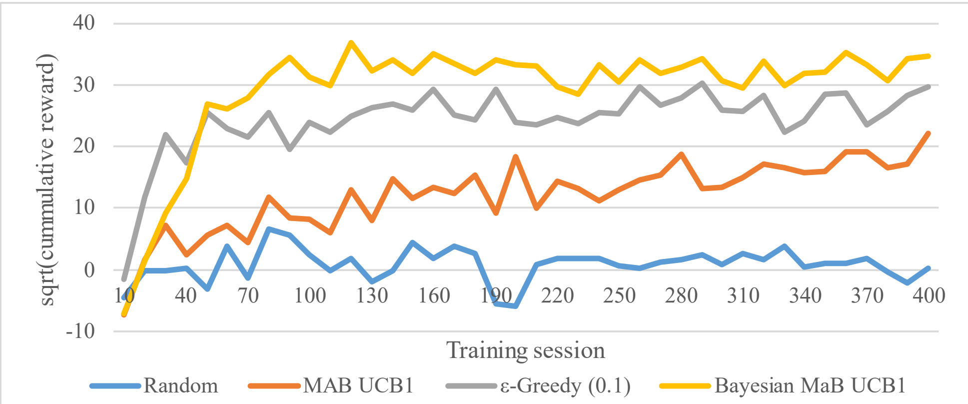


Figure 11. Training Algorithms Comparison – 2 years timeframe

The algorithm that provides the best cumulative reward during training is the Bayesian Multi-Armed Bandits UCB1: 1175; next was the ε-Greedy strategy (975.8), followed by simple MaB UCB1 (483.3) and random (33.1). The *Selfit* Tutoring model supports the learning process by providing machine learning mechanisms to support the adaptation of the learning program to the trainee's characteristics. For the Novice coach, the sessions were generated using a standard calendar plan, used by trainers in their daily work, without integrating the gender dimension.

8.2 Experiment with Real Users

The goal of an Intelligent Tutoring System is to provide more efficient teaching experiences to students (Clement et al., 2015). The current experiment aimed to evaluate both *Selfit* learning improvement and the overall user experience. The experiment has been split into two phases. *Selfit version 1* was initially tested between January-February 2021, by 18 trainees from France and Romania. Few user interface and session exercise selection bugs were reported by the users, and several improvement features were proposed in this preliminary feedback.

The initial testing phase has been followed by a new development phase, between February 2021 and December 2021, for an improved *Selfit* version, which was rolled out to production at the end of 2021. *Selfit Version 2* included several bug fixes, performance improvements, and a set of new features, based on user feedback. Features include the ability to customize your profile (set up a profile picture, set a motto, birthdate, etc.), an option to pause and resume time-based exercises, an improved interface for inputting RIR per exercise, better tailoring of a session by inputting a list of materials available to train, added body areas trained statistics diagram, integrated Google Analytics, created a new protocol for pre- and post-tests, and others.

Selfit Version 2 was tested in the second phase of the experiment, between January-May 2022, by 42 trainees from France and Romania, which got onboarded in the app on different dates. The goal was to validate the software architecture, and the interface, and to assess if it is possible to learn the best load over each exercise, so that learners are at their optimal level across a training program.

Even though the first phase of the experiment should have lasted for 3 months, to also gather data about how the tutoring module behaves in practice, based on the user's feedback and the bugs reported, this phase has been paused and the issues were addressed. *Selfit Version 2*, with several interface and performance upgrades, has been released internally, in our research group, in November 2021, and released publicly, in the mobile stores, in January 2022.

The updated version has split the population of trainees in two, both using Contextual Multi-Armed Bandits ε-Greedy (0.1) algorithm:

- the first group has used the *Selfit Tutor A* – the tutor is using a wider exploration space (the bandit arms for a movement area exercise include all the available levels, filtered by the available materials);
- the second group has used *Selfit Tutor B* – the tutor is using a narrow exploration space (the bandit arms for a movement area exercise include only the user's estimated level, filtered by the available materials).

We expected the *Selfit Tutor B* to provide more tailored training content overall, due to the smaller size of the exploration space. Even considering the current trainee context, which we assumed it should impact the training load – difficulty of the exercises provided, we expected more engagement and better progress for the participants in Group B.

Users enrolled in the experiment were exposed to one of the two versions of the tutoring component, both implemented using the Contextual Multi-Armed Bandits ε -Greedy 0.1 (Contextual MaB) session generation – one with a higher exploration space (called further Group A), and another one, with a lower exploration space (called further Group B).

The top 5 performers from Group A have the following number of sessions completed: 30, 27, 25, 23, and 16, while from Group B the top 5 performers have: 11, 6, 6, 5, and 5 sessions respectively. Group A has performed 254 training sessions, while Group B has performed 61 training sessions.

The calibration challenges' goal was to classify the user in one of the four-level categories (Beginner, Intermediate, Advanced, or Expert), per each movement type: Upper Body (Push Horizontal, Push

Vertical, Pull Horizontal, Pull Vertical) and Lower Body (Hip Dominant, Knee Dominant). Users can update their levels per movement type only by performing again the challenges, at any moment. Based on the calibration test, users are assigned in the corresponding level per movement type and future exercises will be provided following the current values.

Bandit's recommendations are different between the two groups. Group A, which uses the high exploration space, will have more available arms to choose from – the bandit will choose from all the levels of that movement area, and be filtered by user restrictions and preferences. Group B, which uses the narrow exploration space, will have fewer available arms to choose from than Group A. An example of how the algorithm behaves for two users, with the same training profiles, who are using Tutor A and Tutor B, after the calibration challenge, can be seen in a simulated scenario in Figure 12.

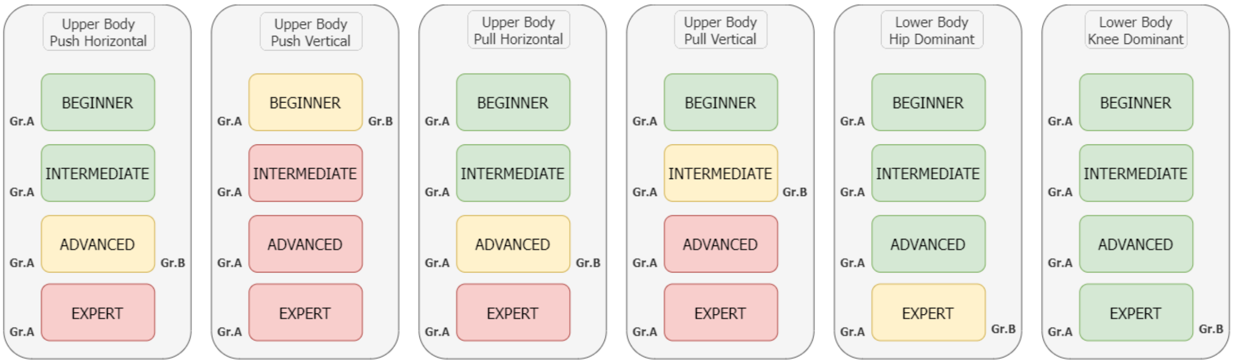


Figure 12. Bandits Exploration Space per each group, based on the Calibration Challenge.

For the Upper-Body-Push-Horizontal movement type, the current level is Advanced. In Group A (Gr. A), exercises provided can be either Beginner, Intermediate, Advanced, or Expert, while in Group B (Gr. B), the exercises will be only from the Advanced category.

8.3 Results of Agent's Learning

The experiment's goal of learning was twofold. First, we aimed to validate the calibration challenges protocol and the sport exercises classification. For this, Group A and Group B followed the same calibration tests and were classified within corresponding groups. Considering the higher exploration space for Group A, we expected, at the beginning of the training program, to expose smaller rewards on average than for Group B. RIR values were expected to be closer to 0 for Group B, and farther from 0 for Group A for the first mesocycle.

Second, we aimed to validate the efficacy of the Contextual Multi-Armed Bandits algorithm on learning. For this, the average rewards at each step were computed in each group and the bandits' learning is discussed. This phase also presents the potential noise in a few athletes' data and describes an exclusion protocol for faulty data.

The 42 trainees involved in the experiment, split among groups – 22 in Group A, and 20 in Group B, involved in 315 training sessions. A more detailed view of the number of sessions per user and its group can be seen in Figure 13. We can conclude that Group B had many light trainees – 9 users with only one training session and 2 with two training sessions, while Group A had many heavy trainees – 12 users with more than 12 sessions, and none in Group B.

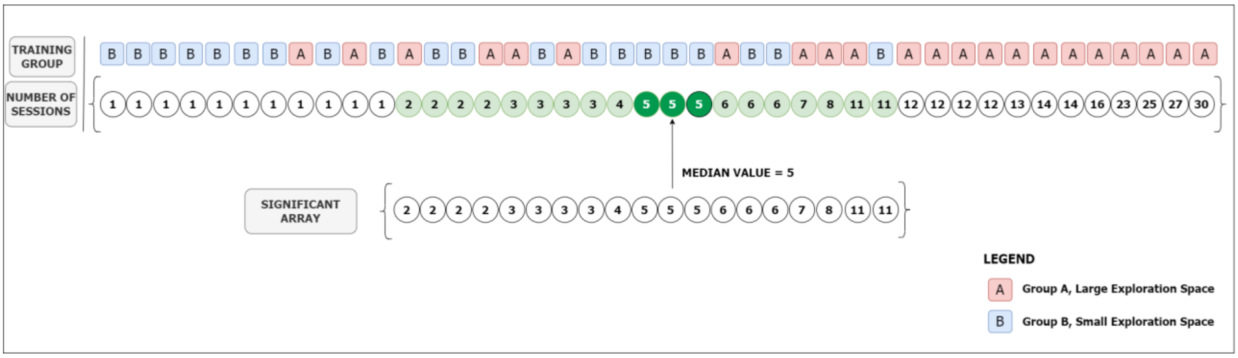


Figure 13. Number of sessions per user and their corresponding training group.

Group A, characterized by a wide exploration space from the bandit, required more states than Group B to provide a better reward across time. We considered it relevant in Group A, based on the simulations presented in 8.1, users who performed more than 12 sessions. The selected interval included 12 users and had from 57 to 169 actions taken by the bandit based on the current trainee state. The results of the average rewards for top performers in Group A can be seen in Figure 14. The figure presents each bandit prediction step, from 1 to 144, and the average reward across users tends to increase over time.

Even though the most active trainee in Group A trained for 169 steps, we considered in the current analysis the averages of at least three trainees at each datapoint. This is the reason the number of bandit steps in Figure 14 stops at 144, the last step when there were three users with predictions. We can state that, at each User ID, the number of trainees at that bandit step is equal to the value of that identifier (value of User ID). For example, in step 153, 2 trainees were using the system, and starting step 154, only one remained.

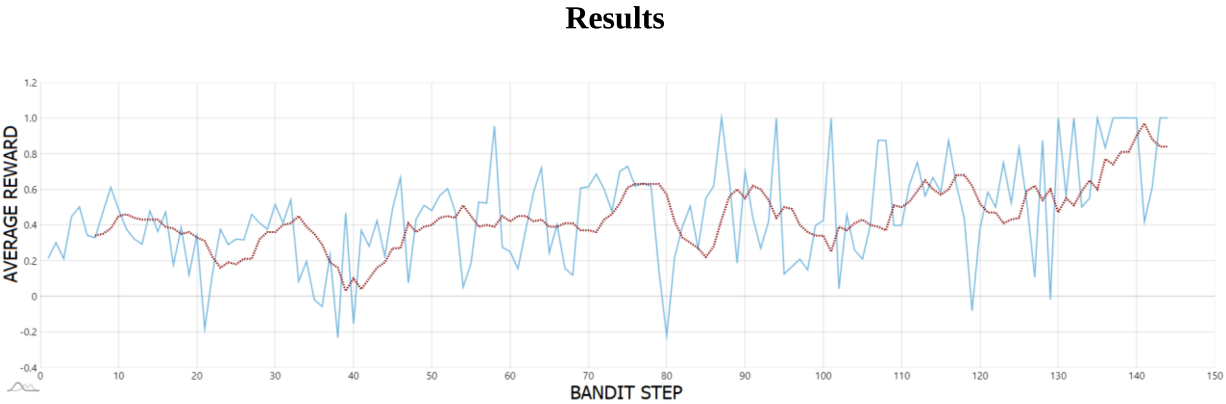


Figure 14. Average Rewards and Moving Average (window size = 6 steps ≈ 1 session) Rewards per Bandit Step for Top Performers in Group A (> 11)

Same for bandit step 78, 8 trainees were using the system, and starting step 79 to step 81 there were 7 trainees, and so on. Similarly, for group B we computed the average reward across all trainees at each prediction step but, due to the limited data, we looked between 3 to 11 sessions, which covered a number of 6 trainees, and considered in our analysis steps where at least 2 trainees are involved.

The data gathered from Group B is not sufficient to make a strong point on bandit learning from the smaller space exploration, even though we see an overall tendency of growth. More data would be required to justify the bandit algorithm learning for this group. Tutor A shows, though, promising results for the trainees who followed the training program for more than 12 sessions.

8.4 Results on User Experience

Selfit Version 2 phase tested lasted for 5 months, between January and May 2022, and involved 42 trainees, from France and Romania. They got enrolled in the system on different dates and trained between 1 and 30 sessions, the median value was 5 sessions. *Selfit Version 2* did not store any personal data about the user. They enrolled within the system with a nickname, a password, and a security question, as a backup for forgetting the password. No real data about the user was required or either available to fill in, such as email, phone number, name, or address.

After each log into the system, users could configure their profile, filling in general information on their gender, birth year, bio, or setting up a profile picture. Out of the 42 users, only 10 users filled in the optional information in their profiles. Only the bio and the profile picture fields were public and visible to the other members enrolled in the system. All the users were involved in the pre-test - the calibration challenge performed when they started to train using *Selfit*. 10 of them also completed the post-test, at the end of their training program.

At the end of May 2022, the trainees received a user experience survey to fill in. The structure of the survey was the same as the one described in the previous section, for *Selfit Version 1*, based on the AttrakDiff questionnaire, and included 9 new questions, where we aimed to assess the training shape of the user, involvement in the experiment, and some open questions on the overall perception of the user. 21 trainees out of the initial 42 (50%) filled in the questionnaire. Based on our knowledge, most of the trainees involved in the *Selfit Version 1* experiment also used the new version and trained from January-May 2022. We aimed to assess if there is any visible improvement in the overall User Experience between the two versions, what were the main pain points and strengths of the system, and if there is any link between the motivation to train and user experience.

The AttrakDiff questionnaire values for *Selfit Version 2* can be seen in Table 5. Values in bold mark a difference greater than 0.5 on the 7-point Liker scale between the two evaluations. We can state that overall user experience has improved in *Selfit Version 2*, as many hedonists and pragmatic quality values are better. The negative differences between the two versions indicate that the users perceive the new system as a bit more technical overall and feel like the system does not fulfill their need on bringing people together, the social component.

Table 5. *Selfit Version 2* User Experience Feedback based on AttrakDiff questionnaire.

UX Quality	M (SD)	UX Quality	M (SD)	UX Quality	M (SD)
Pleasant	**5.90** (1.26)	Connective	4.14 (1.64)	Human	3.85 (1.38)
Inventive	**5.76** (1.71)	Simple	**5.66** (1.65)	Professional	**6.0** (0.83)
Attractive	5.19 (1.56)	Practical	5.66 (1.42)	Likeable	5.95 (1.21)
Straightforward	5.52 (1.36)	Stylish	4.90 (1.44)	Predictable	4.66 (1.49)
Premium	4.76 (1.54)	Integrating	4.95 (1.29)	Brings people closer	4.05 (1.30)
Novel	5.47 (1.49)	Motivating	5.90 (0.74)	Captivating	5.40 (1.39)

Users involved in the experience survey were asked also to fill in how many trainings they performed on average by the week before and during the experiment. 5 users involved in testing *Selfit Version 2* were not training at all before the experiment (23.81%), and, e.g., 1 user was training every day of the week (4.76%). During the experiment, most users were training either 2 or 3 times per week, 5 users in each category, 3 users trained only one time per week, while the same user as before the experiment continued to train 7 times per week.

9 Discussion

9.1 Advantages of our Approach

RO1: Design an effective knowledge representation model for the psychomotor skills development in an Intelligent Tutoring System.

The current thesis introduces an ontology to model learning in the psychomotor field, called *OntoStrength*. The proposed modeling is dedicated to enhancing psychomotor skills and associated bio-motor abilities, with a more comprehensive description of the strength skill. *OntoStrength* has been built by our team with cross-disciplinary expertise, with a background in muscular, biomechanical, sports training, and computer science fields.

It was developed using Ontology 101 Methodology (OD101), SPARQL was used for queries, and the views were implemented using the semantic graph database GraphDB. OWL is the formal representation language, and the software used for development was Protégé.

OntoStrength was further integrated and used within an intelligent tutoring system for psychomotor development, called *Selfit*. The knowledge described was mapped to the ITS components. Domain module addresses the movement field by first considering the diversity of human movement activities – daily life, leisure, or professional – and their description – muscular contraction, human body joints movements, or fundamental movements. Second, it includes the movement metabolic profile with its duration and intensity. Moreover, the domain is also related to the specific development rules and constraints of the different sub-skills used by the development program.

The student module considers the evaluation domain of psychomotor skills. From this perspective, *OntoStrength* includes performance indicators and associated evaluation rules for each sub-skill considered by the development program. The ontology also addresses performance indicators used to monitor trainee responses to the training workout and to adjust the planned program to the reality of the effects of its application.

The ontology was mainly developed based on the sports training theory described by Bompa (2017) and recent work on the psychomotor field, including the updates of the psychomotor taxonomy (Hoque, 2016), and similar work developed for other use cases: Goldberg et al. (2018) – for military training, or PRB de Campos (2018)- for learning engineering. Nevertheless, *OntoStrength* has a central role in the current thesis as it grounded the development of effective tutoring and the elements rendered in the graphical user interface.

Discussion

RO2: Provide personalized sports exercise' recommendations for the mass population when training in open environments.

Numerous external factors might influence trainee fitness, fatigue, and willingness to train, such as daily life, professional, or other psychomotor activities. External factors which impact the training content are the fourth set of characteristics. The consequence is that trainee fitness and fatigue levels might be superior or inferior to the state assumed by the tutoring system. In addition, when starting a new training session users might be injured and incapable to perform part of the psychomotor training tasks.

On top of these psychomotor field characteristics, the tutor should decide what is the optimal sequence of activities that maximizes the average competence level overall skills for each trainee. This is difficult to address as the users have a limited time to practice training activities – they cannot test all the available exercises to see which are the best for them, and there are individual differences between trainees – a learning task that is optimal for one user may be inefficient for another user with a similar profile.

Our initial implementation in a simulated environment shown this personalizing approach is efficient, and it provides high-performing learning sequences after six months of continuous training. We assessed the effect of Contextual MaB in an experiment with real users, which involved 42 users who trained for 6 months. The participants used one of two versions of the *Selfit* system, with two adaptive strategies – Tutor A with a wider exploration space (simple and difficult exercises shown to the users in Group A), and Tutor B, with a narrow exploration space (only current user level exercises shown to the users in Group B). The participants were asked to perform 12 training sessions, and also an initial and final calibration session.

We observed the participants in Group B have quit much faster the trainings – no user performed the full training program (11 training sessions for the top trainer in this group), while in Group A there were 12 participants who followed the full training program, and also some top trainees – the top three performed 30, 27, and 25 sessions. This was a surprise for us, as the initial experiment setup assumed similar engagement overall, and even Group B to surpass Group A training time.

Our findings highlight the importance of the diversity of exercises, through wide exploration, in order to maintain the motivation to train and keep the user engaged. The results for top trainees showed an increase in the average reward across time and, even though they did not follow the exact training planification as for the simulation, the results of the experiments are slowly converging to the simulations, which was in line with our expectations. The Contextual MaB method for personalizing learning in psychomotor training has shown promising results overall.

Discussion

RO3: Implement an intuitive and effective Communication Module that facilitates the assessment of the sport trainee's progress in open environments.

Good communication skills are essential for people who work with other people and certainly for teachers (Woolf, 2010). Current work introduces a Communication module to support the exchange of information between the users and the tutor, to support psychomotor skills development. The Communication module interacts with the other three ITS components – domain, student, and tutoring modules.

The Communication module proposed has the following components: (a) Authentication component, (b) Trainee Calibration component, (c) Feedback component (self-evaluation – before and after session, exercise-level feedback, per each set – acute feedback), and (d) Training workout component (video demonstrating the movement, workout setup, workout summary, past workouts). Trainees are required to create an account at their first interaction with the *Selfit* system. No personal data is stored in their user profile.

Trainee Calibration sub-module is a set of component interfaces that has the role to exchange information with the user to estimate his current level across the main movement areas. The Calibration module includes a maximum of 24 exercises to execute, 4 per each movement area, ranked based on the difficulty (from level 1 to level 4). If a specific level is not passed, the more difficult exercises of that category – higher levels – will not be shown. To pass a specific level, the user has to watch the video with those specific exercises, execute the number of repetitions shown, and then input the number of executions he was able to execute. Trainee Calibration is required before the first session using *Selfit*, and it will be available at any time for users on the home page. It is recommended to redo the calibration challenge after finishing a mesocycle and to be in a good shape when performing it.

Training workout component exchanges information with the learner on the training program and includes the setup of the training (location to train, time to train, available materials, preferred muscles to target), the training summary page, the past pieces of training list, and the flow of training. While training, a video demonstrating the movement and details required to accomplish the correct load (i.e., number of sets, number of repetitions, rest between repetitions and between sets) is displayed for each exercise.

The Communication module implemented within the *Selfit* system has been tested with real users and a user experience survey has been conducted using the AttrakDiff questionnaire. 21 users filled in the questionnaire and the overall feedback was that *Selfit* was perceived as pleasant, inventive, simple, and professional.

9.2 Limitations

The dataset obtained during data collection is not fully matching the size of the simulations. Simulations performed in the virtual environment have demonstrated the learning of the contextual multi-armed bandits' algorithms. These showed that the users should train for at least 48 sessions to have a visible increase in the average reward across sessions, while in the real experiment the top performer trained 30 times.

Even though we published the system on the mobile stores and the Internet, and made it available across the world, for free, we had a limited budget to promote it and to reach a high number of people (42 trainees engaged). The sports individualization theory applies the same rules based on age differences and professions, considering the description of the trainee profile – gender, injuries profile, diseases. Our findings support the generalizability of the system up to a certain degree.

In terms of data collection while training, the measurement of perceived effort per each exercise – repetitions in reserve (RIR) has been assessed using the subjective input from the trainee, which can be noisy. A more accurate measurement of the perceived effort is monitoring the heart rate while training and correlating with the input of RIR. The heart rate variability indicates if the user is training or not, and what is the approximate fatigue. It may also be a good indicator of counting the repetitions executed. Measuring the heart rate requires an external smart device, such as a smart band, smartwatch, or chest strap, which the users involved in the experiment required while training.

Another limitation we mention is the complexity of the strength psychomotor training field. Even though we can conclude we obtained good modeling of the strength field, through *OntoStrength*, which was emphasized by our results, we did not map all the parameters which influence the sports training individualization. This was due to both time constraints and limited knowledge of cross-disciplinary expertise, such as the dietary dimension, where we lacked the required knowledge.

Also, another limitation is generated by the overarching development of the *Selfit* system, over the last 4 years, which was not heavily tested and may throw bugs in some edge cases. Our team did not have a Quality Assurance (QA) engineer assigned to develop test cases and execute them periodically. This exposes a vulnerability of the *Selfit* system overall. An overview of all available flows and edge cases should be described for any software, to have a better view of the potential bugs which may occur. Based on the Visual Studio[4] analytics using Code Metrics Calculator, the current version of the *Selfit* system has 221.873 lines of code.

[4] https://visualstudio.microsoft.com

9.3 Envisioned Applications

The first part of the thesis has a more theoretical nature, the objective being to build the foundation OntoStrength has a comprehensive description of the psychomotor profile and planification for training programs, for each phase – session, micro-cycle, mesocycle, and macro-cycle. Together with a database of over 1.000 exercises which are labeled based on muscles involved, movements, joints, materials required, videos, and difficulty, OntoStrength will be soon published under an open license and the knowledge base will be available for free.

The work presented for OntoStrength can be used to improve certain learning scenarios. Other systems targeting strength training can reuse the OntoStrength modeling and extend the work to other psychomotor fields – such as endurance, or flexibility.

Our approach introduced an algorithm that relies on the empirical estimation of the learning progress, called RiERiT – Right Exercise at the Right Time, implemented in Python[5]. This work can be used in other adaptive tutoring scenarios. Other systems which involve an adaptive component, in psychomotor training, may use the current approach as a starting point.

The user interface model has been built as a monolithic system, using Microsoft tech stack – ASP.NET MVC[6]. The code source will soon be published publicly on the GitLab platform[7]. Specific features, such as calibration challenges, wearables integration with the most known providers (Garmin[8], Fitbit[9]), session flow, and profile configuration by the users may be reused by other researchers in their systems.

Overall, as the governments are more and more interested in mass population health, and the lack of physical activity is a high concern for the more-developed countries, we envision the current work as the foundation of a larger-scale research project, over the next years, with focus to digitize the sports training field and develop several solutions which aim to improve the lifestyle of both beginners and intermediate trainees. We consider the timing is right for such a research project, the technological advancements support the required developments, and our core team can provide the expertise for leading the development of relevant solutions further.

[5] https://www.python.org
[6] https://dotnet.microsoft.com/en-us/apps/aspnet/mvc
[7] https://gitlab.com
[8] https://www.garmin.com/en-US/
[9] https://www.fitbit.com/

10 Conclusion

Insufficient physical activity is a global public health concern, affecting millions of people in developed and developing countries (Guthold, Stevens, Riley, & Bull, 2018). The social, economic, and environmental transitions have led to physical inactivity and large amounts of time spent sitting (Owen et al., 2020), which is associated with an increased risk of common non-communicable diseases, such as type 2 diabetes, cardiovascular disease, musculoskeletal disability, or the major cancers.

In a society that is more and more interested in global public health (McCuaig & Quennerstedt, 2018), the goal of the current thesis was to study how and if ITSs may be built and used for training psychomotor skills. The work presented is at the crossroad of two main fields, Artificial Intelligence in Education (AIED) and sports training. Our approach introduced an ontology in the psychomotor field, called OntoStrength, used by the ITS for knowledge modeling.

Also, based on the user's training constraints – limited time, fatigue, and volatile motivation, we introduced a tutoring personalization approach based on RL contextual multi-armed bandits, which was shown previously to be efficient in educational scenarios. Our simulations have shown promising results for using this approach in psychomotor training, and an experiment with real users has been performed between January and June 2022 which has shown the potential of the proposed method, but additional experiments are still needed in this area. The following section describes the personal contributions based on the three research questions formulated initially. Afterwards, some directions for future research are presented.

10.1 Personal Contributions

The development of multiple systems, and the contributions in various research areas – including computer science, knowledge modeling, or data science, all converging into a unified approach at the crossroad of informatics, educational science, and sports science, are just the highlighting points of the current thesis. The goal of our research was to understand which are the main requirements and implications for digitizing the psychomotor training using intelligent tutoring systems. Our work provides an inter-disciplinary approach, covering:

- *informatics*, with emphasis on reinforcement learning as support for adaptive tutoring, and computer engineering for the development of the interface and communication modeling;

- *educational sciences,* for the intelligent tutoring systems study-cases, to discuss transferability and implications on the psychomotor field;
- *sports science*, for grounding the knowledgebase and developing the modeling using the ontological approach.

The preliminary work of this research was a systematic literature review on intelligent tutoring systems for psychomotor training which was published at the Intelligent Tutoring Systems Conference[10] in early 2020 and the work was cited and used by other researchers worldwide in similar projects. The thesis proposed further three systems, *OntoStrength*, *RiARiT*, and *Selfit*, which were developed by the author, under the direct guidance of both thesis supervisors: Sébastien Travadel and Răzvan Rughiniș. In terms of knowledgebase, the strength training field knowledge has been developed together with three members of the MINES ParisTech research center – Vincent Guarnieri, holding a master's in sport sciences and sports training coach, and Eric Rigaud, researcher, holding a Ph.D. in computer science and athletics training coach, and Didier Delaitre – researcher, doctor in forensic medicine.

The developed knowledge by the sports specialists was further modeled and integrated within the Protégé software by Laurențiu Neagu and Eric Rigaud. The ontology was further exported in .owl format, shared across our team, and visualized initially using WebVOWL - Web-based Visualization of Ontologies, then using GraphDB. The initial version of the ontology has been published and accepted as a full paper at the GIFT Symposium in 2020[11]. An updated version has been developed in the years after, also a REST integration layer has been developed in the .NET Core technology, using C# programming language, which allows OntoStrength to interact with other systems.

The second contribution, *RiARiT*, was a method proposed for personalizing the learning sequence in psychomotor training. This method implied using Contextual Multi-Armed bandits' algorithms for providing sports exercise recommendations while training. This is the first level of adaptation we envisioned – called Novice Trainer – and is using templates of training sessions which are filled in by exercise recommendations. *RiARiT* has been initially simulated with populations of virtual trainees and shown the potential of the approach. This method has been published at the Intelligent Tutoring Systems Conference in 2021[12]. *RiARiT* was further integrated into the tutoring component of a system for psychomotor development and tested with real users.

[10] https://link.springer.com/book/10.1007/978-3-030-49663-0
[11] https://gifttutoring.org/projects/gift/wiki/Overview
[12] https://link.springer.com/book/10.1007/978-3-030-80421-3

The third contribution, *Selfit*, was built on top of the previous two. *Selfit* is an intelligent tutoring system prototype that uses the knowledge model *OntoStrength*, and the personalization module *RiARiT* to exhibit the potential of such a system in psychomotor development. The User Interface module was developed entirely by the author of the thesis and, using ASP.NET MVC framework, and C# programming language.

Our team of sports scientists developed further a custom calibration protocol, more specific than the FMS test, which was implemented in the next version of the *Selfit* system. Also, in this version, users were not required to record themselves while performing the calibration, they could just manually input the perceived effort. Also, a computer vision module has been implemented, separately from the *Selfit* system, to assess the risk of injuries for female athletes. This experiment used OpenCV[13] to track the movement angles and assess the risk of injuries. This implementation was not integrated within *Selfit*, as OpenCV cannot be added to the mobile application directly, and it does not work in real-time. It requires recorded, offline videos to make an analysis. For the scope of the experiment, we explored the potential of computer vision on psychomotor assessment, and we published our work as a full paper at the Smart Learning Ecosystems and Regional Development (SLERD) conference in 2021[14].

The final refined version of *Selfit*, which was tested with real users between January-May 2022, with several features enriching the overall user experience (auto-mode, a chart with body area progress, home and gym specific training configuration, favorite exercises, roll/change an exercise, and others) was published for the third year in a row at the Intelligent Tutoring Systems Conference in 2022[15]. To conclude, we consider that the initial goal to assess the requirements and implications of building an intelligent tutoring system for psychomotor development has been addressed through the multitude of learning tasks implemented and such a system has great potential in the field.

10.2 Directions for Future Research

One direction that requires further improvement is the accuracy of user assessment. The method implemented in the current thesis for assessing user progress relies on user manual input of the perceived effort. The number of repetitions in reserve is directly reported by each user. A method that has the potential to be more accurate for assessing the user effort per exercise is through the correlation of the *Selfit* current screen shown and the reported value of the heart rate through a

[13] https://opencv.org
[14] http://slerd2019.uniroma2.it
[15] https://link.springer.com/book/10.1007/978-3-031-09680-8

wearable. Integration with main wearable manufacturers would be required and synchronization within the training session.

The variability of the heart rate is a good indicator of the perceived effort, both acute and chronic (short-term and long-term effects). This method can be used in conjunction with user input. We initiated the development for this module which currently permits the integration of Garmin and Fitbit data, but does not make the correlation with the actual exercises in the session. Also, this module should be optional, and act only as an improvement in assessment accuracy for users who have such wearables and agree on sharing this sensitive data with us.

Another method for user assessment and also an improvement of the overall user experience is integrating a computer vision module. This module aims to measure the number of correct repetitions executed and automatically start the rest time chronometer and move to the next exercise when the required number of executions is completed. The computer vision feature is useful to compute the number of repetitions when the trainee performs less than the number of repetitions required. If the user can perform more than the number of repetitions shown in the interface, a wearable or user's manual input is required to assess the perceived effort.

Another area to focus on further is extending tutoring personalization from the Novice trainer to the Intermediate and Advanced trainer. The current version of the adaptive tutor can personalize the learning sequence at the exercise level, using pre-defined session templates. The Intermediate trainer should be able to discover optimal sessions (movements to train and order of exercises to train), generated by different sets of rules, but not pre-defined, and it should be used in conjunction with the Novice trainer. The Advanced trainer should be able to generate micro-cycles, mesocycles, and macrocycles for each user, and not use pre-defined templates. The more advanced personalization modules will enable a fully customizable training experience for the users.

One improvement of the system proposed is the integration of the food dimension. Training programs should consider what people eat and drink. Recommendations on meal plans and nutrition, based on trainee profile, will improve training overall efficacy. The food dimension will require updates on knowledge modeling and the user interface module.

Selfit is currently used for strength training. Other training directions, such as flexibility or endurance, are also of high interest, especially for people with medical issues which prevent them from following a strength training program. The development of the new training directions is already our focus in future research. The flexibility module is currently under development and will be released in the following months.

List of Publications

ISI Proceedings

1. Neagu, L.-M., Cotet, T.-M., Dascalu, M., Trausan-Matu, S., Badescu, L., & Simion, E. (2019a). Semantic Author Recommendations based on their Biography from the General Romanian Dictionary of Literature. In 7th Int. Workshop on Semantic and Collaborative Technologies for the Web, in conjunction with the 15th Int. Conf. on eLearning and Software for Education (eLSE 2019) (pp. 165–172). Bucharest, Romania: "CAROL I" National Defence University Publishing House. (WOS: 000473322400022) *
2. Neagu, L.-M., Rigaud, E., Travadel, S., Dascalu, M., Rughinis, R.-V. (2020). Intelligent Tutoring Systems for Psychomotor Training – A Systematic Literature Review. In: 16h Int. Conf. on Intelligent Tutoring Systems (ITS 2020) (pp. 335-341). Springer, Online. (WOS: 000720068400040)
3. Neagu, L.-M., Toma, I., Dascalu, M., Trausan-Matu, S., Hanganu, L., & Simion, E. (2020). A Quantitative Analysis of Romanian Writers' Demography Based on the General Dictionary of Romanian Literature. In 5th Int. Conf. on Smart Learning Ecosystems and Regional Development (SLERD 2020) (pp. 253–261). Bucharest, Romania (Online): Springer. (WOS: 000783452900022) *
4. Neagu, L.-M., Rigaud, E., Guarnieri, V., Travadel, S., Dascalu, M. (2021). Selfit – An Intelligent Tutoring System for Psychomotor Development. In: 17th Int. Conf. on Intelligent Tutoring Systems (ITS 2021). Springer, Athens, Greece (Online). (WOS: 000718916000032)

BDI Proceedings

1. Neagu, L.-M., Cotet, T.-M., Dascalu, M., Trausan-Matu, S., Chisu, L., & Simion, E. (2019). Semantic Recommendations and Topic Modeling based on the Chronology of Romanian Literary Life. In 12th Int. Workshop on Social and Personal Computing for Web-Supported Learning Communities (SPeL 2019) held in conjunction with the 18th Int. Conf. on Web-based Learning (ICWL 2019) (pp. 164–174). Magdeburg, Germany: Springer *
2. Neagu, L.-M., Dascalu, M., Trausan-Matu, S., Chisu, L., & Simion, E. (2020). Automated Modeling of Romanian Literary Trends in History using Topics over Time and Co-Occurrences. In 8th Int. Workshop on Semantic and Collaborative Technologies for the Web, in conjunction with the 16th Int. Conf. on eLearning and Software for Education (eLSE 2020) (pp. 151–158). Online: "CAROL I" National Defence University Publishing House. *
3. Neagu, L.-M., Guarnieri, V., Rigaud, E., Travadel, S., Dascalu, M., Rughinis, R.-V. (2020). An Ontology for Motor Skill Acquisition Designed for GIFT. Proceedings of the 8th Annual Generalized Intelligent Framework for Tutoring (GIFT) Users Symposium (GIFTSym8). Online.
4. Toma, I., Neagu, L.-M., Dascalu, M., Trausan-Matu, S., Hanganu, L., Simion, E.. (2020). Emerging Patterns in Romanian Literature and Interactive Visualizations based on the General Dictionary of

Romanian Literature. In International Conference on Human-Computer Interaction (RoCHI2020): 91-103. Online: MatrixRom. *

5. Neagu, L.-M., Rigaud, E., Guarnieri, V., Matei, G.-D., Travadel, S., Dascalu, M.: Selfit – Accounting for Gender Differences in Personalized Motor Skills Learning. In: 6th Int. Conf. on Smart Learning Ecosystems and Regional Development (SLERD 2021). Springer, Bucharest, Romania (Online) (2021)
6. Neagu, L.-M., Rigaud, E., Guarnieri, V., Dascalu, M., Travadel, S.: Selfit v2 – Challenges Encountered in Building a Psychomotor Intelligent Tutoring System. In: 18th Int. Conf. on Intelligent Tutoring Systems (ITS 2022). Springer, Bucharest, Romania (Online)
7. Scheibenzuber, C., Neagu, L.-M., Ruseti, S., Artmann, B., Bartsch, C., Kubik, M., Dascalu, M., Trausan-Matu, S., Nistor, N.: Fake News Framing, Emotion, Argumentation, and Dialogic Social Knowledge Building in Online Discussions: An Exploration Including Natural Language Processing Data. In: 15th International Conference on Computer-Supported Collaborative Learning (CSCL) 2022. Hiroshima, Japan (Online)

Journals

ISI Journals

1. V. Pojoga, Neagu, L.-M., M. Dascalu (2020). The Character Network in Liviu Rebreanu's Ion: A Quantitative Analysis of Dialogue. *Metacritic Journal for Comparative Studies and Theory*, 6, 2, 23–47. *
2. Neagu, L.-M., Rigaud, E., Guarnieri, V., Radu, E.I., Travadel, S., Dascalu, M., Rughinis, R. (2022). *OntoStrength: An Ontology for Psychomotor Strength Development*. IxD&A (Interaction Design and Architecture (s)) Journal, 52, 101-118.

Patents

1. Ruseti, S., Neagu, L.-M., Toma, I., & Dascalu, M. (2021). *Metodă de Învățare Automată de Reprezentări Vectoriale în Grafuri de Cunoștințe pornind de la Modele de Limbă*. Romania. Cererea A/100184 / 19.04.2021. OSIM. *

The publications marked with * are studies conducted within several research projects at Politehnica University of Bucharest, which are not directly linked with the current thesis

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