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Student Behaviour Modelling and Adaptive Techniques for Social Robots: Data-driven and Teacher-Perceived Evaluations

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Abstract

User modelling and knowledge representation are important steps towards building personalised systems. Users' attention and communication are examples of social factors that go beyond simply analysing task efficiency, adding additional complexity to achieving effective human understanding. More specifically, in the educational domain, while the technical performance of adaptive methods plays a primary role in their adoption by researchers, secondary factors, such as teachers' ability to understand and their intention to adopt, can also influence the implementation and broader acceptance of social robots with adaptive behaviours. In this paper, we validate our high-level proposal for user modelling targeting activities with social robots in the classroom from two different perspectives: the performance of the methods using data from a real-world scenario, and the perceptions of teachers. For the data analysis, various decision-making methods were compared. These included two user-parametrised approaches (a simple rule-based and a fuzzy system, both previously co-designed with teachers) as well as five established supervised machine learning algorithms. For validation of teachers' perceptions, five teachers were interviewed to gather feedback on their thoughts about our proposal and its practical implications. The findings demonstrate that while teachers initially preferred the semantic modelling offered by the fuzzy system due to its interpretability, three out of five teachers changed their preference after being presented with the results of our data analysis. They favoured the most accurate method over the one they found more intuitive.

Keywords User modelling · HRI for education · Social robots · Teachers · Adaptive systems

1 Introduction

Personalisation in Human-Robot Interaction (HRI) is a key component for achieving better engagement of the users with a robot, which commonly leads to higher rates of user enjoyment statements and perceptions [1]. Its advantages of making users more engaged are noticeable in both short and long-term interactions. In the short-term, the system can momentarily boost the users' motivation by adapting itself to address punctual difficulties and supporting students to overcome pits of performances [2]. On the other hand, in the long-term, personalised systems can foster rapport building and extend the advantages of using social robots in classrooms after the novelty effect has passed [3]. This strategy has a growing application in educational scenarios since it affords personalised learning for students who interact with these systems [4].

However, the success of the adaptation relies on the correctness of the user's model, where the system tries to read and understand users' answers, attitudes, and signs to decision-making about the adequate adaptation based on this model. In autonomous robots, the extraction of these users' features is commonly performed by cameras and microphones, and the interpretation of the collected data is done by using classification algorithms. Although there are already many existing models, the designing of the model customised to a given task or context is a potential alternative to optimise and processing resources [5]. Despite the increasing accuracy of these methods in recent decades, it remains imperative to integrate them into a meaningful

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representation to interpret accurately the current state of the user. When it comes to the HRI field, all the challenges from Human-Computer Interaction are inherited and combined to new complexities brought by the embedded components of the robots plus the social elements which a human-robot interaction needs to deal with [6].

The complexity of this process at hardware and software levels is constantly pointed out as one of the main challenges of social robots in education, especially the systems that aim at autonomous behaviours [7]. Furthermore, the difficulty of providing efficient adaptive methods is attributed as one of the main causes of few works addressing long-term studies in HRI for education [8]. As an alternative, presenting intuitive ways for teachers to support the system on this objective was pointed out as a potential solution for leveraging the use of adaptive systems in learning activities [9].

In addition to these challenges, external factors should be considered in the educational context. For instance, increasing transparency in the robot behaviour has been shown to commonly increase the student's learning experience, but nothing is mentioned about the teachers' opinion [10]. On the other hand, works investigating teachers' opinion rarely explore technical details or designing processes with them. Nevertheless, their intention to adopt social robots in their activities, their lack of knowledge and the time they need to get familiarised with new technologies are often acknowledged [11]. Teachers' involvement in research on social robots is normally considered at a qualitative level, but few studies for long-term present reachable and concrete tools and methods to be deployed for this end. Mostly because, in practical terms, implementing social robots in educational settings presents challenges that can hinder their widespread adoption. Integrating social robots into classrooms requires teachers to invest considerable time to learn about the technology and address various logistical issues, which can impede their regular teaching activities, besides the technical knowledge adaptation they think they have to acquired [12].

We postulate that teachers' understanding and active participation are fundamental for modelling the student's behaviour in HRI for education, in complement to technical factors of the adaptation method. Moreover, explaining the adaptation methods to teachers in layman's terms and discussing their implications can illuminate previously unconsidered topics. For instance, high-performance classification methods typically consume more energy and require more data due to their high demand for computational resources. To further investigate our hypothesis, we researched methods that could present better understandability to implement our high-level proposal of students' modelling behaviour.

Even so, it is evident that data-driven algorithms generally outperform user-parameterised algorithms, regardless of the users' level of . However, accuracy is not the sole factor influencing teachers' preferences when selecting social robots for classroom exercises. By validating the design of more interpretable methods with teachers in real-world scenarios, we can compare their performance metrics to those of established methods that autonomously extract knowledge from data. This comparison can offer valuable insights into the trade-offs between explainability, accuracy, and other factors that are essential for teachers when adopting adaptive social robots.

Building on these observations, we have reformulated the following research questions:

- **RQ1:** How the performance of user-modelling and adaptive algorithms, designed in collaboration with experts for greater understandability, compares in their optimal parametrisation to supervised ML algorithms?
- **RQ2:** How can the characteristics of this implementation, such as explainability and accuracy, influence teachers' opinions and intention to adopt adaptive social robots in classrooms?

To evaluate the research questions, an experiment was conducted where a robot approached the teaching content using the Robotic-Cognitive Adaptive System for Teaching and Learning (R-CASTLE) [13]. The R-CASTLE, The robot's activity followed a quiz mode, providing explanations and asking three questions. During the sessions, a person with experience in education adjusted the difficulty level based on children's verbal responses and non-verbal cues. We analysed the outcome of adaptation algorithms in terms of accuracy with the collected data and teachers' preferences. From their performance in the data, we compared the 2 already implemented customizable version of adaptation in this system (rule-based method and Fuzzy-system) to supervised algorithms of machine learning (ML). For the teachers' opinion, we performed semi-structured interviews with five teachers, exploring their views on social robots, classroom research, and the impact of the adaptation methods on technology adoption in Brazilian schools.

Therefore, the contribution of this paper is three-fold: (i) a high-level description of several steps towards implementing user-modelling and adaption for real-world applications of social robots in classroom, taking teachers opinion and participation in the design; (ii) a technical analysis over the data regarding the performance of the resulting algorithms and a comparison to consolidated methods of supervised learning; (iii) evaluation of teachers, external to the designing phase, in relation to the user-modelling and adaptation system and their intention to adopt social robots according to the results they are presented with from the technical analysis.

2 Related Works

2.1 Social Robot Interaction Adaptation

The adaptation of robots for the users' needs has been widely researched in the last decades [14]. According to Mitsunaga *et al.* [15], robots should be able to read subconscious comfort and discomfort signals from humans and adjust its behaviour accordingly, as other humans do, for better human-robot interactions (HRI). This claim is supported by findings of studies on the topic.

In studies aimed at learning the multimodal behaviours and conversational strategies of the agent to dynamically optimize the users' engagement and impressions of the agent showed a higher evaluation of user enjoyment when the agent was programmed with adaptive behaviour. The authors concluded that the effects of the person's preference highlighted the importance of considering the users' expectancies in human-agent interactions [16].

Robots that take into consideration humans displaying of emotions and humours are also successfully accepted by the users. A proposal of a system for personalising humour for interactive robots had a higher preference for users compared to a human comedian [17]. The system was equipped with natural language processing and emotion recognition techniques that allowed multimodal mapping of the users' humour state, which afforded decision-making techniques for the robot to display appropriate jokes and timing.

A growing trend in adaptive HRI can be noticed in industrial applications as well [18]. The analyses of adaptive mechanisms comprise physical [19], psychological [20], and social mapping of human collaborators in their applications [21], taking into consideration several user inputs, such as visual cues and even EEGs. The results constantly point out a high acceptance of robots programmed with adaptive methods in industrial scenarios, which is shaping the horizons for the industry 4.0 [22].

However, Pollmann *et al*. [23] raised the ethical issues regarding the users' autonomy and manipulation of them. As a result of their observations, the authors proposed three design principles to balance user experience and ethical considerations in personal HRI for social robot behaviour: (1) a gradual model of emotionality, (2) adaptive responsiveness, and (3) a progressive reduction in immersion and motivation over time. These principles are grounded in cascading models, which begin with user characteristics and preferences as a baseline. The robot's expressiveness is then progressively adjusted to maximize the user's positive experience while remaining within ethical limits.

In [24], a conceptual model for dynamic robot role adaptation for an enhanced flow experience was proposed as a result of their observation in the literature gap. Many robot adaptation strategies in social human-robot interactions are limited by their static and single-dimensional objectives, which fail to capture the dynamic and multi-dimensional nature of human interaction. Additionally, another prominent finding from the authors implies that personalization, in the most of HRI studies, has predominantly focused on content customization, such as adjusting learning materials or curricula, while neglecting the potential of robots as embodied social agents. This narrow approach often reduces robots to the role of personalized content providers, with a limited adaptation of their behaviour policies to enhance social engagement.

The complexity of the proposed algorithms for adaptation presents a wide variation, from simple rule-based methods to complex multimodal systems. Rule-based systems show results of satisfactory adaptation with a good trade-off in the observed mainly in those cases that their goals are very simple or very specific [25], such as adapting the robot's speech while talking to the users or whether to talk or change the robot's personality [26, 27]. More sophisticated algorithms are also employed. A mathematical model can be used either to formalize simple things or very complex adaptation systems, such as the Theory of Mind (ToM). In [28], the authors presented the perception, cognition, and decision-making of humans through a dynamic mathematical framework by introducing a novel formalization and an extension to fuzzy cognitive maps (FCM). This modelling was proposed based on the pillars of transparency and generalisability and outperformed previous state-of-the-art methods. However, the proposal was not validated from the users' understandability point of view.

Finally, in addition to offering more engaging and enjoyable interactions, the robot's behaviour adaptation also displays broader influences on users. For instance, the level of automation of a robot adaptation can be related to what users think about the robot [29]. This phenomenon can also be expected in education, where the level of autonomy of the system motivated changing the students' perception of the robot. Students participating in autonomous conditions rated the robot as more intelligent than students in a teleoperated condition, even without knowing about the robot's operation condition [30].

2.2 Adaptation in Education

Adaptation and personalisation have also long been investigated in the educational realm [31, 32]. Intelligent Tutoring Systems (ITS), are examples of adaptive systems for education that have been extensively investigated [33–35]. These systems are "designed to incorporate techniques from the artificial intelligence (AI) community to provide (intelligent) tutors who know what they teach, who they teach, and how to teach it" [36]. As a result, ITS allows for personalized learning experiences tailored to individual students' unique learning styles and preferences. Moreover, AI-driven tools offer teachers valuable, data-driven insights into student performance, emotional states, and engagement levels. This enables educators to adapt their teaching methods, implement targeted interventions, and provide timely support to improve learning outcomes effectively [37]. Although they often present increases in learning outcomes, their evaluation can be affected by the nature of control treatments and the adequacy of program implementations [38]. Therefore, allowing customization for adaptive algorithms for stakeholders who are aware of local influences could be seen as a potential solution to ease this issue.

Among the methods investigated for the adaptation mechanisms, using fuzzy systems as part of ITS modelling can show better performance in the students' outcome and the accuracy of the adaptation system [39]. The fuzzy system applications for ITS have successfully implemented in programming platforms [40], augmented reality (AR) scenarios [41], and even in social robots [42].

Another important feature of fuzzy systems is their understandability through their semantic implementation. Incorporating such strategies into self-regulated learning scenarios suggests an increase in the students' understanding of their learning process [43]. By understanding how the system personalizes learning in semantic terms, making it more comprehensible from a human language perspective, students can reflect on their learning and identify areas for improvement. These findings instigate deeper analyses regarding how teachers would be triggered by understandability of autonomous adaptation of social robots for education.

2.3 Adaptation in Social Robots for Education

Adaptation and personalisation have shown increased student performance compared to static robot behaviours [4, 44]. The applications for adaptive robot learning have a wide range. For language learning, students who interacted with a robot that personalized its affective feedback strategy showed a significant increase in valence as compared to students who interacted with a non-personalizing robot [45]. For maths, a robot that adaptively scaffolded instructions was able to help children get better in the topic and was seen more as a friend the more it personalised the conversations [46].

The main practice for achieving that is to experiment with a particular set of users and check out their common behaviours and perceptions [47]. Nonetheless, there is no standard agreed measurement framework for assessing the effectiveness of the adaptation achieved by these systems. Furthermore, these methods are mostly based on multiple-choices and lack of multimodal assessment of students. Hence, a common strategy used is to add a layer of observed features on top of adaptive methods from technological learning scenarios, such as proposed in [48]. The challenge in using such a method is to incorporate the social features (extra layer) added by the social robots to the learning experience, and consequently to the user modelling. However, the robot's advantage for enhancing the learning experience by providing a more concrete interaction when compared to other devices, as tablets, is a trade-off worth being paid [49]. In all cases, the propagation of errors in autonomous classifications of features is a crucial point to pay attention to when analyzing its results. Thus, it is important not only to evaluate but also to ensure that the evaluation uses the correct methods. Otherwise, this can lead to wrong conclusions [50].

Moreover, although the adaptation generated by user modelling techniques often tends to improve the user-system interaction, in the majority of systems, these techniques make the system more complex to understand. Consequently, it should be evaluated whether the adaptation improves the system and the user prefers the adaptive version from it [51].

For that reason, the utilisation of devices that can have a cleaner reading of users' intentions might present a more accurate user modelling. In [52], for instance, the authors introduced a novel fuzzy-based system for cooperative learning, integrating a brain-computer interface model and a fuzzy markup language based reinforcement learning agent. The system uses agents to support human-robot interactions in education, with experiments showing robot teachers boost motivation and learning. The agent personalizes content and predicts physiological indices to enhance co-learning. While highlighting the promise of human-robot co-learning, the study does not assess user understanding of the methods.

However, although approaching the social capabilities of the students in the interactions often lead to better results, concerns about side effects of these interventions are raised, such as privacy, security, and workload of the teachers [53]. Therefore, the teachers' participation and willingness to adopt social robotic systems are the key to the successful implementation of adaptive robots in classrooms.

Similarly, a work performed with teachers using adaptive robots in classrooms showed important findings regard to teachers' understanding and perceptions about the topic [9]. The outcomes suggest that robots in educational settings should address repeated classroom questions, adapt to children's emotions and personalities in real-time through dialogue-based mechanisms, and dynamically adjust their roles using memory adaptation. Culture-based adaptation is crucial for language learning tasks, and an easy-to-use interface for teachers to update lessons is essential for maintaining long-term engagement.

2.4 Teachers' Adoption

The use of artificial intelligence (AI) in robots for education in the last decade has presented a remarkable increase. A study analysing the works in the literature pointed out a boom in the number of published papers starting from 2019 using AI in robots for education. Most of the works (more than 85%) focus on social features for the robots to interact with students [54]. However, the authors detected a serious gap in the investigated work on human-centred AI (HCAI), which the authors define as *"AI taking humanities as the primary consideration, which requires explainable and trustworthy computation for continuously adjusting AI algorithms through human context and societal phenomena to augment human intelligence with machine intelligence, thereby enhancing the welfare of human kinds"*. One of the potential reasons for explaining this phenomenon is the search for high-accuracy methods rather than explainability, which means methods that are easier to understand by the users and stakeholders.

This philosophy aligns with the growing trends still regarding the explainability [55], and transparency in human-robot interactions [56]. Explainability in HRI is defined as novel computational models, methods, and algorithms for generating explanations that allow robots to operate at different levels of autonomy and communicate with humans in a trustworthy and human-friendly way [57]. On the other hand, transparency in HRI focus on the importance of user awareness of the robots' attitudes to foster trustiness [58].

Nevertheless, while it is shown that explainability increases the robot acceptance in other domains [59], and explainable AI (XAI) is earning space in education [60], more investigation is required specifically for explainable HRI in education. More than increasing teachers' adoption, XAI is crucial in learning domains to guarantee that the employed methods are utilised responsibly and ethically.

Although there is a gap in the literature related to studies investigating the impacts of explainable strategies fostering the adoption of social robots for teachers, main aspects and concerns can be transferred from similar applications of technology in education. The exploration of explainable AI methods to interpret deep learning-based models for STEM teachers [61]. After being exposed to explainable AI methods, participants reported a higher trust and technology acceptance in the classroom discourse models.

Similarly, the intention of adopting theoretical contents related to technology requires the acceptance of teachers for adoption. A study investigating 180 grade 5 students and 6 teachers concluded that teachers' intention of adoption is highly correlated with their interest [62]. They were submitted to mandatory Computer Science Continuing Professional Development program over an academic year and evaluated through interviews, and survey throughout the program.

Results showed that teachers' self-efficacy and interest significantly influenced the likelihood of content adoption, with interest playing a pivotal role. Teachers with low ICT experience needed onboarding, while middle-aged teachers required more convincing to adopt CS content. The findings highlight the importance of the interest, and establish the interplay between contextual, prior, and acceptance factors in adopting CS pedagogical content for primary education that was observed to increase a long time, the more teachers understood the methods.

In addition to the typical concerns associated with conventional technologies, social robots introduce unique challenges related to social and ethical issues. These challenges include questions about privacy, the appropriate use of AI, and the implications of robots simulating human-like behaviour. Such concerns create paradoxical dilemmas. On one hand, researchers strive to design robots that exhibit human-like manners and social intelligence to enhance user acceptance and engagement. On the other hand, these very human-like qualities often lead to discomfort and rejection among users, who may perceive such robots as uncanny or fear potential misuse of their human-mimicking capabilities. This critical disjunction highlights a fundamental tension in social robotics, as efforts to make robots more relatable and effective can sometimes undermine public trust and acceptance [63]. For these reasons, explaining how the algorithms work to afford these social behaviours is the key point for fighting the barriers of their adoption.

3 User Behaviour Modelling

To implement research in classrooms, one key element is to provide understandable and minimally impactful interventions and tools for teachers. At the same time, designing computational models for human behaviour representation is a complex task. Aiming to present a solution that finds a good balance between these two assumptions, the R-CASTLE framework was proposed [13]. Its main goal is to provide intuitive content programming to be addressed by a social robot, that also affords adaptive behaviour of the robot that can be customised by the teachers. Since customization and adaptation are crucial for ensuring the success of long-term studies and activities in classroom settings, the proposed system must provide these capabilities while maintaining ease the parameter configuration.

While previous studies proposed and initially validated two adaptation algorithms, in this paper we are delving into the analysis from the data perspective and from teachers' point of view. Nevertheless, we bring key elements from our works previously published to highlight the important points of this study and to make its analysis clearer.

The robot is programmed to approach the content with the students using the strategy of constructivism, where a concept is presented and then the interlocutor can build a line of thought on the concept and ask questions about it to guide the listener through the learning process using constructivism. This strategy is one of the most used paradigms in social robots for education [64]. Hence, it can be modelled in the robot as a quiz-mode game, in which the adaptation is analysed in windows related to every question. Regardless of the algorithm used for adaptation prediction, we proposed a generalized modelling of the students' behaviour, resulting from interactive design performed with teachers of elementary school that participated in previous experiments. We identified some measures we could take autonomously with the cameras and microphones of the robot and clustered these measures in superclasses of students' skills when learning. In an oversimplified way, the goal of this adaptation mechanism is to translate audiovisual observable manifestations of the students into the user-modelling proposal of the system.

The observable student's manifestation are signals captured by microphone and cameras of the robots and processed by a set of recognition algorithms. The signals are: Face gaze (Fg), Posture quality (P), the Number of spoken Words (nW), the correctness of the answers (Right/Wrong answer represented by RWa), the balance between good and bad emotion by facial expression (Em), and the Time the student takes to answer a question (Tta). From a coding perspective, the observable signals were extracted as follows: The Face Gaze is detected by the Haar Cascade method [65], the emotion classification is the corresponding value of positive emotions minus negative emotions detected by a Convolutional Neural Network (CNN) [66], the number of words is counted by taking the user's verbal answer with Google Cloud Speech API through the Python Speech Recognition[1] into a string, which is also the input to the algorithm that generates the Right/Wrong questions according to a matching pattern with the expected answer. This process is better explained in [67].

Table 1 Reading values grouped by observed users' skills

Attention (α)	Communication (β)	Learning (γ)
Face gaze (Fg)	Number of Words (nW)	Right/Wrong answers (RWa)
Posture (P)	Emotions (Em)	Time to answer (Tta)

They were proposed to be clustered in the superclasses of major skills of *Attention* (α), *Communication* (β), and *Learning* (γ), as presented in [68]. Table 1 summarizes the measures in their respective major skills.

The measures are taken during a cycle of interactions between the student and the robot, called here as *adaptive window*, and denoted by *t*. An *adaptive window* is predefined by the programmer, and it is usually a set of robot questions or requisitions to evaluate the success rate of the user's response or a given time in seconds predefined before the interaction starts. Therefore, results from each one of the major skills are taken by calculating (regardless of the method used) the following functions: $\alpha(t) = (Fg(t), P(t))$, $\beta(t) = (nW(t), Em(t))$ and $\gamma(t) = (RWa(t), Tta(t))$ in an adaptive window *t*. Likewise, the calculation of the final adaptation in a given *t* ($F_{Adp}(t)$) based on these three skills would be mathematically represented as in Eq. 1, in which the functions themselves can vary according to the chosen method, as presented in the following subsections.

$$F_{Adp}(t) = F_{Adp}(\alpha(t), \beta(t), \gamma(t)), t \in \mathbb{N} \tag{1}$$

Two adaptation methods were previously proposed based on the reading signals of the users in the R-CASTLE and briefly described in the next subsections. The Simple Rule-Based System, briefly described in Sect. 3.1, and the Fuzzy Decision-Making System, briefly presented in Sect. 3.2. In both of them, the person running the activities (normally the teacher) has to set some values of references for each one these variables to guide the system into this process. Thus, the *Knowledge* present in the algorithm is estimated by an expert. Next, we want to evaluate how Machine Learning algorithms, that can learn and set parameters from the dataset, can predict adaptation results compared to the previously proposed methods.

3.1 Simple Ruled-Based System (SRB)

The Simple Ruled-Based (SRB) decision-making algorithm is proposed in [68]. In summary, in this method, the user needs to set maximum values for every readable variable that will be used to transform each output value in the interval [0, 1]. Signal values going outside this interval are capped. The result of each major skill will also be a normalized value, in the same interval, that makes an average of each value belonging to that major skill, multiplied by a weight given by the user for each one of the major skills, as in Eq. 2.

[1] https://pypi.org/project/SpeechRecognition/ Accessed Feb 2024.

$$F_{Adp}(t) = (w_\alpha * \alpha(t) + w_\beta * \beta(t) + w_\gamma * \gamma(t)), t \in \mathbb{N} \quad (2)$$

The system decides then to increase, maintain, or decrease the intensity of a given behaviour (that in the experiment of Sect. 4 will be the difficulty of the questions) according to the activation function, *Act*(*t*), depending on the resulting value of $F_{Adp}(t)$, given by Eq. 3.

$$Act(F_{Adp}(t)) = \begin{cases} 1, & if F_{Adp}(t) \geq 0.66 \\ 0, & if 0.33 < F_{Adp}(t) < 0.66 \\ -1, & if F_{Adp}(t) \leq 0.33 \end{cases} \quad (3)$$

3.2 Fuzzy Decision-Making System (FDMS)

The fuzzy modelling was implemented in collaboration with teachers and built upon the ideas of the SRB algorithm [69]. The goal, however, was to provide more intuitive modelling through the semantic rules. It was developed using the Python library SkFuzzy 0.2,[2] which requires defining fuzzification and defuzzification mechanisms, fuzzy sets for linguistic variables, and corresponding fuzzy rules. Triangular fuzzification was selected for its simplicity after testing other shapes (Gaussian and trapezoidal) with similar accuracy. The inference method, proposed by Ebrahim Mamdani in 1975 [70], and Center of Gravity defuzzification were used.

Teachers contributed to defining the linguistic variables and rules, enabling a hierarchical fuzzy structure. Each major skill (e.g., Attention, Communication, and Learning) undergoes an independent fuzzy process (fuzzification, semantic association, and defuzzification) before combining the results into a final adaptive fuzzy system. Users map numeric inputs to semantic variables (e.g., 3 deviations = "Rare", 2 seconds to answer = "Fast", 14 words to answer = "Talkative", and so on) and can customize semantic rules, although default rules are provided. Thus, this is the foremost advantage of fuzzy modelling regarding understandability. The variables can be associated through semantic rules that are more understandable for humans. For instance, if "Time to answer" is fast and "correctness of answer" is high, then learning (γ) is high.

The final adaptive measure, called the Fuzzy Adaptive Function (FAF), calculates the level of adaptation for the questions presented to the students. It integrates the three measures (α, β, and γ) using MaxMin operations and outputs terms such as Decrease, Maintain, or Increase to guide adaptation.

3.3 Dataset Creation

To acquire a testing dataset for performance and teachers' perception validation, we performed activities in a video room of an elementary school, where a total of 39 children from 5th grade participated by individually interacting with a humanoid robot, NAO, answering questions about "Environmental Health". Their teacher programmed the content to be addressed through the GUI of R-CASTLE. This content was composed of 30 questions divided into 5 levels of difficulty.

The interaction sessions with the robot were run following the Wizard of Oz technique [71], in which a hidden person teleoperated the robot to trick the users that the robot had life by itself. The person operating the robot was a 3rd-year student of learning science that we hired.[3] She was asked to perform her judgment for the robot's behaviour change in-loco and in real-time. Furthermore, we also asked her to base the decisions on the observations she made regarding students' audiovisual signals, according to the measures presented in Table 1. However, we did not mention preferences for any measures.

The robot started making a question of difficulty level 3 and, after the current student answered the question, the person controlling it chose if the difficulty level of the next question would be increased, decreased, or maintained, based on the current student's answers and body signs, as described. Thus, the dataset true labels are given by a human decision of the adaptive function.

Sessions were made in natural conditions of the school, meaning no actions were taken to minimize potential noises such as light or sound filters. We decided to perform a test in this way to stay as close as the setup faced when experimenting in real-world scenarios. Afterward, measures of these indicators were extracted in the videos recorded from the robot's camera using the R-CASTLE off-line evaluation feature. It uses machine learning algorithms for audiovisual recognition to extract users' observable values. A resulting dataset of these measures was created, comprising all the autonomously read data and the true labels regarding the robot's behaviour adaptation [72]. The adaptive window was set for the time of each question. Therefore, each sample comprises one tuple containing 5 out of the 6 reading values (we could not use the posture measures properly in this experiment), considering the time interval in which the current question started until the time it ended. Each tuple is considered an adaptive window and the labels are decrease (−1), maintain (0), and increase (1) the content's

[2] https://pythonhosted.org/scikit-fuzzy/overview.html Accessed Dec 2024.

[3] In this course, students in the 3rd year have already studied pedagogy strategies and have hands-on experiences supporting teachers in classes of Elementary schools.

difficulty level. A total of 117 samples of adaptive windows were collected.

The dataset has the limitation of being unbalanced, as visible in the confusion matrix of Table 4. There are more samples of the *Decrease* class than the others. Nevertheless, we opted to retain the dataset in its original form, acknowledging the likelihood of student errors outweighing correct responses, particularly in activities introducing new subjects. Consequently, we aim to investigate the system's performance under these conditions to gain insight into its behaviour in challenging learning scenarios as they are.

3.4 Supervised Algorithms

To verify the performance of the given methods face to ML algorithms, we have considered the methods: Multilayer Perceptron (MLP), Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Random Forest Classifier (RFC), and Logistic Regression (LR). Please note that this last method of linear regression has a very similar approach to the rule-based system. We chose these methods because each one of them has a different approach to extract the knowledge from the dataset, as well as to perform a searching for the best model of prediction in the possible solution space [73]. In this case, there was no division in the skill measures (α, β, and γ) since these supervised methods implementations are only being made for performances comparison and database analysis, whereas the division of the skills measures in the rule-based and fuzzy system allows to use and analyse the skills individually.

The algorithms were implemented using the Python Scikit-Learn library.[4] All the parameters not reported were used as their default. We run exhaustive Grid Search[5] to find the best parameters for each method, using a 10-fold cross-validation. Results are reported in Table 2.

4 Data Performance Validation

In this section, we are providing analyses of the proposed algorithms based on their performance over the acquired dataset and comparing them to ML methods of supervised learning. Our objective is to understand how the performance of the proposed user-parametrised algorithms compares to algorithms that learn from data.

Table 2 Best parameters from the Grid Search, with the best performers in bold

Method	Parameters
KNN	n_neighbors: [3, 5, **7**]
MLP	hidden_layer_sizes: [(50,), (100,), **(50, 50)**], alpha: [0.0001, **0.001**]
SVM	C: [0.1, **1**, 3, 5, 10], kernel: [rbf, **linear**]
RFC	n_estimators: [50, 100, **200**], max_depth: [**5**, 10, None]
LR	C: [0.1, 1, **10**]

Table 3 Best weights and operational parameters for SRB and FDMS methods

Method	w_α	w_β	w_γ	Fg	Em	Nw	Tta	RWa
RBS	0.0	0.4	0.9	20	413	5	59	1
FDMS	na	na	na	30	500	4	78	1

Table 4 Confusion matrix with the Precision, Recall and F-Measures of the RBS and FDMS

Labels	RBS			FDMS		
True\Given	−1	0	1	−1	0	1
−1	**54**	7	0	**53**	3	6
0	10	**2**	1	11	**1**	1
1	10	9	**24**	11	2	**29**
Precision	0.73	0.11	0.96	0.70	0.17	0.83
Recall	0.89	0.15	0.56	0.87	0.08	0.67
F-1	0.80	0.13	0.71	0.77	0.11	0.74

4.1 Human Parametrised Algorithms

Considering the parameters of the systems RBS and FDMS, we took the results from the previous validation phases of these algorithms and presented them to the teachers who participated in the data collection phase during a post-experiment feedback session. We also shared the performance of these two methods over the acquired data, along with various parameter configurations changes, to provide a clearer understanding of how these variations affected accuracy. Teachers and experimenters realised that the accuracy of the human-parameterised tests for both algorithm was below 50% with the initial parametrisation teachers chose. It was agreed that, for a better comparison with ML algorithms, we needed to determine the optimal configuration for this parametrisation. Subsequently, we conducted an exhaustive grid search for these parameters with the teachers, based on the dataset, and the best parametrisation found is shown in Table 3. Since this configuration had already been computed in prior analyses with the teachers, we did not perform cross-validation, but instead used the entire dataset and evaluated it per class (as shown in Table 4. Therefore, our goal in this part was to validate the design of these two methods - developed in collaboration with the teachers during the design phase - rather than to optimise their parametrisation.

4 https://scikit-learn.org/stable/. Accessed Feb 2024.

5 https://scikit-learn.org/dev/modules/generated/sklearn.model_selection.GridSearchCV.html, Accessed Dec 2024.

In Table 4 is presented the confusion matrix as well as the measures of precision, recall, and F-1, for both methods RBS and FDMS, presented by each one of the classes: *Decrease* (−1), *Maintain* (0) or *Increase* (1) the difficulty level. The database is unbalanced, being 61, 13, and 42 samples of the classes *Decrease*, *Maintain*, and *Increase*, respectively. Thus, evaluating the methods by their accuracy (correct predictions divided by the total classification attempts) is not a fair analysis, being left behind in this discussion. Hence, the values of precision, recall, and F-measure (or F-1) were used. The metrics of these methods in all the dataset plus their accuracy are shown in Table 5.

4.2 Supervised ML Algorithms

Table 6 shows the resulting metrics (average and standard deviation) on the performance obtained for the supervised algorithms in a 10-fold cross validation. The methods were parametrised with the best parameters found using the Grid Search method, as pointed out previously. The metrics were calculated using the class-weighted method due to the imbalance of the classes.

4.3 Discussion

Analysing the videos, it was possible to note frequent outliers from the Face Gaze and Emotions due to luminosity problems, even though we tried our best to parametrise this method in the R-CASTLE offline laboratory. Thus, the classification measures are expected to be slightly altered for this reason. Overall, the RBS results showed a higher performance of this method with lower values for w_α, w_β weights, which is justifiable once these outliers are given less weight in the final adaptation classification. Although low accuracy is not the desirable outcome in this situation, the proposed modelling of separating in weights and the major skills facilitates an easy workaround to overcome this technical limitation. The FDMS presented similar measures to RBS. Results of their precision and recall showed that they have very close behaviour related to the false positives and true negatives (a small variation of 0.02 points), except for the *Increase* class, that presented the measures: precision 13% higher and a recall 11% smaller in RBD compared to FDMS. This means that FDMS increased the difficulty more than it should, whereas RBS chose to decrease more than it should for this dataset.

According to the teachers in the post-experiment feedback, normally, reducing difficulty beyond the actual requirement might lead to increasing students' boredom, as he may feel less engaging. However, teachers have noted that this approach does not necessarily result in learning regression. On the contrary, improperly increasing difficulty could indeed foster a more challenging environment, but it also carries the risk of potential learning setbacks. Hence, solely evaluating the effectiveness of these methods based on quantitative measures, without considering their impact on students' perception, may fail to accurately assess the true implications of such algorithmic adjustments.

Table 5 Measures of the SRB and FDMS overall

Method	Precision	Recall	F-1	Accuracy
SRB	0.6	0.53	0.54	0.61
FDMS	0.56	0.54	0.54	0.66

Table 6 Average (SD) of a 10-fold cross validation for different models

Model	F1	Precision	Recall	Accuracy
KNN	0.65 (0.13)	0.64 (0.13)	0.70 (0.13)	0.70 (0.13)
MLP	0.62 (0.18)	0.67 (0.14)	0.62 (0.20)	0.62 (0.20)
SVM	0.77 (0.09)	0.75 (0.08)	0.81 (0.09)	0.81 (0.09)
RFC	**0.79 (0.09)**	**0.77 (0.09)**	0.82 (0.08)	0.82 (0.08)
LR	0.79 (0.09)	0.75 (0.09)	**0.83 (0.10)**	**0.83 (0.10)**

Table 7 Features importance

Feature	RFC	LR
RWa	0.620176	0.969261
Tta	0.150759	0.000861
Em	0.087800	0.001305
Gf	0.071711	0.062469
Nw	0.069554	0.019805

The RFC and the LR were the ones that presented higher metrics. Checking the Feature Importance[6] of these algorithms, shown in Table 7, is possible to observe that the most relevant features was the threshold in the correctness of the answers (RWa), followed by the time to answer (Tta). It means that the correctness of the answer given by the students was also the most relevant feature in the classifications, just as observed with RBS with the higher values to γ and the FDMS, in which more extreme values of γ (Learning skill) led to more accurate predictions for this dataset. In fact, the importance for the RWa feature in the LR was 0.96, that matches with the obtained value for the SRB for the γ parameter that was 0.9. These findings suggest that the person operating the robot when it needed to make the decision prioritized the students' right answers rather than the other measures. This fact was later confirmed by the professional hired for the in-loco labelling.

Results obtained of ML classic methods corroborated with the outcomes of both approaches, RBS and FDMS, previously implemented. These findings also supported the findings of other multimodal classification studies [74], reporting constant setbacks and difficulties for adaptive behaviour in HRI.

[6] A measure that goes from 0 to 1 of each feature, where 0 means not relevant at all and 1 means relevant to the classification.

Higher values in the F-1 of supervised methods (almost 20% more in the largest case) may influence one to believe that supervised algorithms are a better decision-making solution to these problems. However, it is also important to consider that they take time to collect previous data for training; their parameter configuration is not intuitive (mainly for non-programming people) and they may present overfitting to this dataset. These facts can be critical once they may compromise the viability of the system as a facilitator for teachers in practical exercises.

By these results, we conclude that the performance of methods with higher explainability are always outperformed by the tested ML methods in their best parametrisation. This difference happens at minimum at 11%, in the case of the F-1 for KNN, and maximum 25% for the RFC. These findings answer our question **RQ1** (How does the performance of adaptation algorithms with high-explainability can compare to supervised ML methods?).

5 Teachers Assessment Validation

To validate our proposal from the teachers' perspective, we conducted a qualitative analysis of the data collected from interviews performed with 5 teachers who did not participate in the user modelling proposal.

The recruitment was done by sending the invitation to social media groups of teachers, and the first ones to subscribe to the project would be taken if they fit the inclusion criteria. The inclusion criteria were teachers of elementary school that have more than 5 years of experience in classrooms, regardless of the use of technology they have in their classroom or their familiarisation with the topic. To preserve participants' opinions unbiased, the final goal of the interviews (checking their perception of adaptive methods for social robots in a classroom) was not informed in the call for participation. Instead, the announcement only informed that they would participate in a 60-minute conversation about technologies in classrooms.

5.1 Participants

Registered participants were 5 teachers (named here T1 to T5) belonging to elementary schools from different cities in the state of São Paulo, Brazil, with age in average of 43.6 y.o (SD 9.39) and 24 (SD 8.86) years of experience in classrooms. To preserve their identities, we provide their profiles that can be useful to understand their opinions. The first participant (T1) was a retired teacher working for more than 35 years until 2019 only in public schools with children around 6 y.o. The second and fourth participants (T2 and T4), had similar profiles, working only in the same private school, and both of them described their school's profile as "Very motivated to adopt high-tech and innovative solutions for education". Finally, the third and the fifth participants (T3 and T5) were teachers working both in private and public schools. They were asked to give their feedback based on both scenarios and to be clear about each one they were talking about. The participants were all women, which is a fair representation of the Brazilian scenario, since almost 90% percent of the primary level teachers in there are women, according to Unesco.[7]

5.2 Methodology and Structure

We used semi-structured interviews, in which one interviewer (always the same experimenter) supported the teachers to fill out Likert scale questions and also answer open-ended questions regarding their responses afterward to collect their opinions on overall and specific points. The support was provided if the interviewer identified that teachers were hesitating regarding what the questions meant. This procedure was adopted to guarantee a common interpretation from all the teachers about the proposed questions." Although most of the data was structured for objective measures, two researchers analysed the videos and scripts, checking the conclusions we can draw from teachers' opinions, following a simplified version of the work done in [75].

The interview was structured in two phases: one **contextualisation** phase and a **discussion** focused on user **modelling and adaptive methods** for social robots, both planned to last 30 minutes each. First, we have a generic discussion about technologies in classrooms, social robots, and a high-level explanation of the R-CASTLE, for a better contextualisation of these teachers in the project. Afterwards, we started the discussion of the computational modelling of the students and presented our modelling and results to foster the discussion, as detailed in the next subsections.

5.3 Contextualisation Phase

In the first phase, we analysed the participants' familiarity with technology and how they use popular devices in their daily activities. We also asked for their perceptions and opinions on social robots, without properly defining what we meant by the term to validate how much they would know about the topic. We then presented a scientific definition and videos and asked similar questions to see if they had any new ideas.

As the scientific definition, we used the one presented in [76] that says "*A social robot is an autonomous robot*

[7] https://data.uis.unesco.org/index.aspx?queryid=3801, visited in Dec 2024.

that can connect and communicate with humans and other social robots by adhering to the social behaviours and rules associated with its role in a group". After, we showed videos about social robots[8] (from minute 2:45 to 3:35) and the R-CASTLE video[9] (from minute 3 to minute 7).

Before defining the term, teachers reported seeing and understanding social robots more as personal assistants, such as Amazon Alexa and Apple Siri, and not having a physical body. After explaining and showing the videos and assuming social robots would have a physical body, they kept their opinion that it has the potential to support them as personal assistants but also to practice content already taught. At this point, teachers have already manifested their beliefs about the most known advantage of social robots at first compared to traditional methods: the novelty factor [77], and the importance of adaptation in such systems. Participants also mentioned the fact that adaptation can be crucial both for regular personalisation for each student and also for the personalisation to children with special needs, like autistic children.

One teacher T4 also mentioned how to use influencing variables to extend the students' motivation to play with the robot: "*I believe the time they are exposed to the robot also can influence how fast they can be bored at this [the robot]*". This strategy has been long time evaluated and deployed in other scientific works, and they indeed tend to show better results when applied [78].

Finally, all of them brought at some point the practical challenges that social robots face to be part of their regular teaching toolkit, that are also well-known issues according to literature. For example, the high financial cost of social robots [79], the lack of technological knowledge of teachers to deal with these robots [80], how learning new methodologies, specially such a complex one, had an impact on their time management [81], and how administrative layers of their school and children's parents acceptance play a role in the social robots' adoption [82]. Although these points are relevant and merit further discussion, this work focuses solely on teachers' opinions and feedback regarding the adaptive methods that were tested. Nevertheless, it was evident that the methods presented in this paper have the potential to support teachers in addressing key challenges, such as familiarising themselves with the technology and reducing the time required to design and evaluate activities involving social robots.

This first part was a fruitful opportunity to understand, in general lines, at what stage teachers' opinions regarding social robots take place in the Brazilian context. It also suggested that teachers' theoretical and practical perceptions are somehow aligned with common findings in the literature.

5.4 Adaptive Methods Discussion

5.4.1 High-Level Adaptive Modelling

Finally, we presented to them the proposed modelling (presented here in Sect. 3, however, obviously in simplified terms and not using technical jargons), asking for their opinion about it, as well as comparisons with the manner they normally perform student's evaluation for content adaptation themselves. Additionally, we investigated whether they judged the modelling suitable for their context and questioned how it would work in a specific context they have (or used to have) daily in their activities.

We also explained that we are aware that evaluation by human observation is still better. Nonetheless, when it comes to computational modelling, and given the technical limitations at the moment this implementation was done, we should keep attached exclusively to quantitative measures that the recognition algorithms provide and perform an analysis based on their outputs.

Teachers show plurality in their answers, as shown in parts of T3 and T5 mentioned to follow, but all of their answers converged to analysis extremely peculiar of human sense, observation and assessment. T5 said, *"I normally try to understand the line of thoughts that they [the students] are building when answering my questions. Not always they come with the right answer, but, by doing that, I can have a hint whether they are on the right way and, if not, how I can take advantage of parts of their thinking process to correct them"*. Similarly, T3 claimed: *"I found very interesting this modelling, especially because we can split the measures into the major skills [attention, communication, and learning]. I say it based on my own experience. Oppositely to what people think, I base my evaluation on the students' answers more in their communication than on the correctness of the answers. [...] In their answer [students], they can just replicate something they hear and don't understand, and when I ask them why they think it is correct what they just said, their facial expressions tell me a lot of things that were hidden in their verbal answer"*.

Although such a feature of providing critical assessment to machines seems still far from being implemented, these thoughts shed light on the complexities in truly understanding and modelling human behaviour and communication, in which points the human evaluation is still outperforming machine evaluation. After these two teachers acknowledged that they understand that machines are still not able to perform the evaluation they mentioned, they both agreed that

[8] https://youtu.be/j23qqcDGUrE?si=j4g9BhAUblqoi4Cg%26t=165.

[9] https://youtu.be/GlNj98L1Mrc?si=8HDQv5AHc5OWcTys.

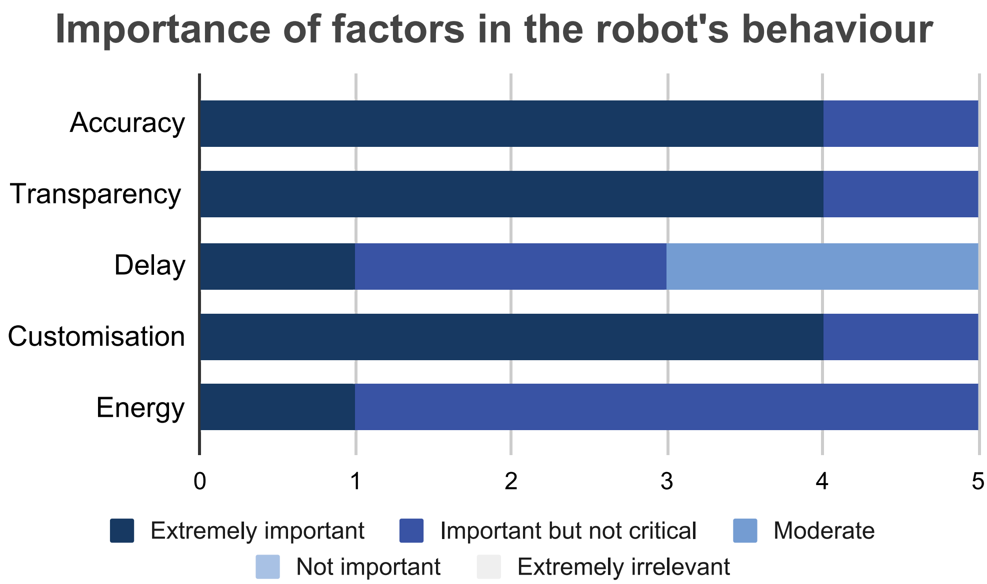

Fig. 1 Teachers classification given weights 0 to 5 (0 most important) to the main factors regarding the robot behaviour

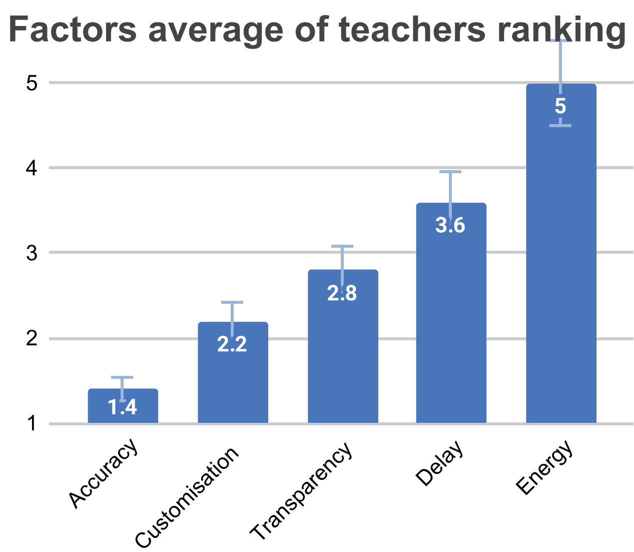

Fig. 2 Ranking of factors from the most important (smallest) to the least (highest)

the computational modelling presented was adequate for its aims.

5.4.2 Impactful Factors for the Adaptive Method

When this last topic had concluded, we asked them for their opinion on the importance of the 5 factors we hypothesised that they could interfere when using adaptation methods. They are: *Accuracy* of correct behaviour, *Transparency* (teachers' understanding of what the algorithm is doing), *Delay* in response time, Ease of algorithm *customisation* for each activity, *Energy*/battery consumption. Participants were first invited to give importance to the factors on a Likert scale, and second to rank these factors in ascending order of importance. The ranking was important to understand teachers' initial preference for each particularity of the methods if they had to choose between them, because, based on our experimenting so far, none of them could present all of them combined.

Important to note that, even though we did not evaluate the algorithms in Sect. 4 in terms of time to respond and energy consumption, we consider it relevant to bring them in discussion with the teachers.

As illustrated in the chart of Fig. 1, 4 out of 5 teachers rated "extremely important" in the factors of accuracy, transparency, and customisation. However, when they have to prioritise one over another, teachers most of them classify accuracy as the most important factor, followed by customisation, transparency, response time and energy consumption, respectively, as illustrated in Fig. 2.

5.5 Teachers' Preferences of the Implemented Methods

For the validation of the adaptation methods from the teachers' perspective, we presented the three mechanisms discussed in this paper-Simple Rule-Based (SRB), Fuzzy Decision-Making System (FDMS), and supervised machine learning methods-through a high-level overview. We explained the core ideas behind each approach, including practical aspects of parameterisation and simplified descriptions of their internal workings, without disclosing any results. Regarding the machine learning methods, the interviewees described them as "*computational procedures that, after being presented with several examples, calibrate themselves to classify new entries*." All ML methods were grouped into a single category to emphasize that they require multiple runs with different children to achieve adequate calibration.

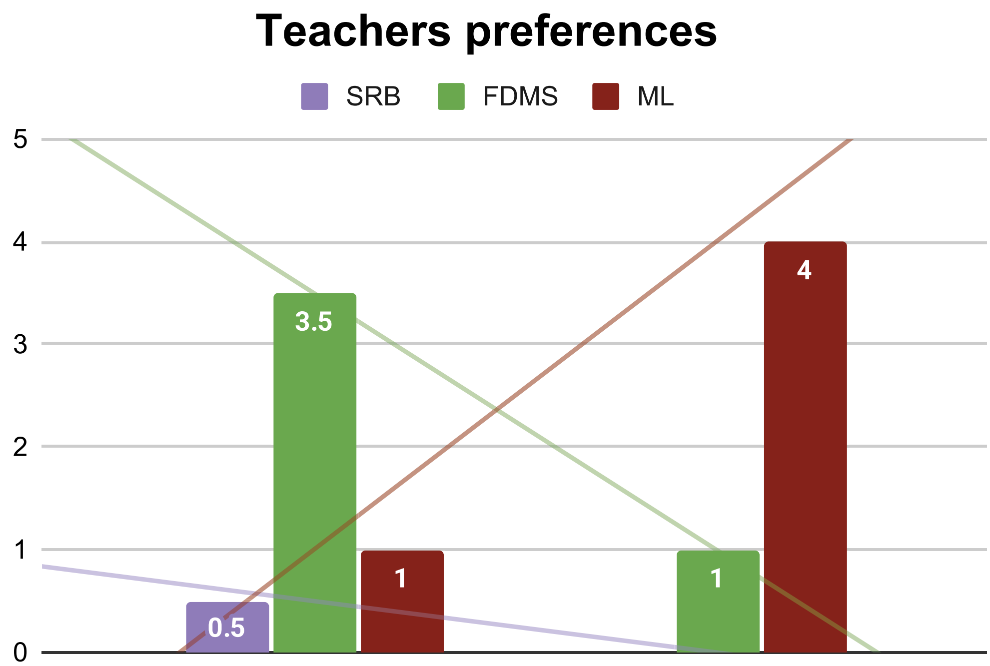

Fig. 3 Teachers preferences for the adaptation methods before and after being exposed to the method's performances, as in Sect. 4

We asked the teachers which of the presented methods they would prefer to use if the system were implemented in their classrooms, and invited them to elaborate on their reasoning. At this stage, all teachers indicated they would need more time to make a confident choice. Based on their initial understanding, 3 out of 5 teachers preferred the semantic configuration (FDMS) (T3, T4, T5), one teacher expressed a preference for either the SRB or FDMS (T1), and one teacher preferred the supervised method (T2), as shown in the first group of bars in Fig. 3. Please note that for a better representation in the figure regarding the teacher who chose both SRB and FDMS first, we marked as 0.5 for each one of her choices.

When asked their reasons, teachers who have chosen the FDMS claimed it was because of the ease of setting their parameters, as exemplified by the phrase of T5: *"If I understood correctly, I can easily change the configuration between activities, right? So, since I work with many activities during the day, I prefer having an understandable parametrisation because I believe I can work faster this way"*. The teacher that chose either RBS or FDMS justified her choice as *"Since in both the mathematical method and in the 'wording' one I have to set numbers, but in the second I have to set word-rules too, I might rather stay only with the numbers sometimes. But the semantic method looks more efficient when I need more detailed adaptation"*. On the other hand, T2 explained her choice for the supervised machine learning algorithm as "*... for me, it is easier and better to just show samples of student's attitudes when I want the robot to learn how to adapt its behaviour*".

Finally, we debriefed the teachers on the results presented in Sect. 4, highlighting that system performance may vary across different scenarios, but that the current figures reflect outcomes from experiments conducted in real-world settings. As a result, three teachers (T3–T5) changed their preference to the supervised machine learning methods, as illustrated in the right-hand bar of Fig. 3.

When inquired for their reasons for changing, their answers were mostly grounded on what would be best for the students from their point of view but also the rest of the school staff, as said T2: *"I think if the deliberative board of my school knows about this difference in the accuracy, they would push me towards using the supervised methods. It is how they report to the children's parents that the school is always doing the best for their kids"*. Conversely, T5 said she would change voluntarily: *"We are pushed to use so many new methods that are given to us [from the deliberative board] that one more or one less would not make much difference to me [about getting used with the supervised methods, even if that was not the one she said it would be more intuitive for her]. I would be happy knowing that I would be using the best methods for my students though [...]"*.

T5 even empathised her reasons with a sort of joke: "*I would change because it was scientifically proved to me that this [supervised machine learning algorithms] can have a better performance*" while she gigged. This opinion change is not surprising, given the rank they did before knowing these results, where they assessed the accuracy of the adaptive methods as the most important factor.

On the other hand, T1 kept her choice with the explanation of still preferring fast setting-ups rather than having higher accuracy achieved over a longer period. "*Since my activities were very dynamic, I would take a lot of time to* *make the accuracy good with many samples, so I would still prefer the semantic configuration [the FMDS]. Even rather than the mathematical model [RBS], on second thought*", she concluded, however, with no justification to drop the RBS.

As a final step of the interview, we explained to the participants that, with appropriate parameter tuning and across different scenarios, the other methods could also achieve improved accuracy. We also briefly discussed the challenges involved in collecting the amount of data required for the supervised algorithm to converge. Overall, participants concluded that, regardless of the method used, several trials would be necessary for them to form a well-grounded opinion about the presented approaches-highlighting the need for further long-term experiments. Lastly, they expressed satisfaction and were impressed with the information provided during the study.

5.6 Considerations

Based on our observations and experience during this study, we identified several insights that could benefit future research. For example, to obtain more meaningful qualitative feedback and encourage greater teacher engagement, it was essential to clearly explain our application and ensure participants fully understood our goals. In this study, teachers initially perceived the robot as a personal assistant until we clarified its intended role as a social robot. After this explanation, they developed a clearer understanding of its purpose and could better appreciate its potential benefits in educational settings.

Unlike previous studies in the literature, where teachers were only presented with lecture-style and group-work in role-playing scenarios [75], the exposition to a real-world scenario and a live discussion of the results afforded a more concrete view and judgment of social robots in classrooms to participant teachers. Especially in cases where adaptation and its aspects are explored.

Furthermore, while previous studies have shown that teachers see potential in social robots to support learning by guiding students, modelling behaviour, offering emotional support, and adapting to individual needs [14, 83], our study went a step further by enabling teachers to understand the adaptive methods and their implications. This deeper understanding appeared to extend beyond their immediate teaching practice, influencing how they might justify their choices to broader stakeholders such as parents and school administrators-suggesting a wider impact on the school ecosystem.

All participants agreed that a protocol in which researchers clearly explain their goals and reasoning in layman-friendly terms facilitates faster communication between all parties and leads to more meaningful research outcomes. This was exemplified by T2, who stated: "*[...] Of course, I believe it is better [referring to her improved understanding of the research]. If I understand it better, I can not only use it better, but also explain it more effectively to my superiors and the parents about what I am using in my activities*".

In opposition to previous findings in the literature [80], where teachers valued the students' privacy and security more, in our findings, teachers valued the school decision board and parents' opinion more. In fact, none of the teachers have touched on the topic of data privacy. Similarly, they did not seem aware of the implications of algorithms and devices with high levels of energy consumption can be harmful to the environment. However, there is a need to find ways to make this debate less impactful on teachers' time, as brought by T3:*"Oh yes, that is true [when asked about the fact of not brining privacy for the discussion]. I have not thought about it, but we have so many things to think about already that some important things, like these, are left behind sometimes. But if we don't act like this, we are never moving forward"*.

When asked why they had changed their preferred adaptation method, teachers explained that it was easier to justify using "the best" methodology to both their superiors and the children's parents. An interesting observation was that only T1 did not change her opinion-she was also the only teacher working exclusively in public schools. This suggests a possible correlation: in private education settings, teachers may feel more pressure to adopt high-performing methodologies as a way to justify parents' financial investment. Hence, and as well as also concluded by the findings of [82], all the stakeholders play a key role in the decisions taken in educational setups for HRI, and all the stakeholders should be aware of social and moral implications of research in human-robot interaction for education.

Some of our findings align with existing literature. For example, in [9] authors concluded that children's personalities are fluid and context-dependent, suggesting that robots should adapt dynamically through dialogue rather than relying on fixed personality types. In their study, teachers also emphasized the importance of real-time personality and emotion detection to personalize interactions and enhance learning. For long-term engagement, they highlighted the need for teacher involvement, including tools to update lessons and control robot behaviour. They also supported memory-based adaptations, enabling robots to recall past interactions to motivate students.

In our study, we presented teachers with an interface and the results of a field experiment, and the points raised in the cited work were reflected in our findings. For instance, by allowing teachers to select adaptation methods and manage new content through the interface, we addressed the need for dynamic adaptation. The ability to visualize system performance through graphs and switch between methods further reinforced this. Combined with other components of our architecture-such as the user preferences module-we propose that long-term, memory-based interactions can be effectively supported.

Therefore, our conclusions address **RQ2**, which explores how the characteristics of adaptive methods influence teachers' adoption and perception. While teachers acknowledged the importance of understandability, they were more strongly influenced by the performance of the methods. This was evident both when they ranked influencing factors and when they changed their preferred method after reviewing the results of a specific case. However, for quicker setup and activity configuration using R-CASTLE, teachers indicated they would initially opt for the more intuitive algorithms.

6 Conclusion

In this work, we presented an evaluation of user modelling and adaptation algorithms by the data analysis performed over an experiment in a real classroom scenario, considering the teachers' perspective on the obtained solutions. Methods with higher understandability, rule-based and fuzzy decision-making systems, presented similar performance. However, they presented inferior performance, when compared to supervised ML algorithms. In the initial stages of the experiments, teachers tended to prefer the methods they could easily understand. However, after reviewing the experimental results, many shifted their preference toward higher-performing methods-even if they did not fully understand how those algorithms functioned.

When analysing the data, we found that it is possible to prioritise certain weights by checking the importance of the parameters in the ML algorithms and also in the best performing weights of the RBS and FDMS. Although more experiments are requested to validate this hypothesis also from the dimensions of attention and communication, our findings suggest a high potential of the proposed modelling to be quickly adaptive for dynamic scenarios, while still keeping a desired level of understandability.

It is worth highlighting two major contributions of this work. The first is the role of stakeholders, helping to adjust the parameters of the R-CASTLE system and demonstrating that AI techniques can be a powerful tool in the learning process. The second is the advantage of conducting this research in real-world settings, making the adaptation of the system more true and trustworthy.

Finally, we can conclude that the best alternative would be a combination of the presented methods, in which, initially when no data is still acquired, teachers can use the methods with high explainability, whereas the more data they collect in specific activities, the better ML algorithms can be trained to achieve higher performances. The easy switching between these methods for every activity is a key element for fast customisation in classrooms that R-CASTLE provides.

Limitations of this work include, notably, the small dataset used to assess algorithm performance and the analysis performed solely at the immediate adaptation level. For a deeper, comprehensive evaluation of the implications and advantages, long-term experiments are necessary. Furthermore, in relation to qualitative analysis, it is important to note that this work does not aim to draw a general conclusion on teachers' opinions regarding adaptive algorithms for social robots. Rather, it seeks to illuminate common situations and attitudes arising from synergy among these agents.

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Author Contributions DT and RR contributed to the conception of the studies and methods. DT programmed the user studies and the robotic environments. DT wrote the paper and performed the data analysis and interviews. RR provided formal supervision, project administration and partial funding. All authors contributed to the article and approved the submitted version.

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Data Availability Dataset can be found at [72].

Code Availability The code of the architecture, as well as the adaptation methods and analyses, can be found in the GitHub link: https://github.com/LAR-Educational/R_CASTLE_Windows/tree/master/LAB/SORO.

Materials Availability Transcriptions of the interviews with teachers can be provided over request due to ethical procedures asked by the Brazilian Ethics Board.

Declarations

Ethics Approval and Consent to Participate This experiment was approved under the protocol number 72203717.9.0000.5561 by the Brazilian Ethics Board.

Consent for Publication All participants (or their guardians) gave their signed consent for publishing the given results.

AI Support We would like to acknowledge the use of Microsoft Copilot under their agreement and licence with UCL for improving the readability of some paragraphs with high density of information and table formatting. The original writings are kept for conference.

Competing Interests The authors declare that the research was conducted in the absence of any commercial or financial relationships.

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