Enhancing Learning in Robot-Child Tutoring with Personalized Timing Strategies

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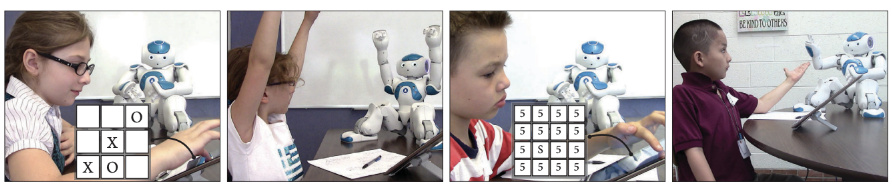
Abstract. This study focuses on optimizing learning in robot-child tutoring by implementing personalized timing strategies. Non-task breaks are commonly used in education to address children's limited attention spans and promote cognitive rejuvenation. Robots offer a unique opportunity to deliver tailored breaks that meet the individual needs of students, thereby enhancing their learning experiences. In this research, we develop an autonomous robot tutoring system that monitors students' performance and administers breaks based on personalized schedules aligned with their progress. Through a field study, we compare the effectiveness of different timing strategies, including a fixed timing approach, a reward strategy that aligns break timing with performance improvements, and a refocus strategy that aligns break timing with performance declines. The results demonstrate that personalized timing strategies significantly optimize learning outcomes in robot-child tutoring compared to the fixed timing strategy. Additionally, we observe immediate benefits, such as increased efficiency and accuracy in completing educational tasks, following personalized breaks. This study highlights the importance of personalized timing in promoting effective learning and offers insights into improving robot-child tutoring experiences.

1 Introduction

This research focuses on exploring personalized timing strategies to optimize learning in robot-child tutoring. Non-task breaks are commonly used in education to address children's limited attention spans and promote cognitive rejuvenation. Robots provide a valuable opportunity to deliver personalized breaks tailored to the specific needs of individual students, enhancing their learning experiences. We develop an autonomous robot tutoring system that assesses students' performance and administers breaks based on personalized schedules aligned with their individual progress. Through a field study, we compare the effectiveness of different break strategies, including a fixed timing approach, a reward strategy that aligns break timing with performance improvements, and a refocus strategy that aligns break timing with performance declines. Our results demonstrate that personalized strategies significantly enhance children's learning outcomes compared to the fixed strategy. Furthermore, we observe immediate benefits in terms of improved efficiency and accuracy in completing educational tasks following personalized breaks, underscoring the restorative effects of breaks when provided at optimal moments. These findings contribute to the understanding of how personalized timing strategies can optimize learning in the context of robot-child tutoring. But how to develop a robot system that meets the needs of its users in an industry 4.0 environment? An answer has to take User Experience (UX) into account, which – according to Alben [2] – comes everywhere into play were humans interact with a system. This includes cooperation and usability but also factors such as perceived safety, stress, or emotions [3]. The study presented in this paper illustrates how a UX study helped improving a standard-software to a physical interaction interface for real-world usage. We used a multi-perspective camera approach and well-established UX questionnaires with actual factory in their actual working environment. Developing a robot system that meets the requirements of users in an industry 4.0 environment necessitates considering User Experience (UX), which encompasses all aspects of human-system interaction, as highlighted by Alben. This encompasses cooperation, usability, and factors such as perceived safety, stress, and emotions. This paper presents a study that demonstrates how a UX study played a significant role in improving a standard software to a physical interaction interface for real-world application. The study utilized a multi-perspective camera approach and established UX questionnaires in an actual factory working environment.



(a) Game play: tic-tac-toe (b) Physical exercise: stretch activity (c) Refocusing activity: spot-it (d) Relaxation: breathing activity

Fig. 1. Stages of the Proposed Framework

The goal was to explore if there is a difference in the UX between a robot with remote-HRI (previous study: robot A) and a technical revised version of this robot with physical-HRI (current study: robot B). Both robots offered two control modi: remote control via touch-panel and direct-manual control via physical guidance. The touch-panel for remote control featured a graphical user interface consisted of buttons to steer the robot and to save the teached movement trajectories. The physical-HRI mode enabled the operators to control the robotic arm directly, manually and without an additional intermediate layer. Robot A was optimized for remote control, whereas the improvement of robot B consisted of an extended physical HRI. Five participant were recruited to participate in the two studies. This small participant number can be sufficient to identify the most severe usability problems and was already discussed by [9]. The current study was conducted one year after the previous one. Within this time, robot

A was upgraded to robot B, so robot B could only be examined after to robot A. However, both studies had the same structure: (1) Introduction of the robot: Each participant was introduced to the robot and its control mechanisms. The participants were told to teach the robot predefined trajectories. In order to relief stress and increase compliance, the participants were assured that the focus of investigation was only the robot's performance and there were no negative implications for them. (2) Conducting the user study: Each participant was audio- and videotaped with two cameras in order to generate a holistic perspective. This included a headmounted camera (first-person view) and a hand camera (contextoriented view). (3) Post-study questionnaires, including NASATLX, SUS, and self-developed items. The aim of the analysis was to compare the temporal demand, and the UX (including usability and performance expectancy) of the first and second version of the robot prototype. The findings will be used for a the third (and last last) technical revision before the robot is deployed in the normal factory environment. The analysis of the video data (comments, reactions and feedbacks) consisted of (1) a rough clustering of all relevant issues, (2) a detailed description of their key features, and (3) overlapping topics were merged to categories or differentiated from each other. Social robots have demonstrated great potential as educational technology due to their ability to provide personalized instruction for individual students [5]. Previous research in this field has primarily focused on content-based personalization, where the robot's behavior is tailored to the specific learning task [14]. For example, Leyzberg et al. found that providing personalized lessons based on cognitive skill assessments significantly improved performance compared to non-personalized or no lessons [14]. Similarly, Westlund and Breazeal showed that personalizing the difficulty level of vocabulary words in a story-telling task led to vocabulary improvements over time [34]. Schadenberg et al. explored personalizing the difficulty level of a game played with a social robot, successfully adapting the level to each individual based on ongoing performance assessments [28]. In contrast to previous studies, our work investigates the impact of non-content personalization on learning outcomes.

Learning involves various supportive mechanisms beyond the immediate cognitive task, such as help-seeking behavior, affective support, and rapport-building. Prior research in human-robot interaction (HRI) has explored personalizing robot behavior based on these mechanisms. For instance, Ramachandran et al. demonstrated that a robot employing adaptive strategies to regulate a child's use of help during math problem-solving improved learning gains [26]. Gordon et al. studied affective personalization, using reinforcement learning to determine the affective states preferred by each child during a learning interaction [4]. Likewise, Henkemans et al. presented a health education robot that personalized its behavior by referring to a child's name, favorite activity, and color during conversation [6]. In our study, we focus on personalizing the timing of breaks during tutoring to enhance learning outcomes. The HRI community has also explored computational methods for estimating user engagement and attention, aiming to create effective learning experiences. Leite et al. developed data-driven classi-

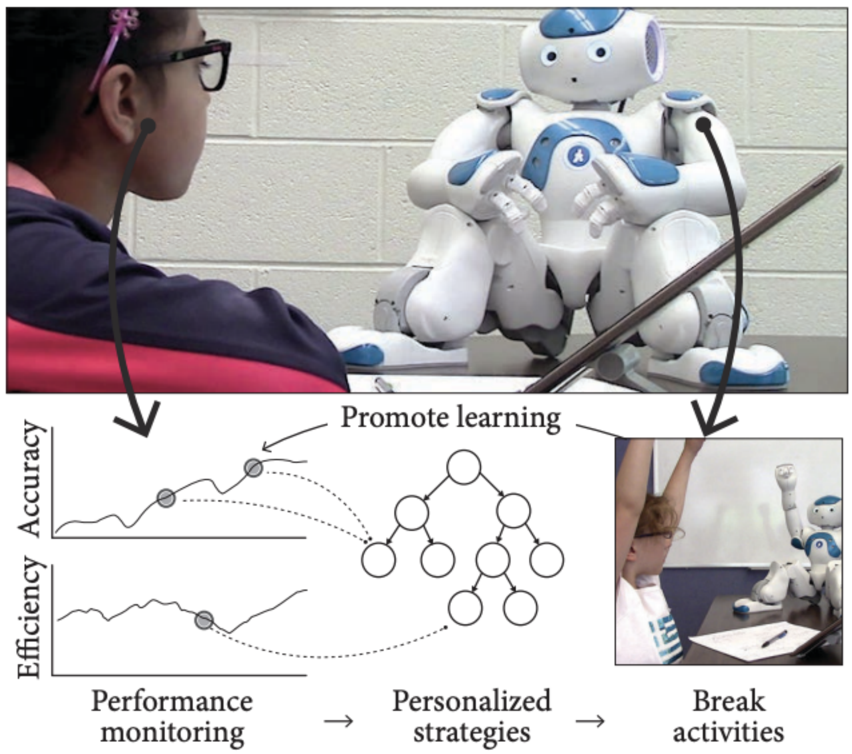


Fig. 2. Personalized strategies for providing breaks to promote children's learning during one-on-one tutoring with a robot.

fiers to detect disengagement in groups of children and individual children [11]. Lemaignan et al. proposed an online method for assessing a child's attention during a learning interaction [13]. Szafir and Mutlu utilized real-time EEG sensor data to monitor attention and adaptively improve student recall ability [30]. In contrast, our approach employs performance-based features during learning to guide tutoring interactions.

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In this context, a new framework for classifying human emotions based on contactless PPG signals was proposed. The proposed framework uses the MAHNOB-HCI emotional database, which is a widely used emotional database that contains video recordings of human emotional responses to various stimuli. The proposed framework applies signal normalization and segmentation techniques to preprocess the PPG signals before classification. The segmentation technique divides the PPG signal into smaller segments, allowing for the identification of transient changes in heart rate that are related to specific emotional states.

For classification, a new spatio-temporal network 1DCNN-LSTM was proposed. This deep learning architecture combines a one-dimensional convolution neural network (1DCNN) and a long short-term memory (LSTM) network. The 1DCNN is used to extract the spatial features of the PPG signals, while the LSTM is used to capture the temporal dependencies of the signals. The proposed method achieved an accuracy of 73.33% in valence and 60% in arousal, which is superior to the state-of-the-art methods in the literature. These results demonstrate the potential of contactless physiological signal extraction methods for use in the field of automatic human emotion recognition. The proposed framework for classifying human emotions based on contactless PPG signals provides a novel and non-invasive approach to automatic emotion recognition. The results obtained demonstrate the effectiveness of the proposed approach in achieving accurate emotion recognition. The proposed spatio-temporal network 1DCNN-LSTM is a promising architecture for automatic emotion recognition, and future studies can build upon this work by exploring other deep learning architectures and improving the signal preprocessing techniques.

Current remote heart rate (HR) measurement methods can be divided into two categories based on camera and light source configurations. The first category involves monochromatic sensing, similar to traditional pulse oximetry, with specialized high-end cameras or controlled monochromatic light sources. Although these methods can achieve precise remote HR measurement, they require expensive equipment. The second category uses consumer-grade RGB cameras such as digital webcams and smartphone cameras, which are more widely accessible but present challenges due to the broad wavelength range sensed by each R, G, and B channel. Previously, non-contact remote HR measurement methods using RGB cameras have mainly relied on explicit feature extraction and linear regression. However, this approach has limitations in accuracy and efficiency. Thus, we propose a novel approach using neural networks to extract remote HR information from all three color channels. Our approach is inspired by the optophysiological model for remote HR measurement, which utilizes deep learning to monitor remote HR in a contactless way with regular RGB cameras. Compared to previous non-contact methods, our approach offers several advantages, including better accuracy, reduced discomfort and sanitation concerns, and broader accessibility. Our results show that our approach achieves superior accuracy compared to state-of-the-art methods in valence and arousal classification, with a recognition rate of 82.8% and 70.7%, respectively. Additionally, we demonstrate the explainability of our model by visualizing the weights for the RGB channel combinations, which also show consistency with Previously, non-contact remote HR measurement methods using RGB cameras have mainly relied on explicit feature extraction and linear regression. However, this approach has limitations in accuracy and efficiency. Thus, we propose a novel approach using neural networks to extract remote HR information from all three color channels. Our approach is inspired by the optophysiological model for remote HR measurement, which utilizes deep learning to monitor remote HR in a contactless way with regular RGB cameras.

2 Method

In addition to the personalized strategies, our system also implements several basic support mechanisms, including providing necessary information on the tablet application and exhibiting engaging robot behaviors, to facilitate tutoring interactions with young learners. All behaviors described in this section apply to all students regardless of the assigned conditions for the user study described in Section 4.2. At the start of a tutoring session, the robot greets each student and conducts a small, interactive lesson on an educational topic. After the lesson, the robot presents a series of questions on the taught topic for the student to practice. We carefully designed robot behaviors to give the students the impression that the robot was responsible for facilitating the learning interaction. For instance, the robot looks at the students when speaking and looks at the tablet while they work on practice questions. The robot also uses gestures throughout a session, often extending an arm towards the tablet to invite students to direct their attention towards it. The content selector chooses each practice question from a bank of problems with multiple difficulty levels to accommodate a variety of learners. All students start with the lowest level of questions available and can only advance to subsequent levels after demonstrating a specified level of mastery. The robot provides feedback on whether an answer is correct or incorrect after each individual problem. If the answer is incorrect, the robot also provides general feedback about how to solve the problem, while the tablet displays the associated worked-out solution. Moreover, the tutoring application helps manage the flow of the tutoring interaction by providing buttons on the screen that allow the student to initiate the presentation of the next problem and disabling buttons displayed on the tablet while the robot verbally delivers tutoring information. Upon reaching the allotted time,

3 Experimental Results

Five male assembly workers, selected as a representative sample from the collaborating factory, participated in both studies. Each participant underwent a 30-minute interview, followed by filling out demographic questionnaires. The average age of the participants was 45.4 (SD=5.7), and they had no prior experience with robotic systems. Four out of five participants had previous experience with computers and automated systems. The teaching duration using remote control (robot A) and physical control (robot B) modes was determined from video recordings. Table I presents a 23.11% decrease in average duration and a significant shift from software-controlled to manual control usage. This shift towards direct manual guidance of the robot was also reflected in two dimensions of User Experience (UX): Usability and Performance Expectancy. Usability was assessed using the System Usability Scale (SUS), while Performance Expectancy, which represents the belief that using the system will enhance job performance, was measured using two items derived from [4]. Table II demonstrates an increase in the dimensions of Usability, Learnability, and Performance Expectancy.

Table 1. Average durations of the teaching process in study I and II including the percentage of both control modes

Duration (m:s)	Robot A	Robot B
Average Total [SD]	6:25 [2:27]	3:36 [1:03]
Remote Control [%]	6:25 [100.00]	1:01 [28.43]
Physical [%]	0:00 [0.00]	2:35 [71.57]

Table 2. User experience in study I and II including Performance Expectancy (PE), System Usability Scale (SUS), and its subscales Usability (SUS-U) and Learnability (SUS-L)

Scale[range]	Robot A [SD]	Robot B [SD]	Diff. [%]
PE [0-5]	2.40 [1.08]	3.40 [0.89]	1.0 [20.0]
SUS-U [0-4]	2.00 [0.73]	2.53 [0.27]	0.5 [12.5]
SUS-L [0-4]	1.70 [0.76]	2.60 [0.65]	0.9 [22.5]
SUS [0-100]	48.50 [13.99]	63.50 [3.79]	15.0 [15.0]

4 Conclusion

Based on the feedback received from workers in a previous user study, the HRI mechanisms of the initial robot prototype underwent technical revisions. In the current study, the same group of workers tested the revised robot's HRI mechanisms, and the findings were compared to those of the previous version. It is unlikely that the results can be attributed to practice effects, as there was a one-year gap between the studies and the interaction methods were completely different. The findings from the current study will inform the final technical revision of the system (robot C), which will introduce improvements in ergonomics and supportive artificial intelligence.

The HRI mechanisms of robot C will be based on the concept of joint/shared attention, which involves the shared focus of two individuals on an object. Joint/shared attention occurs when one individual directs the attention of another person to an object through verbal or non-verbal cues, such as eye-gazing or pointing gestures. Implementing this paradigm will result in gesture-based HRI mechanisms for robot C, aiming to emulate the dynamics observed in human-human or human-animal interactions.

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