J. Comput. Educ.
https://doi.org/10.1007/s40692-021-00213-9

Examining the Effects of Embodied Interaction Modalities on Students' Retention Skills in a Real Classroom Context

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Received: 19 July 2021 / Revised: 2 September 2021 / Accepted: 26 November 2021

Abstract Embodied cognition theory denotes that knowledge is incorporated into the body's sensorimotor system, which facilitates learning and understanding abstract concepts. In this context, several interaction modalities have been introduced to design learning experiences that promote multisensory processing. This study examined the impacts of the type of embodied interaction modality on learning gains in a real classroom context. The researchers designed learning interfaces involving different interaction modalities including tablet application, tangible user interface, motion-based technology, and multimodal interaction. Thirty-six primary school students (aged 7 to 9) were assigned to four groups to learn the basics of the human body anatomy. The study adopted an immediate and a 20-day delayed post-test to measure students' knowledge retention. Regardless of interaction modality type, participants showed significant immediate learning gains. However, participants in the multimodal embodiment conditions performed better on the delayed post-test. The findings suggested that multimodal embodied interaction, merging between body movements and tangible user interfaces, may lead to better knowledge

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Published online: 06 January 2022

retention. The process of performing body movements and physical interaction offered an alternative and a complementary encoding strategy for understanding and memorizing the learning concepts.

Keywords Human–computer interaction · Embodied learning pedagogy · Retention skills · Quality education

Introduction

Embodied learning relies on the premise that the cognitive process is dependent on the human body's sensorimotor capacities (Varela et al., 1991). According to Wilson (2002), it is a multimodal and playful learning process in which students' bodily experiences and interactions with the environment facilitate the meaning of learning. As Montessori (1966, p. 36) cited: "Movement, or physical activity, is thus an essential factor in intellectual growth, which depends upon the impressions received from outside.". From this perspective, knowledge is built through the experience gathered with senses, perception, and mediated by the body (Kosmas et al., 2018).

Driven by embodied theory, researchers and practitioners in the Human–Computer Interaction are proposing the design of embodied learning experiences. Driven by embodied theory, researchers and practitioners in Human–Computer Interaction are proposing the design of embodied learning experiences. Initially, tablet devices were proposed to afford students a touch-based interaction with the learning content (Besançon et al., 2017). With the advance of technology, motion-based technologies (e.g., Microsoft Kinect, Nintendo Wii, Intel RealSense) were proposed to support the implementation of embodied activities (Abrahamson, 2014; Hwang et al., 2020; Rutten et al., 2012). Such devices are characterized by the ability to capture and interpret students' body movements and gestures (e.g., selecting, dragging, or jumping) while interacting with projected learning content (Gelsomini et al., 2020). Further studies focused on offering students a physical interaction with the learning content using tangible user interfaces (Blackwell et al., 2007; Markova et al., 2012). These interfaces are mainly based on physical objects introduced as means to interact with digital representations directly in the real-world context without using controllers, WIMP interfaces, or mouse devices (Ishii & Ullmer, 1997).

In this context, a growing body of research reported that technology-enhanced embodied learning increased students' knowledge gains on a variety of learning topics related to different education fields such as in physics (Lindgren et al., 2013) and language acquisition (Kosmas et al., 2018). Further studies pointed out the gains in terms of students' engagement (Kubicki et al., 2015) and knowledge retention as revealed by delayed post-tests (Johnson-Glenberg et al., 2016). Yet, conducted studies on embodied interaction are driven by specific technical innovations and supported by limited empirical evidence regarding how different levels of embodied interaction may affect students' learning (Gelsomini et al., 2020).

The aim of this paper is to extend prior research on embodied interaction through purposefully comparing different interaction modalities to inform the design of an adaptive learning experiences in a real classroom context. We focused on comparing four interaction modality types ranging from low to medium bodily involvement including a tablet application, a tangible user interface, a motion-based technology, and a multimodal interaction (i.e., involving body movement and tangible objects). As education is mainly based on retaining material for future application (Abrahamson, 2014), this study sought to mainly gain a deeper understanding of the potential impact of embodied interaction modality on immediate and delayed learning gains. Accordingly, the main research question of this study is: Can the type of the embodied interaction modality impact differently students' knowledge retention in a real classroom context?

This paper is constructed as follows. The next two sections provide the theoretical approaches of embodied interaction and explore relevant research studies related to its implementation. The fourth section introduces the adaptive embodied learning environment. Section five describes procedures implemented to conduct the experimental study followed by reporting and discussing the results. Finally, in section seven, concluding remarks are presented.

Theoretical Background

Embodied cognition considers that the body, together with the mind, plays a key role in the cognitive processes (Wilson, 2002). It highlights that learning occurs when body movements, physical interaction, and sensorimotor capacities are connected to the learning content (Johnson-Glenberg et al., 2016). As an aspect of embodied cognition theory, embodied learning is a contemporary pedagogical learning approach that highlights the use of the body in learning experience (Kosmas et al., 2018). According to the embodied approach, incorporating physical engagement in learning allows both the body and mind to create considerable amounts of knowledge. As Montessori (1966) pointed out, students need to actively discover their environments to learn and construct knowledge. Thus, performing action (e.g., waving arm, grasping, jumping) in response to learning content, as well as manipulating physical objects, allows stimulating deeper cognitive processing (Lindgren & Johnson-Glenberg, 2013).

The association between the body and the environment affords mental representation and meaning making of the embodied content (Anderson, 2018). According to Johnson-Glenberg et al. (2016), during a lesson, when learners physiologically feel movements and exercise agency over them, they may more deeply comprehend the targeted learning concepts in the real-world context. Incorporating body movements in the learning activities may stimulates students' cognitive processing of abstract concepts and impacts their information retention (i.e., denoting the process of keeping memory in human memory stores) (Barsalou, 2010; Spear, 2014). Consequently, when learning in an immersive learning environment involving multimodal interaction modalities to stimulate students' auditory and visual perceptions, memories from performed actions and gestures may prepare students to memorize concepts that can be further retrieved to solve related tasks (Gelsomini et al., 2020; Kalantzis & Cope, 2004).

Related Work

In education technology, Johnson-Glenberg et al. (2014) proposed a taxonomy defining four levels of embodiment based on "the amount of motoric engagement, gestural congruency, and perception of immersion". The fourth level highlights the highest level of embodiment in which learners immerse into the learning environment with a high degree of sensorimotor engagement. At this level, the embodied interaction is achieved through locomotion and developed to be very congruent to the learning content. However, in the first level, learners are subjected to limited body movements not relevant to the learning content (e.g., watching a video, observing simulation). The second and third levels are merging between the fourth and first, according to the degree to which the body movements are implicated (e.g., ranging from minimum ensured through tablets to a maximum reached by motion-based technologies) and correlated with the learning content. Based on the proposed taxonomy, the embodied interactions range from high, medium, and low body involvement. At the high level, body movements are proposed to be highly correlated with the learning content, which is not the case with the low level of embodiment (Johnson-Glenberg et al., 2016).

The degrees of embodied interaction guided researchers and practitioners in Human–Computer Interaction (HCI) with proposing interaction modalities ranging from finger touch screen, free-form gestural interfaces, to tangible user interfaces. The emergence of tangible user interfaces proposed new possibilities for interacting with the learning content by mixing between touch and physical interaction with objects and digital concepts (Nathoo et al., 2020). Moreover, performing body movements through motion-based technologies may enhance students' learning experience while interacting with virtual learning content (Abrahamson, 2014). Within this domain, several studies have been performed to assess the learning impacts of embodied activities implemented by tangible user interfaces and motion-based technology.

Body Movements to Support Cognition

In learning environments, body movements stimulate learners' cognitive process of abstract concepts (Barsalou, 2010). With the evolution of technology, the appearance of motion-based technologies (e.g., Microsoft Kinect) supported the implementation of kinesthetic activities in the education field (Johnson-Glenberg et al., 2014; Stefanidis et al., 2019). According to Hu et al. (2015), the gesture of indexing or point, with or without touching any object or surface, affects students' information processing and promote their understanding of abstract concepts. Performing hand gestures representing learning concepts allow the young students to model and represent the object spatially, thereby helping them to process the presented information (Fischer & Hoellen, 2004). The study of Smith et al. (2014) supported these findings. In a motion-controlled learning environment, the study explored the impacts of gestures that mimicking angle measurements on students' understanding. The researchers examined 20 primary school students' understanding of angles. Results of the conducted tests revealed that gesture-based multimedia presentation had positive effects on participants' understanding and empowered their performance with 15%.

Further research studies exploring language education suggest that involving kinesthetic activities in the learning experience might support students' vocabulary retention. For instance, the study of Kosmas et al. (2018) explored the use of a motion-based embodied learning game to develop students' memory performance in the context of second language learning. The system was evaluated through a comparative study including 52 elementary school students for four months. The data collection involved pre-post tests to measure participant's short-term retention and learning performance. The results revealed that sensorimotor experience increased students' retention skills with a mean score of 8 concepts on a scale of 10, compared to participants learning with a mouse-based interaction (Mean = 6.2). The study of Kourakli et al. (2017) examined the impacts of embodied learning games on primary school students' language retention. The evaluation of the proposed system within a pre- and post-test questionnaire highlighted that interacting with the learning content using motion-based technology improved students' cognitive abilities and performance by a Mean value of 3.64.

Further studies proposed the implementation of immersive learning environments. For instance, Lindgren and Johnson-Glenberg (2013) explored full-body interaction in smart environments to teach students Newtonian physics. A controlled comparative study was conducted including 113 participants from seventh grade. Findings highlighted an increase in students' learning performance (Mean = 4.92), compared to the group learning via Pc-based application (Mean = 4.45). More recently, Gelsomini et al. (2020) proposed an embodied immersive space to empower young students' factual knowledge. The manipulation of the learning content imposed capturing students' hand gestures and body movement via an IR-depth camera. The researchers evaluated the effects of the immersive environment on students' retention skills through pre- and post-tests. The results revealed an increase in students' retention skills. Findings highlighted a mean score of 18 concepts on a scale of 20 at the long-term level for students subjected with embodied interaction, compared to 7 concepts among those learning in a conventional classroom.

Overall, findings of relevant studies emphasize the hypothesis that incorporating body movements in students' learning experience activate their cognitive processing and may provide an interactive learning experience where students are physically engaged in the learning tasks (Kosmas et al., 2018; Smith et al., 2014). Most of these studies explored the impacts of kinesthetic activities on students' knowledge gains and temporary learning impact (Gelsomini et al., 2020). However, they rarely assess the effects that interaction modalities type might have on students' retention skills in a classroom context. Furthermore, there is a lack of research evaluating the implementation of a motion-based learning system as a part of a classroom curriculum in a real classroom context (Kosmas et al., 2018).

Tangible Interfaces to Support Cognition

The potential of tangible user interfaces (TUIs) to support embodied learning is mainly related to the physical manipulation of concrete objects (Ishii & Ulmer, 1997). According to Piaget (1964), the mental image of children regarding the real world is shaped through concrete manipulation of physical objects. In this context, Kubicki et al., (2015) applied TUIs to teach 16 young children (aged 3–5 years) basic colors. The learners interacted with TangiSense table through sorting tangible objects in their appropriate colored areas. The results of the conducted tests pointed out that participants memorized objects colors and words. Furthermore, findings revealed better motivation in the experimental group than the group subjected to learning with colored stickers. Accordingly, the researchers suggested to incorporate the developed device to empower students' understanding while learning difficult or problematic learning concepts.

The study of Marco et al. (2013) introduced the NIKVision tabletop dedicated to children aged 3–6. They proposed to teach learners about farm animals by manipulating plastic animal toys having fiducials markers attached to their bases. Quantitative and qualitative results revealed that merging tangible interaction and 3D animations increased learners' language understanding and ability to link word meaning to physical objects.

De Raffaele et al. (2017) taught university students the concepts of normalization in databases using tangible objects embedding fiducial markers of the ReacTIvison library. The tangible objects represented the attributes fields of the selected databased (e.g., student ID, achieved grade, degree program). The results of the conducted pre-post tests revealed that TUIs increased students' achievement grades by 13% compared to the lecture-based approach. Findings emphasized the impact of TUIs on empowering students' learning performance and knowledge building. In the same context, Nathoo et al. (2020), introduced a tangible tabletop to teach students basic concepts of the Internet of Things. The study measured the effects of manipulating tangible objects on students' learning performance and usability experience using Nielsen's usability metrics. The results of the pre-post tests pointed out that the tangible tabletop increased students' knowledge by 37.5% compared to lecture-based learning. Furthermore, findings showed that about 60.6% of participants expressed their satisfaction regarding learning with tangible objects.

Further research studies examined the implementation of TUIs to increase collaborative learning. Anastasiou et al. (2014) proposed an interactive tangible table presenting the production of electricity of a windmill. Their study focused on evaluating students' behavior while resolving tasks with their peers. The results showed that 85.4% of the learners' gestures were correlated with resolving tasks through manipulating objects (i.e., tracing, rotating, and moving objects). The interaction modality developed a mutual and collaborative understanding of modeling a complex environment.

The existing research findings revealed that tangible user interfaces can offer an alternative modality for establishing a meaningful and engaging embodied learning experience (Kubicki et al., 2015; Nathoo et al., 2020). However, there is still a necessity for empirical evidence concerning the learning effects of tangible objects in the context of an authentic school environment (De Raffaele et al., 2017). Furthermore, most of the explored studies focused on evaluating TUIs in means of learning performance (Marco et al., 2013), and usability (Nathoo, et al., 2020), but lack examining their effects on empowering young students' knowledge gains.

Methodology

According to Antle (2013), the development of embodied learning pedagogy relies on children's cognitive process, age, and acquired abilities. For instance, while a similar cognitive process may operate through a learning task using motion-based technology, students' limited motor skills and abilities to perform gestures may affect their behavior and performance while solving a task. Consequently, a lack of considering student's ability, motor-perceptual states, and age may negatively affect the successful completion of the embodied activity (Antle, 2013). Applying this perspective guided us with proposing a multimodal adaptive learning environment to support students' knowledge acquisition. As presented in Fig. 1, the environment includes different interaction modalities to empower students' cognitive processes and assist their perception, processing, understanding, and retaining abstract concepts.

According to Johnson-Glenberg et al. (2016), learning is based on "what we perceive, and what we expect in the world as we move about it, in addition to how we interact with the objects and situations discovered". Based on this premise, the proposed embodied learning environment focuses on merging perceptual interpretations and motoric interactions. On the perception side, the learning environment includes projection areas to stimulate students' visual and auditory senses, which will further support their ability to retain, retrieve, and transform knowledge. On the action side, different forms of interaction modalities (i.e., tablet, motion-based, tangible interface, and multimodal interaction) are used to expand the classroom space via sensorimotor activities.

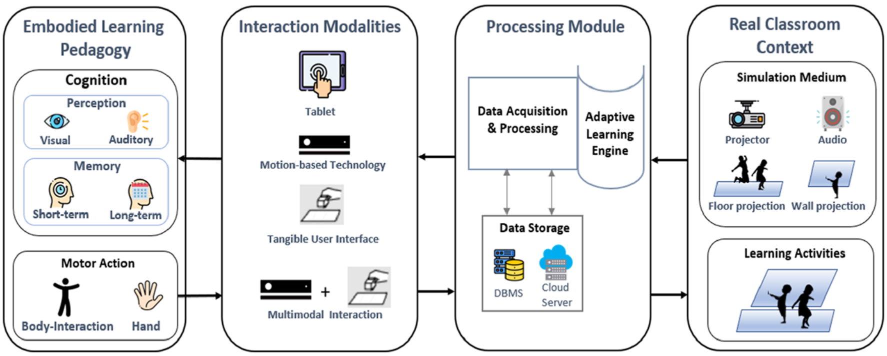

Fig. 1 Overview of the proposed adaptive learning environment

As an interaction modality type, Tablet was selected as a touch interface to allow students interact with the learning content on a screen with fingers, instead of using a control device. Furthermore, as a gestural interface, the motion-based technology was chosen to enable a richer embodied experience that takes advantage of the representational power of movements and gestures (Gelsomini et al., 2020). The production phase of motion-controlled learning experiences included the development of algorithms to extract the 3D positions of the body's joints in space using a depth camera. The gathered data will be further processed to register and capture body movements. In the postproduction phase, the generated algorithms will be integrated into the Unity3D engine to develop an embodied learning activity involving gestures congruent with the defined teaching and learning goals.

Furthermore, tangible user interfaces are integrated to augment the real physical world and take advantage of children's abilities to grasp and manipulate physical objects (Mendoza & Baranauskas, 2021). The main target is to engage students in a unique process of physical action that may empower their abstract thinking. Within this interaction modality, physical objects are firstly designed to represent abstract concepts based on the defined learning goals. According to the tangible user interface architecture, each physical object has a fiducial marker attached to its base to allow its detection and interaction with tangible tabletop (Kaltenbrunner & Bencina, 2007). The physical architecture involved a tangible tabletop including a transparent acrylic glass and embedding a mobile camera to detect the fiducial markers. Moreover, the learning activity is developed through the ReacTiVision library to track tangible objects using an IR camera. At this level, the captured information is sent to the learning interface using the TUIO protocol to create simulations and generate feedback.

Incorporating body movement into the learning activity advocates the value of learning by doing. However, if the students were unable to connect a gesture to its visual representation, this might negatively impact his/her learning experience (Anastopoulou et al., 2011). To overcome these difficulties, the proposed learning environment includes a multimodal embodied interaction merging between two modalities: motion-based technology and tangible user interfaces. The usage of a tangible interface focused on ensuring an embodied experience that takes advantage of the students' natural inclination toward manipulating physical objects. Students could firstly explore an abstract concept using representative tangible objects attached to fiducial markers. Then, the IR-depth camera will be used to detect students' position, body movements, and gestures (e.g., pointing, walking, or jumping) to manipulate the generated interactive visualization displayed on one of the projection areas.

Based on the proposed embodied interaction modalities the learning environment will be able to identify students' interaction behavior, level of knowledge, and mastery skills based on the analysis of their interactions with the learning activities. At this level, the adaptive learning engine will analyze the gathered data to create a learning profile for each student (e.g., behavior, performance, prior knowledge). Profiling students will serve to recommend a suitable embodied interaction modality and engaging learning activities. We hypothesis that by adaptivity it is possible to achieve the objective of "quality education", through supporting all students (i.e., with and without special educational needs) in mainstream education with a tailored embodied learning experience.

Experimental Study

Considering the aim of designing an adaptive learning environment to ensure a tailored embodied learning experience, we conducted an experimental to observe whether interaction modality type can differently empower students' immediate and delayed learning gains. Our goal is to answer the following research question: Can the type of the embodied interaction modality impact differently students' knowledge retention in a real classroom context? Based on the theoretical background and the emphasized research question, our study attempts to test the following research hypothesis: differences in students' retention skills (i.e., short and long term) might emerge when they learn through different types of interaction modalities.

Interaction Modalities

We adopted four interaction modalities, as presented in Fig. 2, including: a tablet application, a tangible user interface, a motion-based technology, and a multimodal interaction (i.e., merging between body movement and physical interaction with tangible objects). The explored interaction modalities cover different levels of embodied interaction ranging from low (i.e., Tablet) to medium level (i.e., tangible user interface, motion-based technology, and multimodal interaction) (Johnson-Glenberg et al., 2014). The notions educated in the proposed learning systems targeted the basic concepts of the human body, including the body's joints (i.e., elbow and shoulder) and internal organs (i.e., lungs, heart, and digestive system). The learning topic used for this study was identified in collaboration with the teacher based on the difficulty of the topic, and the novelty of the content to the involved student to avoid possible threats to internal validity.

Tablet-Based Interface

We have developed a tablet-based application to examine the effect of touch interaction on students' learning gains (Fig. 2a). The student is asked to answer the question by dragging and dropping an item into the blue rectangle. Icons were used to graphically represent the body's parts to guide the student to recognize them. After submitting the response, a prompt message appears as a feedback to confirm the answer.

Tangible-Based Interface

The tangible learning interface (Fig. 2b) denotes a user interaction requiring the manipulation of the physical objects (De Raffaele et al., 2017). Thus, as represented in Fig. 3, we have created physical objects representing internal organs, body's

(a) Tablet-based interface

(b) Tangible-based interface

(c) Motion-based interface

(d) Multimodal-based interface

Fig. 2 Embodied interaction modality types

joints, and questions. These objects have fiducial markers attached onto their base to permit students interaction with the learning tasks (Nathoo et al., 2020). Furthermore, a tracking system based on the ReacTiVision library was developed to detect the fiducial markers and control the interactive visualizations projected on the wall area.

For the tangible tabletop, as shown in Fig. 2b, we used a transparent acrylic glass as a surface to manipulate the tangible objects. The table was installed at a height of 81 cm with a working area of 1 m $\times$ 0.7 m to ensure an ease manipulation of the tangible objects (Nathoo et al., 2020). Furthermore, a mobile camera was situated under the table surface to track the fiducial markers and determine their orientation. The tabletop was also illuminated with infrared LED lamps to properly capture the fiducial markers.

The process of interaction was performed as following. The student starts by selecting a question and the appropriate tangible physical object to answer it. Based on teachers' recommendations, the questions included pointing joints responsible for the abduction, flexion, and extension movements, as well as sorting nternal organs

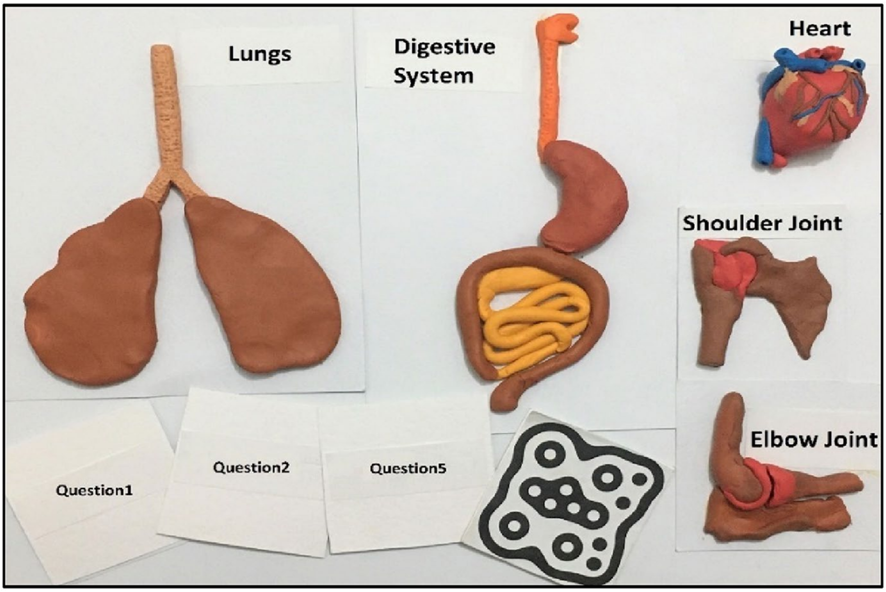

Fig. 3 Tangible objects illustrating the body's joints and the internal organs

in their appropriate location. The learning interface, as illustrated in Fig. 4, included a visual feedback using smiley faces (i.e., happy, and sad).

Motion-Based Interface

The motion-based technology, as presented in Fig. 2c, was used to implement a motion-controlled learning environment. The environment included the use of an IR-depth camera to detect and recognize students' gestures (Gelsomini et al., 2020). The learning tasks, designed using Unity engine, included two types of interactions with the learning content.

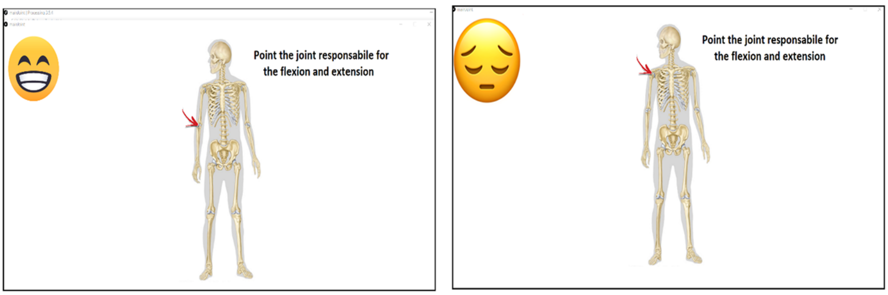

Fig. 4 Tangible-based learning interface

The student is asked to perform two actions: imitating the bird's wings movement and drawing an angle of 180 and 90 degrees. The main target is to guide the student to feel the movements of the shoulder and elbow joints. After performing each action, a skeleton is projected on the top of the students' body to guide them with locating the joints. The students are required to position their hand on their body to locate where they felt the performed movement.

Furthermore, the learning interface included questions asking the students to recognize the location of the joints (i.e., shoulder and elbow) and the internal organs (i.e., heart, lungs, and digestive system) presented as 3D images. To answer these questions a virtual hand appears, and the student grabs (close hand), drags (move hand) and releases (open hand) the 3D image in the corresponding location on his/her body. Once the object is correctly placed, a visual and audio feedback appear.

Multimodal-Based Interface

The interface activities were designed to include body movements to recognize the joints and tangible objects, instead of hand gestures, to locate body's internal organs. After recognizing the fiducial markers, the ReacTiVision framework is used to convert the tangible objects into digital representations. At this level, as illustrated in Fig. 5, the IR-depth camera served to detect students' actions while interacting with the displayed learning content.

Participants

The study was conducted in an elementary school with 36 student (7–9 years) from third and fourth grades. The age group was selected due to the chosen sensorimotor

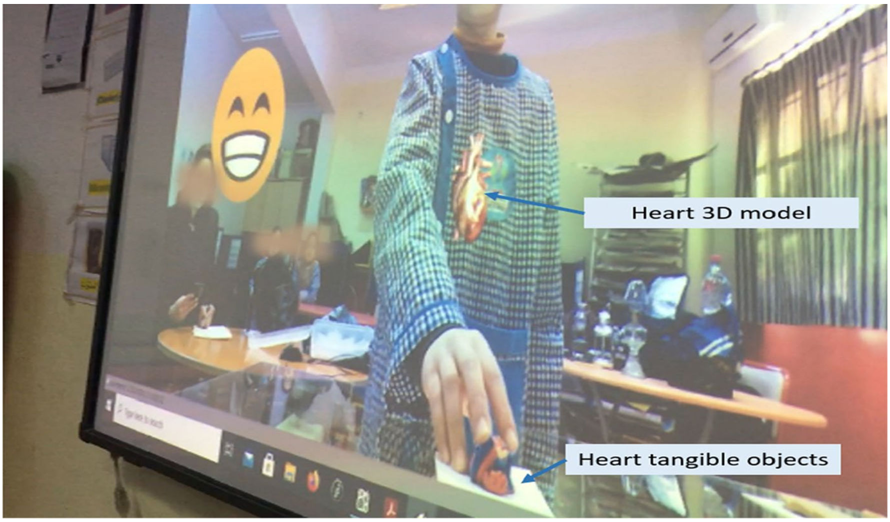

Fig. 5 Student interacting with motion-based technology and tangible objects to locate the heart on his body

activities adopted in the study. To efficiently define the participants' age group, we have tested the designed activities with students aged 7–12. The observations of students' interaction pointed out that the proposed sensorimotor activities seemed proper for the motor abilities of students aged 7–9. Besides, two primary school teachers, known to all students, were implicated in the study to manage students' learning through different interaction modalities, guide them, and assess their answers on the pre-post testing.

Furthermore, prior to the study, a consent form was signed by the school administration, the teachers, and participants' parents regarding the use of the data recorded during the experimental study. We have assured that participants' personal information is protected and kept private by saving only their IDs and test scores.

Procedure

The study was conducted in three phases for all groups. During the first phase, participants watched an educational video explaining the anatomy of the human body. Then, they were asked to perform a pre-test (i.e., baseline test). Teachers loudly read the questions, and participants were given 20 min to complete the 10 questions without obliging them to finish the test on time. The achieved scores after the pre-test permitted to homogeneously divide students into four groups of 9 participants each. The first group (TUI) was subjected to learn with tangible user interfaces. The second group (TAB) used the tablet-based learning application. The third group (MBT) used the motion-based technology to interact with the learning tasks. Finally, the fourth group (MBTUI) was subjected to learn through multimodal interaction.

During the second phase (learning), the participants attended two learning sessions (for 25–35 min). Firstly, the interaction modalities were presented to the dedicated groups. The participants were informed about the device they would use to manipulate the learning tasks (i.e., performing gestures, interacting with physical objects, or tapping on the tablet touchscreen). The teachers accompanied participants during the three learning sessions and adopted identical guidance for each group. Participants were permitted to ask for the teacher's help if they encountered any difficulty while interacting with the learning content.

During the third phase (evaluation), participants were asked to take the post-test at the end of each learning session. The main target is to measure the impacts of interacting with the learning modalities on their short-term retention of learned concepts. After 20 days from the short-term post-test, participants were subjected to perform an identical test to assess their long-term retention of learned concepts.

Data Collection

The impacts of the interaction modality type on students' retention skills were measured through the difference in participants' post-testing results. The paper-based pre- and post-tests were identical for all groups and proposed by the teachers. They involved the same ten questions with different difficulties to evaluate whether participants progressively improved their knowledge gains while learning with the dedicated interaction modality. To assess students' knowledge gains the conducted tests included short answers questions (e.g., which joint is responsible for abduction movement?), and labeling questions to identify internal organs and their location in the human body. Regarding the scoring, one point was assigned for the correct answer and zero to each wrong one, for a maximum score of 10. The grammatical mistakes and typos were not considered as wrong answers.

Regarding the post-tests, they were divided into two categories. A short-term test was conducted identically to all groups the day after finishing the third learning session, in the same form and manner as the previous post-tests. After 20 days from the short-term test, a long-term retention test was performed. The test was similar to all participants and included different questions to assess students' knowledge gains. For 20 days, students participating in the experimental study did not attend any lesson or worked on homework related to the learning topic.

Results

The results of the pre-test led to the allocation of 36 students in four experimental groups. The average pre-test score of students in the TAB group is 3.11 (SD = 1.46), while in the TUI group it is 3.33 (SD = 1.60), compared to an average score of 3.78 (SD = 0.93) among MBT group and 3.56 (SD = 1.72) in the MBTUI group. The results of the pre-tests revealed a p-value = 0.023, highlighting a statistically insignificant difference in students' prior knowledge. In order to examine impacts of the interaction modality type on participants' learning gains, we have measured the changes in the values of the scores obtained at these three times points. Table 1 illustrates the descriptive data of the tests results.

One-way ANOVA was used to examine differences in participants' scores obtained from post- to short-term testing across all groups. ANOVA was chosen over a t-test as it allowed us to compare the four groups subjected to different embodied interaction modalities. To perform ANOVA, we have started with testing different assumptions (i.e., random independent samples, normality, homogeneity of variance, independence of the covariate, and the dependent variables).

Participants were randomly assigned to each of the four groups independently, but the pre-test scores were not normally distributed. As illustrated in Table 2, the conducted Levene's tests indicated a non-significance level, validating the homogeneity of the variances. Based on ANOVA's robustness, where the data normality is

Table 1 Results of groups in post- and short-term tests

Groups (N = 9)	Post-test 1 M(SD)	Post-test 2 M(SD)	Post-test 3 M(SD)	Short-term test M(SD)
TAB Group	5.38 (1.08)	7.28 (1.00)	8.61 (0.93)	7.09 (0.83)
TUI Group	6.39 (1.32)	8.39 (1.45)	9.50 (0.61)	8.09 (1.07)
MBT Group	7.06 (1.31)	8.61 (1.24)	9.44 (0.83)	8.37 (1.13)
MBTUI Group	7.28 (1.71)	8.78 (1.06)	9.67 (0.70)	8.57 (1.04)

Table 2 Levene's test of equality of error variances

Tests	F*	df 1	df 2
Post-test 1	0.91	3	32
Post-test 2	0.56	3	32
Post-test 3	0.34	3	32
Short-term test	0.93	3	32

*α value set at 0.05

violated without violating the homogeneity of the variances (Rheinheimer & Penfield, 2001), we have continued using the one-way analysis of variance (ANOVA) for the data analyses. The further conducted statistics informed that the covariates (post-tests) were dependent of the interaction modalities with, respectively, post-test 1 ($F = 3.42$, $p > 0.05$), post-test 2 ($F = 2.84$, $p > 0.05$), and post-test 3 ($F = 3.19$, $p > 0.05$).

The immediate effect of the intervention after the three learning sessions, defined as the average number of notions retained after one day, was measured based on changes in the values of the score obtained during the short-term test with respect to that achieved in the post-test3 after the last learning session. Using groups as the independent variable, the score of the short-term test as the dependent variable, and post-test 3 as the covariate, the ANOVA test [F (3,32) = 3.80, $p = 0.0019$] highlighted statistical significance difference in participants' short-term retention between the four groups. Based on these results, the Tukey HSD test and Scheffé multiple comparison test were applied to determine which of the pairs of groups are significantly different from each other.

The results of the p-values corresponding to the observed value of Tukey Q-statistic revealed a significant difference between TAB and TUI group ($Q = 3.90$, $p < 0.05$), TAB and MBT group ($Q = 3.78$, $p < 0.05$), and TAB and MBTUI group ($Q = 4.76$, $p < 0.01$). These findings were also supported by the results of the Scheffé multiple comparison test highlighting a significant difference between the TAB and the other groups with a p-value < 0.05. Accordingly, statistical results pointed out that the embodied interactions enabled by tangible interface, motion-based technology, and multimodal interaction, lead to statistically better knowledge retention among participants than tablet-based interaction.

The effects of 20 days, in which students have been engaged with learning sessions and activities not related to the topic of this experimental study, were particularly noticeable among all participants according to the achieved long-term post-test scores as illustrated in Table 3.

The impacts of the interaction modality type on students' long-term retention were measured using one-way analysis of variance (ANOVA) based on the difference in the participants' short and long-term retention testing results. The ANOVA test highlighted statistical significance in student's long-term retention [F (3,32) = 12.17, $p < 0.0001$] between the four groups. The result of one-way ANOVA was statistically significant. Thus, we have applied the Tukey HSD test to identify which of the pairs of groups are significantly different from each other.

Table 3 Results of groups in long-term post-tests

Groups ($N=9$)	Long-term post-test $M(SD)$
TAB Group	7.33 (1.68)
TUI Group	9.27 (1.09)
MBT Group	9.33 (0.96)
MBTUI Group	9.48 (0.72)

The results of the *p*-values corresponding to the observed value of Tukey Q-statistic revealed a significant difference between TAB and TUI group ($Q=6.62$, $p<0.01$), TAB and MBT group ($Q=6.95$, $p<0.01$), and TAB and MBTUI group ($Q=7.28$, $p<0.01$). Statistical results, as illustrated in Table 4, pointed out that embodied learning supported by tangible user interfaces, motion-based technology, and multimodal learning interfaces empowered participants' long-term retention skills better knowledge retention than the tablet interaction modality.

Since the MBTUI group turned out to include older participants, a correlation test (Pearson's χ^2) was performed between the age groups and the scores obtained in the short-term test. The results showed no significant association between the age and the short-term test performance for all groups ($pm>0.05$; $pk>0.05$). Consequently, results eliminated the concerns regarding the potential impacts of age on short-term knowledge retention.

The effects of 20 days, in which participants have not been involved in learning sessions or homework related to this experimental study topics, were particularly noticeable in all participants' long-term test scores. Values on Memory Loss (MR), denoting the number of forgotten notions between the short-term and long-term tests, show that participants learning through tablet-based application scored a remarkable memory loss. In particular, as illustrated in Fig. 6, participants subjected to tablet-based interaction remembered an average of 7.33 notions in the test conducted after 20 days. Moreover, it was noted the existence of a variability in the long-term retention among groups subjected to medium bodily involvement. Retention performance was higher when the multimodal-based learning system was used ($M=9.48$ $SD=0.72$).

Table 4 Results of Tukey HSD test

Group pair	Tukey HSD Q-statistic	Tukey HSD p-value
TAB vs TUI	6.62	0.001
TAB vs MBT	6.95	0.001
TAB vs MBTUI	7.28	0.001
TUI vs MBT	0.33	0.89
TUI vs MBTUI	0.66	0.89
MBT vs MBTUI	0.33	0.89

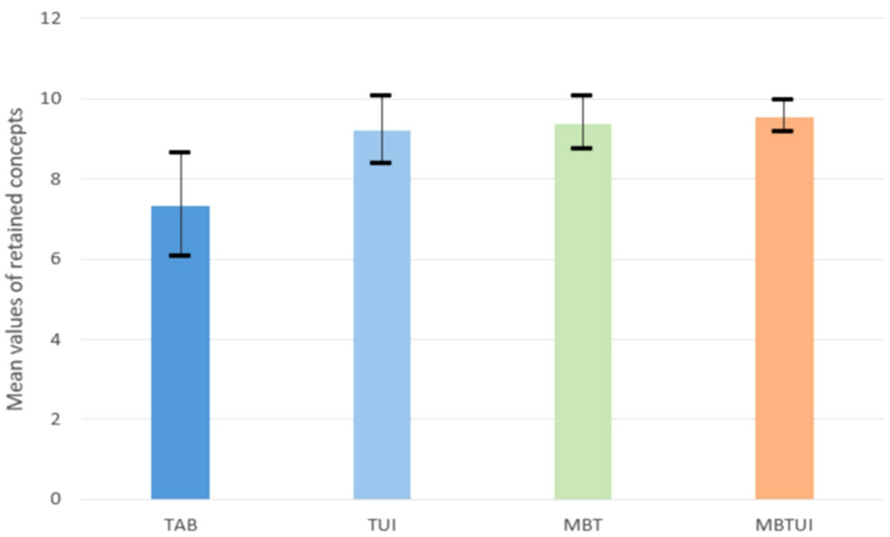

Fig. 6 Impacts of interaction modalities on long-term retention after 20 days

The findings suggest that incorporating tangible objects and motion-based technology has some significant effects for students learning, especially knowledge gains. Such a learning modality may provide a deeper embodied learning experiences by using the power of body motions and physical object manipulation to improve students' retention of learned notions. Consequently, adopting a greater embodied interaction for studying the human body allowed participants to use their bodies to identify the movement of joints and explore the location of internal organs using representative tangible physical objects.

Discussion

The conducted experimental study aimed to evaluate the impact of interaction modality type on students' retention skills in a real classroom context. Overall, the results pointed out that participants in all groups showed notable learning gains and understood the basic concepts of the human body's anatomy. According to the research question (*Can the type of the embodied interaction modality impact differently students' knowledge retention in a real classroom context?)* the responses to the short- and long-term tests revealed differences in participants' retention skills of learning concepts. After the short-term test, students subjected to the tablet-based interface memorized an average of 7 concepts compared to more than 9 concepts among other groups. In the delayed post-test, the participants subjected to medium levels of embodied interaction outperformed the tablet group significantly in the retention of the learning content 20 days after the conducted learning sessions.

Differences in students' short-term retention skills can be ascribed to the mapping between the performed actions and the digital representation of the learning content. According to Segal (2011), assuring consistency between the performed gestures and the digital learning content will support the internal representation of the students and their perception of abstract ideas. Therefore, with the group subjected to tablet interaction, tapping on the screen to identify joints does not represent the behavior of elbow and shoulder joints. However, acting out the bird's wings and drawing an angle of 180 and 90 degrees are gestures congruous with the joint movements. In addition, moving the tangible objects interact to locate organs over students' bodies, naturally and concretely, raised their attention on resolving the learning task. Ensuring gestural congruency with the digital learning content is required to assist students' internal representation of abstract concepts (Cook & Goldin-Meadow, 2006). Accordingly, adjusting the body to act out the joint movements and interacting with tangible objects representing internal organs promote cognition and empower knowledge gains.

Findings of the conducted study highlighted that implementing embodied learning pedagogy through motion-based technology and tangible objects afforded more actions and involved multiple instances of interaction with digital learning content. Performing gestures and manipulating tangible objects may guide students with strengthening the associations between concepts and sensations through physical actions, which form embodied analogies to map the abstract concepts to a concrete situation. These findings were also supported in relevant studies highlighting the increase of students' retention skills learning via motion-based technology and tangible user interfaces (e.g., Gelsomini et al., 2020; Lindgren et al., 2013, Nathoo et al., 2020).

Furthermore, we found that students were more able to retain concepts with multimodal embodied interaction involving body movements and manipulation of tangible objects than with an interface supporting one type of interaction modality. This can be ascribed to the various senses involved while interacting with the learning content. In comparison with the other interaction modalities, multimodal interaction enabled students to perform different actions to convey meanings, which consequently promoted their mental imaging and enabled them to build a representation of the educated concepts (Johnson-Glenberg et al., 2014). Besides, multimodal interaction delivered different interaction modes, which allowed participants to easily interact with a learning modality suitable for their natural inclinations (Gelsomini et al., 2020). Findings bring evidence to the theoretical benefits of merging between tangible interfaces and motion-based technology so young students can build knowledge and understating of abstract concepts.

However, some limitations in this study exist. A key limitation is that the study was conducted in a short time range. Further studies should be conducted to improve the duration and frequency of the students' interaction with learning modalities. Furthermore, to generalize findings, it is required to target a larger representative sample from different education levels. Future research could also include tools and research methods to include participants' learning styles and explore their interaction behavior through measuring their visual attention to the learning content while learning via embodied interaction modalities to understand how they lose concentration and their strategy to solve challenging interaction tasks.

Conclusion

The conducted experimental study examined the effects of embodied interaction modality type on short- and long-term retention skills. We hypothesized that students in the multimodal embodied interaction would outperform those in the other embodied conditions. The results revealed that participants subjected to medium levels of embodied interaction retained more concepts compared to the tablet-based group. However, we noted significant knowledge retention among participants in the multimodal embodied group after the 20 days delayed post-test. According to these results, we may conclude that principles of embodied interaction may be applied for empowering students' retention skills in a real classroom context. Furthermore, we suggest that embodied activity merging between different interaction modalities, by considering gestural congruency and sensorimotor engagement, may empower students' knowledge gains and retention skills in some learning concepts. Our study contributes to the educational technology research community by providing knowledge regarding the pedagogical use of multimodal learning systems in the school context. Examining the impacts of different interaction modalities on students' academic performance can potentially support the design of an adaptive learning environment covering different interaction modalities adapted to the learning needs and interaction behavior of each student to ensure a quality education.

Declarations

Conflict of interest The authors have no conflicts of interest to disclose.

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Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

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