Internet of Things 25 (2024) 101101

Contents lists available at ScienceDirect

Internet of Things

journal homepage: www.sciencedirect.com/journal/internet-of-things

The effectiveness of empathic chatbot feedback for developing computer competencies, motivation, self-regulation, and metacognitive reasoning in online higher education

Elvis Ortega-Ochoa [a,*], José Quiroga Pérez [b], Marta Arguedas [b], Thanasis Daradoumis [b,c], Joan Manuel Marquès Puig [b]

[a] Doctoral School, Universitat Oberta de Catalunya, Rambla del Poblenou 154, Barcelona, 08018, Spain
[b] Computer Science, Multimedia, and Telecommunication Faculty, Universitat Oberta de Catalunya, Rambla del Poblenou 156, Barcelona, 08018, Spain
[c] Department of Cultural Technology and Communication, University of the Aegean, Marine Sciences Building, Mytilene, 81100, Greece

ARTICLE INFO

Keywords:
Artificial Intelligence of Things
Cognitive feedback
Affective feedback
Competency based teaching
Motivation
Self-regulation
Metacognitive reasoning

ABSTRACT

At the forefront of Artificial Intelligence of Things, this paper delves into empathic agents to revolutionize computer competencies acquisition and catalyze motivational, regulatory, and metacognitive dynamics in online higher education. Previous research on student processing of empathic feedback has been limited, often neglecting learning performance and its impact on students' motivation, self-regulation, and metacognitive reasoning. The objective was to analyze the effectiveness of empathic feedback, cognitive and affective, on these four issues in online learning. A quasi-experimental design was used, in which a conversational agent, DSLab-Bot, was integrated into the syllabus and Information Technology infrastructure. Students from an online university's Distributed Systems course participated (N= 196), selected through one-stage cluster probability sampling. They were divided into experimental and control groups receiving feedback from DSLab-Bot and the teacher, respectively. Results showed no significant differences between the groups in learning performance, motivation, or self-regulation, except in one item of motivation (self-efficacy) and self-regulation. There were strong correlations between thirteen cognitive (1–4, 6, 7, 9–15) and seven affective (1, 4–9) chatbot feedback types with conceptual change (MRCC) and personal growth and understanding (MRPGU). There were high weights of similar chatbot feedback types indicating a pronounced influence of these on metacognitive reasoning components, even self-reflection (MRSR). In conclusion, empathic chatbot feedback is as effective as human teacher feedback in facilitating learning, motivation, and self-regulation. Moreover, specific empathic feedback types are crucial in fostering MRCC, MRPGU, and MRSR strongly. Practitioners should consider these specific types of empathic feedback for future empathic agent configurations.

* Corresponding author at: Doctoral School, Universitat Oberta de Catalunya at Rambla del Poblenou, 154, Barcelona, 08018, Spain.
E-mail addresses: egortega@uoc.edu (E. Ortega-Ochoa), quiroga@uoc.edu (J. Quiroga Pérez), martaarg@uoc.edu (M. Arguedas), adaradoumis@uoc.edu (T. Daradoumis), jmarquesp@uoc.edu (J.M. Marquès Puig).

https://doi.org/10.1016/j.iot.2024.101101

Available online 3 February 2024

1. Introduction

In the Organization for Economic Co-operation and Development (OECD) countries member, the average student-teacher ratio in higher education is fifteen to one in public and seventeen in private institutions [1].[1] In this context, it is difficult for educational institutions to respond in a personalized way to the development competencies of each student. In particular, the development of computer competencies is highly valued in higher education [2]. Information and Communication Technology (ICT) mediated learning is a mode of education that supports the solution [3]. Specifically, Pedagogical Conversational Agents (PCAs) as intelligent software agents of the Internet of Things (IoT), better known as educational chatbots, are learning resources that can favor adaptive learning in acquiring skills. In the PCAs, specific agents possess empathy capabilities, which are intended to address the limitations of non-empathic agents [4–6]. However, integrating these empathic agents into the syllabus and Information Technology (IT) infrastructure for learning, and their subsequent impact on online learning have been significantly limited and inadequately evaluated, respectively.

1.1. Problem

The problem has been raised in the literature and evidenced in practice. In addition, these are the main motivations. First, there are limited prior studies on chatbots that aim to enhance computer skills within higher education while incorporating empathic capabilities [7,8]. Those few studies only focused on the assessment of student perceptions, without considering the impact of empathic capabilities on learning performance (e.g., [9,10]). Likewise, few studies have explored support for students' motivational beliefs, and there have been no attempts to evaluate the effect on self-regulation and metacognitive reasoning. In addition, further studies are required to verify the efficacy of cognitive and affective PCA feedback. Second, considering the student-teacher ratio, courses tutoring in higher education institutions have problems in serving many students and require better integration of ICT-mediated learning in online learning [11,12].

1.2. Literature review

Empathic PCAs are educational chatbots that can facilitate the development of skills by integrating empathic capabilities. Recent studies have evidenced the need to configure intelligent chatbots that incorporate these capabilities to mitigate frustrations and conversation breaks. Furthermore, research has suggested quantitative and mixed assessments of their results. Second, computer skills are a complex and broad set of competencies highly valued in higher education. The goal of developing these competencies through online education has promoted researchers to propose and assess learning resources such as empathic PCAs, as well as has favored scientists to work on establishing a reliable way to assess these competencies.

1.2.1. Agents and Artificial Intelligence of Things

The Agents of Things (AoT) concept has been proposed to augment IoT with intelligent software agents, addressing the lack of reasoning and intelligence in the IoT concept [13]. The agentification of IoT through modeling smart objects and networks using software agents offers opportunities for building cognitive IoT applications. That is, by incorporating an agent layer into the other layers of IoT devices (application, network data communication, and sensing; [14]), they can acquire agent characteristics such as intelligence, autonomy, cooperation, and organization [15]. The concept that also integrates Artificial Intelligence (AI) technologies (e.g., Natural Language Processing [NLP], virtual agents, etc.) with IoT devices is Artificial Intelligence of Things (AIoT), where IoT devices act as the digital sensory method and AI serves as the brain of the system. Artificial agents can analyze big data collected from IoT devices and make predictions and decisions based on the analysis [16]. For instance, Rukhiran et al. [17] presented the design of an environment information chatbot system for a smart school framework for the IoT-connected environment information chatbot application. In this regard, artificial agents can contribute to the intelligence and effectiveness of IoT systems by augmenting them with reasoning and decision-making capabilities.

1.2.2. Modeling empathy in artificial agents

Hoffman [18] defined empathy as a "psychological processes that make a person have feelings that are more congruent with another's situation than with his own situation" (p. 30). There are several theoretical models of empathy, some of the most prominent are exposed by de Waal [19], Davis [20] and Davis et al. [21], Omdahl [22], Hoffman [18], Stueber [23], Goldman [24,25], Coplan and Goldie [26], de Vignemont and Singer [27], among others. According to the empathy definition, an empathic artificial agent should be "a synthetic character that evokes an empathic reaction in the user" ([28], p. 310). That is, to simulate the processes inherent within empathy, software agents must be able "to perceive and recognize emotions or moods and react accordingly by simulating a behavior appropriated to the perceived emotion or mood" ([29], p. 441). Relevant data on empathic agents are shown in the systematic literature review of Bilquise et al. [7] and Ortega-Ochoa et al. [8].

The proposals to simulate or replicate empathic behavior in artificial agents are called computational models of empathy, which are models that use computational methods. Yalçın and DiPaola [30] exposed different modeling choices in these computational

[1] This average should be interpreted with caution, given the heterogeneity of institutional characteristics within and across countries. For instance, this average includes face-to-face, online, and blended programs.

approaches, divided into theory-driven and data-driven approaches. Empathy research in psychology, neuroscience, and ethology suggests empathic behavior consists of distinct levels connected through evolutionary processes. These levels are built on top of each other without replacing the previous level, and each level represents a more complex and sophisticated form of empathic behavior. To arrive at a comprehensive computational model of empathy, we adopt the classification proposed by Yalçın and DiPaola [30], who united the theoretical approaches as a set of cognitive and behavioral capacities (components and levels of empathic behavior): emotional communication, emotion regulation, and cognitive mechanisms. Emotional communication competence refers to the ability to accurately perceive and express emotions, while emotion regulation refers to the ability to manage one's own emotions and respond appropriately to the emotions of others. Cognitive mechanisms refer to the mental processes involved in understanding and interpreting the emotions of others, such as perspective-taking and theory of mind.

To evaluate computational models of empathy, it is necessary to use evaluation metrics and questionnaires that are specifically designed and validated for empathic agent research [30]. These metrics and questionnaires should consider different components of empathy, such as emotional communication competence, emotion regulation, and cognitive mechanisms, and should be able to measure the effectiveness and accuracy of models in simulating empathic behavior. Moreover, it is necessary to use state-of-the-art research in affective computing and user modeling research to implement and evaluate the theoretical empathy models. Finally, the greater use of recent IoT innovations gathering affective information, such as skin conductivity, breathing, heartbeat, and electrical activity from the brain, could contribute to progress in the field.

1.2.3. Student processing of feedback: cognitive, affective, and behavioral

The feedback is considered as information that could incorporate all or several of the following components: students' current state, information about where they are, where they are headed and how to get there, and can be presented by different agents [31]. The information's purpose is to have a stronger effect on performance and learning if it encourages students to engage in active processing. According to the feedback model *Describing Students – Feedback Interaction* [32], when students receive the feedback message, they produce cognitive and affective responses that are often tightly interdependent. That is, the student's cognitive appraisal of a task's relevance and clarity of feedback influences their emotional reactions, leading to either adaptive or maladaptive behavioral responses that impact task performance and learning. Lipnevich and Smith [33] emphasize the three types of student processing: cognitive, affective, and behavioral.

The student processing types give a framework, including affective components regardless of whether the feedback type is empathic or not. It is relevant because the analysis of an empathic educational system should not be limited to analyzing only the level of the agent's empathic behavior. The student processing of feedback, which inherently includes the affective processing, and its report is also useful to have an entire photographic of the affective Human-Computer Interaction (e.g., see [34] and [35]). There are more components added to the source (agent's empathic behavior) and student processing of feedback, these are the context where the feedback occurs, the feedback message, the learner's characteristics, and outcomes [33]. We will focus on the student processing of feedback because this is one of the components that capture the interaction of the other components before assessing learning outcomes.

The types of empathic PCA feedback play a relevant role in achieving positive results, affecting variables identified as learning outcomes [34,36]. First, cognitive and empathic feedback are necessary to have positive learning performance [37]. Second, cognitive and affective feedback are useful to have positive student perceptions. Arguedas and Daradoumis [9] concluded that using specific cognitive and affective feedback types has a positive effect on the affective state. Jimenez et al. [10] found that affective dialog, based on encouragement phrases, positively impacts the motivation of students, particularly females. In this regard, gender will influence the results [38].

Evaluating cognitive and affective feedback is often done by asking students for their perceptions. The number of scientific experiments that report on effective cognitive and affective feedback strategies is quite limited. D'Mello et al. [39] present Autotutor, an Intelligent Tutoring System (ITS) that synthesizes affective feedback to respond to learners' cognitive and emotional states. In the Sensitive Artificial Listener project [40], users' verbal and non-verbal behaviors are collected to create emotionally colored interactions. It enabled the provision of distinct types of affective feedback, which can prompt users toward specific emotional states. Robison et al. [41] categorized virtual agents' affective feedback strategies into three types: parallel-empathic, reactive-empathic, and task-based. The parallel-empathic involves exhibiting an emotion like that of the target. The reactive-empathic focuses on the target's affective state and his/her situation. The task-based is supplementary to empathic strategies and involves changing the task sequence. Additionally, Mao and Li [42] developed an emotion-based user-aware e-learning system that aimed to provide various affective feedback types. This system's purpose was to motivate the participant, facilitate their learning process, and improve their mood.

Our research focuses on the distinction between student processing of cognitive and affective feedback. When students are working in the IT infrastructure for learning, they may have doubts related to the topic they are working on or the activity they are supposed to carry out. In such cases, the empathic chatbot is available to provide feedback. It uses textual messages to provide the necessary information, thereby helping them overcome their doubts. Table 4 (a) shows student processing of cognitive feedback types. If a student's questions are irrelevant to the topic or activity they are currently engaged in, or if they are impolite, inappropriate, or distracting in tone, the empathic chatbot will provide them with feedback to redirect their behavior and refocus their attention on the task at hand. Table 4 (b) provides student processing of affective feedback types.

1.2.4. Learning outcomes: learning performance and student perceptions

Ortega-Ochoa et al. [8] showed two variables to evaluate learning outcomes of empathic chatbot feedback: learning performance and student perceptions. Learning performance refers to content, procedures, or attitudes [34,36,37,43]. Tests are the preferred instrument for data collection. The test's content will depend on the domain and objective related to the empathic PCA. The quantitative approach is the only evaluation method applied. As for student perceptions, many dimensions (units of analysis) are considered. Some units of analysis are students' motivation and self-regulation [44], and metacognitive reasoning (self-reflection, conceptual change, and personal growth and understanding; [45]). The main instruments are questionnaires, surveys, and interviews. The indicators are quantitative, although there are also open questions.

Although the learning outcomes because of the empathic PCA feedback in computer competencies have been studied before, it is only focused on student perceptions [9,10], lacking the assessment of learning performance. In addition, studies are needed to validate the effectiveness of such cognitive and affective PCA capabilities and student processing of feedback. Because of the need for a solid framework to evaluate the set of competencies, this study is based on the contributions of Marcolin et al. [2], who conceptualize user competence in three factors: conceptualization of competence, measurement methods, and knowledge domains.

1.2.4.1. Motivation and self-regulation. Few studies have explored ways to support students' motivational beliefs through empathic PCAs. For instance, Kumar [36] utilized the Motivated Strategies for Learning Questionnaire (MSLQ; [46]) to evaluate students' motivational and emotional perceptions of group work during project-based activities. Our analysis focuses on students' motivational beliefs, which is an essential aspect of their academic performance. We specifically examine two factors: self-efficacy and intrinsic value. Self-efficacy relates to an individual's perceived competence and confidence in performing class work. Intrinsic value pertains to the inherent interest and perceived significance of coursework, as well as the preference for challenging oneself and achieving mastery goals. According to the Pintrich and De Groot [44] learning model, higher levels of self-efficacy and intrinsic value are associated with better self-regulation. Self-regulation is a significant aspect of self-regulated learning strategies, which includes metacognitive and effort management skills. However, research on the use and effectiveness of empathic PCAs for distributed programming is still new, and there have been no attempts to evaluate students' self-regulation when utilizing such tools.

This study was based on the initial MSLQ [44] to measure one portion of its potential. MSLQ is a widely used instrument to assess college students' motivation beliefs and self-regulated learning [47]. Its validity has been supported by the extensive literature on college student learning and teaching [48,49]. We adapted the MSLQ focusing on self-efficacy and intrinsic value, and self-regulation behavior. The original MSLQ questions were adapted for our study, considering their application to the programming field and our empathic PCA features, as shown in Table 4 (c).

1.2.4.2. Metacognitive reasoning. A considerable amount of research has investigated the role of pedagogical tutors and the metacognitive support they provide to students, however, there have been no attempts to evaluate students' self-regulation when utilizing empathic PCAs. Molenaar et al. [50] found that using a pedagogical agent to aid in metacognitive activities led to an improvement in students' metacognitive knowledge. Karaoğlan Yılmaz et al. [51] found that students who received metacognitive support from a pedagogical agent showed an improvement in their self-regulation skills. In addition, the pedagogical agent's metacognitive support also had a significant effect on students' self-reflection skills as a side effect of the study. Boaler [52] emphasized the crucial role of self-reflection in empowering learners by involving them in a metacognitive process of contemplating their knowledge. In this context, when students engage in self-reflection, they are thinking about what they have learned and how their initial ideas and knowledge have changed over time. Additionally, affective feedback can inform students of what they did well and help enhance their self-regulation [53]. In this regard, affective feedback provides students with metacognitive feedback, helping them understand their areas of improvement and the steps needed to enhance their work [45]. The metacognitive reasoning's self-reflection types to evaluate are described in Table 4 (e) section of students' self-reflection. They represent generic types of students' metacognitive reasoning based on Hattie and Timperley's [45] theoretical model of feedback. The following sections of Table 4 (e), present the students' conceptual change, and personal growth and understanding.

1.2.5. Integration of empathic artificial agents for developing computer competencies

A few studies have explored the application of an empathic PCA in subject-specific contexts related to computer competencies. For instance, a study in a high school educational setting introduced an Affective Pedagogical Tutor (APT) during a collaborative learning task focused on designing a real-world website [9]. The Empathic PCA was integrated into the didactic sequence and IT infrastructure for learning. In the first, APT complemented the learning and teaching process by being employed at the beginning of the lesson. In the second, empathic PCA utilized the knowledge base of the Moodle forum, requiring the pre-assembly of components. In another study, an ITS called Intelligent Tutor for Object-Oriented Programming (TIPOO, by its acronym in Spanish) provided support for object-oriented programming courses in higher education settings [10]. The ITS integrated an empathic PCA to deliver personalized assistance to students with a friendly demeanor. In this case, the agent's integration was more independent of the primary learning process. That is, it involved planned self-directed learning sessions but did not integrate TIPOO into the IT infrastructure for learning for the main learning activities.

1.2.6. Distributed system course overview and competencies

The Distributed Systems course is taught online. The learning methodology entails students engaging with course learning resources according to the syllabus and actively participating in practice assignments. The students connect to the virtual class from locations with different times and study schedules. One of the main methodological strategies for teaching and learning is learning by doing which fosters learning through problem-solving, critical thinking, and collaboration while enhancing communication and self-directed learning skills [54]. In addition, the course incorporates an online laboratory named Distributed Systems Laboratory (DSLab),[2] designed to assist students with their practice assignments [55]. Table 1 presents the competencies linked to practices, which are fundamental to accomplishing the course's objective [56].

The Practical Activities Competencies of the course encompass two core areas of expertise. Drawing on the insights of Anderson [57] and Kraiger et al. [58] concerning diverse learning outcomes, these competencies can be further categorized into Cognitive Outcomes (CO), Skill-Based Outcomes (SBO), and Affective Outcomes (AO). Table 1 indicates that the Practical Activities' Competencies primarily fall under the CO and SBO domains. The first refers to students' knowledge of various technologies and their usage, while the second relates to their ability to transition from verbal comprehension to practical application and automation [2].

1.3. Research questions, aim, and hypothesis

In this paper, we focus on student processing of empathic chatbot feedback and its impact on learning performance and student perceptions. The research questions (RQ) are:

- RQ1: Has cognitive and affective chatbot feedback significantly increased students' learning performance compared to human teacher feedback?
- RQ2: To what extent has cognitive and affective chatbot feedback enhanced students' motivation and self-regulation for learning compared to human teacher feedback?
- RQ3: Is there a significant relationship between cognitive and affective chatbot feedback types, and students' metacognitive reasoning?

The aim is to analyze the effectiveness of cognitive and affective chatbot feedback on learning performance, motivation, self-regulation, and metacognitive reasoning. The context is the practical assignments of the Distributed Systems course of an online higher education institution. The hypothesis is: "The use of an AI-enabled chatbot 24/7, which reinforces the work of the human tutor, facilitates the learning process of students who connect to the virtual class from locations with different times and study schedules. It also encourages students' motivation, self-regulation, and metacognitive reasoning during online learning."

The subsequent sections provide a detailed report of this research. Section 2 shows the method used, presenting the participants, sampling, empathic chatbot, data collection techniques and instruments, and data analysis techniques. Sections 3 and 4 provide the results and discussion, respectively. Section 5 presents the main contributions, limitations, and potential future research.

2. Method

This study followed a quasi-experiment design with post-test only and intact groups. Through one cluster sampling, the participants were selected. The experiment used an empathic chatbot, which was integrated into the Distributed System course' syllabus. In addition, the empathic chatbot was integrated into the DSLab IT infrastructure for learning, enabling it to exchange data within the AIoT network. The Experimental Group (EG) received empathic chatbot feedback, and the Control Group (CG) received human teacher feedback. After the experiment implementation, the instruments were applied. The instruments collected quantitative data on students' learning performance in each one of the Practical Assignment phases. In addition, the data source was the student processing of feedback and student perceptions. The teachers monitored the data collection. For data analysis, descriptive and inferential statistics techniques were used.

2.1. Participants' characteristics and sampling procedures

The participants were all the students enrolled in the Distributed Systems course in a recent academic term, who belong to the Computer Science Engineering and Telecommunication Engineering programs of an online higher education institution (N= 196). That is, the sample (n) was equal to the population. All the students signed an informed consent to participate. The one-stage cluster probability sampling was used to divide the entire population into clusters representative of the population. Considering that the classes were grouped according to the language of teaching, the clusters were one for Spanish and one for Catalan. Using Simple Random Sampling, the clusters were assigned to the groups. The cluster whose language of teaching was Spanish was assigned to EG (101 students) and the cluster whose language of teaching was Catalan was assigned to CG (95 students). Both groups had teachers who followed the same syllabus. Table 2 shows the sociodemographic characteristics; there is representation from almost all sectors in both groups.

[2] https://sd.uoc.edu/dslab/

Table 1
Breakdown of the practical activities' learning outcomes.

Practical activities' competencies	Learning outcomes	Breakdown
C2 Ability to analyze a distributed system	ALO 1 To know how to analyze the technical descriptions of a distributed algorithm and understand its operation	C2 ALO 1.1 To understand the operation of a distributed algorithm (CO) C2 ALO 1.2 Analyze the technical descriptions of a distributed algorithm (SBO)
C4 Ability to program a distributed system	ALO 1 To program a distributed algorithm and test it in a realistic environment. ALO 2 Understand the operation of distributed systems and understand the challenges of programming them	C4 ALO 1.1 To program a distributed algorithm in a realistic environment (SBO) C4 ALO 1.2 To test the distributed algorithm in a realistic environment (SBO) C4 ALO 2.1 To understand the operation of distributed systems (CO) C4 ALO 2.2 To understand the challenges of distributed systems programming (CO)

Note. C = Competence; ALO = Activity Learning Outcomes; CO = Cognitive Outcomes; SBO = Skill-Based Outcomes; AO = Affective Outcomes.

Table 2
Participants' sociodemographic characteristics.

Sociodemographic characteristics	Clusters		Total
	CG	EG	
Gender			
Male	78	89	167
Female	15	12	27
Others	2	–	2
Age			
21 or younger	–	1	1
22 to 30	30	27	57
31 to 40	36	36	72
41 to 50	22	34	56
51 or older	5	3	8
I prefer not to say	2	–	2
Program			
Computer Science Engineering	87	62	149
Telecommunication Engineering	8	39	47
Total	95	101	196

Note. EG = Experimental Group; CG = Control Group.

2.2. DSLab-Bot: empathic Pedagogical Conversational Agent

The empathic chatbot is called DSLab-Bot, which has a role similar to a teacher. The main pedagogical functions are (1) to give a welcome message, (2) to respond to questions, (3) to detect emotions, (4) to give feedback on the outcome of project execution in the distributed environment, and (5) to receive positive or negative student feedback on its response. These functions are described in depth in the following subsections. The interaction mode used in DSLab-Bot development was the text because it is the main interaction mode of a chatbot and allows the execution of the functions mentioned above. It was integrated into the syllabus and IT infrastructure for learning.

2.2.1. Pedagogical integration strategy

Creating a didactic sequence for educational intervention typically involves either developing from scratch or integrating a new tool into an existing syllabus, with the latter being the case here by incorporating a new tool into the Distributed Systems syllabus. The learning-by-doing methodological strategy paired with Chatbot-Mediated Learning (CML; [59]) formed a novel approach termed Chatbot-Mediated Learning by doing. This approach combined hands-on learning with interactive chatbot technology, aiming to enhance the educational experience holistically. The DSLab-Bot, accessible on Mattermost in DSLab, was a learning resource for this methodological learning strategy, utilized during assignments. Table 3 shows how the incorporation of DSLab-Bot was performed in the Practice Assignments Phases highlighting the feedback it provided during the interactions. This integration focused on practical learning outcomes aligned with the course timeline (see Table 1).

2.2.2. Architecture and system integration

The main components of the AIoT network are software solutions, with DSLab-Bot serving as the core. The physical hardware includes laptops, PCs, and other devices utilized by students to connect to the network. These hardware components are used to collect information and facilitate student interaction within the AIoT framework. Implementing DSLab-Bot required integration into the DSLab IT infrastructure for learning, which facilitates student learning in the course. The integration involved the open-source

Table 3
Incorporation of DSLab-Bot in the practice assignments phases.

Breakdown of the practical activities' learning outcomes	Practice assignment phases	DSLab-Bot's specific functions
Practice 1. A distributed algorithm in a realistic environment (1/2). Theoretical AND Practice. 4 weeks		
C2 ALO 1.1 C2 ALO 1.2	Phase 1: • Theoretical exercise of Time Stamped Anti-Entropy (TSAE) protocol.	• Answer questions related to the TSAE protocol considering the student's emotional state
C4 ALO 1.1 C4 ALO 1.2 C4 ALO 2.1 C4 ALO 2.2	• Implementation and testing of Log and TimestampVector data structures.	• Answer questions related to implementing the TSAE protocol into an application that stores cooking recipes in a set of replicated servers considering the student's emotional state. • Give information on the result of the execution of the project at DSLab.
Practice 2. A distributed algorithm in a realistic environment (2/2). Practice OR Theoretical. 10 weeks (about 2 and a half months)		
C4 ALO 1.1 C4 ALO 1.2	Option A. Implementation of phases 2 to 4: • Phase 2: Implementation of a reduced version of the application and SAE protocol: only add operation; no purge of log. • Phase 3: Extension of phase 2 to purge log with unsynchronized clocks.	• Answer questions related to implementing the TSAE protocol into an application that stores cooking recipes in a set of replicated servers considering the student's emotional state. • Answer questions related to adding a remove operation on the recipe's application considering the student's emotional state. • Give information on the two (phases 2 and 3) results of the execution of the Project at DSLab.
C4 ALO 1.2	• Phase 4: TSAE protocol evaluation and implementation of Remove recipe operation. ○ Phase 4.1. Extend application adding the remove recipe operation. ○ Phase 4.2. Evaluation of TSAE protocol.	• Answer questions related to evaluating how TSAE behaves under different conditions considering the student's emotional state. • Give information on the result of the execution of the Project at DSLab.
C2 ALO 1.1 C2 ALO 1.2 C4 ALO 2.1 C4 ALO 2.2	Option B. Theoretical exercise	• Answer questions related to the main concepts of the Blockchain system considering the student's emotional state.

Note. C = Competence; ALO = Activity Learning Outcomes.

collaborative tool Mattermost[3] and the university's Single Sign-On Authentication system. This integration enables DSLab notifications to be sent to students through Mattermost via private messages. Moreover, Mattermost's Representational State Transfer Application Programming Interface (REST API) was employed to automate the registration of teachers and students, organize them into classes, and introduce the bot engine via webhooks. Mattermost's Representational State Transfer Application Programming Interface (REST API) was employed to automate the registration of teachers and students, organize them into classes, and introduce the bot engine via webhooks.

The bot engine, BotEngine, is a Java-based application that integrates fully with Mattermost and other components. This engine intercepts messages and provides responses when a student interacts directly with DSLab-Bot or asks questions that can be answered by the empathic PCA. Simultaneously, a database was utilized to store the questions asked by students, chatbot's provided answers, feedback on the usefulness of the answers, and emotional evaluations of the students. The AI engine powering DSLab-Bot has been developed using the RASA tool.[4] Through BotEngine's REST API, queries are made to the RASA engine. RASA incorporates a TensorFlow-based core. A classifier approach was opted for to determine the most probable answer that RASA should provide. The training process, which was crucial for the chatbot's performance and often labor-intensive in AI tool development, involved collecting frequently asked questions posed by students to teachers over multiple semesters.

Regarding the infrastructure supporting DSLab-Bot, a dedicated server was employed for DSLab, Mattermost, BotEngine, and RASA. Additionally, a MySQL database stores information related to questions and answers. Fig. 1 depicts a diagram illustrating the architecture comprising all these components.

The emotional capabilities of DSLab-Bot were enabled by its integration with a fuzzy logic classifier, developed using Java programming language. This model is explained in depth and patented by Arguedas et al. [60] and Arguedas [61], respectively. In the following lines, we explain briefly how this fuzzy logic classifier worked and the empathy-based model of DSLab-Bot behavior. This classifier encompasses a neural network that adeptly tokenizes incoming sentences, assigning specific emotional significance weights to individual words. The assessment of these weights occurs across multiple dimensions, as a single word may hold varying emotional weight in different contexts. Consequently, the analysis culminates in a well-defined outcome, representing a matrix of concrete emotional states. This mechanism allows the DSLab-Bot to perceive emotional cues, facilitating a more nuanced and human-like interaction experience.

2.2.2.3. Empathy-based model of DSLab-Bot behavior. The model utilizes fuzzy logic for emotion detection and leverages affective

[3] https://mattermost.com/
[4] https://rasa.com/

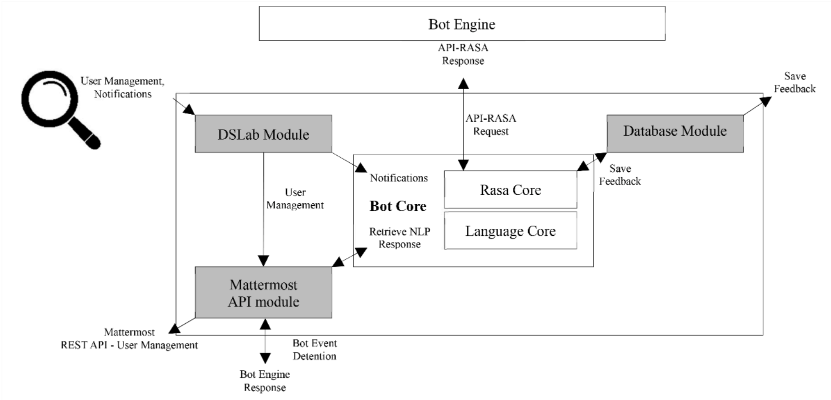

Fig. 1. Diagram of architecture used by DSLab-Bot.
Note. DSLab = Distributed Systems Laboratory; API = Application Programming Interface; REST API = Representational State Transfer Application Programming Interface; NLP = Natural Language Processing.

dictionaries to understand the emotional weight of words. The emotions identified are joy, confidence, fear, surprise, sadness, disgust, anger, and anticipation. In addition, the emotional states identified by the model are love, submission, flit (dismay), disapproval, remorse, contempt, aggressiveness, optimism, fault, curiosity, desperation, envy, cynicism, pride, fatalism, delight, sentimentalism, shame, outrage, pessimism, morbidity, domination, anxiety. These emotions and emotional states are based on Plutchik's [62] model. In addition, these are identified using a combination of dimensional (Pleasure, Arousal, Dominance; [63]) and categorical (emotions) approaches [62]. The fuzzy classifier is based on the centrality and dispersion measures calculated from the Affective Norms for English words [64] and the categorical affective load and valence (positive and negative) for each of the words obtained from the NRC Emotion Lexicon affective dictionary [65]. The system uses twenty-four rules derived from the emotional axes of Plutchik's [62] model to determine emotional states.

2.3. Data collection techniques and instruments

The test (practice assignments) and questionnaire were used as instruments. The practice assignments' objective was to determine the student's Learning Performance (LP) in the Practical Assignment phases in both EG and CG (see Table 3). DSLab automatically evaluated these practice assignment phases. Depending on the results of each student, these results were from 0 to 4. For example, 2 means that the students had a positive evaluation in phases 1 and 2 (see Table 4). The questionnaire's objective was to evaluate the student processing of feedback, Cognitive Feedback (CF) and Affective Feedback (AF), and units of analysis, Motivation (M), Self-regulation (SR), and Metacognitive Reasoning (MR). The questionnaire included 52 items divided into five sections (CF = 15 items; AF = 9 items; M= 7 items; SR = 6 items; MR = 15 items) adapted for each group, using a five-point Likert-type scale ranging from 1 (strongly disagree) to 5 (strongly agree), as well as the student may not respond to one or more items in both CG and EG (see Table 5).

The validity and reliability of the instruments were based on the criteria of the American Educational Research Association et al. [66]. The validity of practice assignments and questionnaire were the positive consequences obtained in their application in previous semesters and research, respectively [44,45,67]. The practice assignments' reliability consisted of standardization of administration and scoring using the DSLab automated assessment tool. The questionnaire's reliability was ensured by using Cronbach's alpha coefficient. The values obtained were higher than 0.70 in both groups, which reinforces reliability. The values were 0.930 and 0.973 in the CG and EG, respectively. In addition, the Skewness and Kurtosis were examined to check the multivariate normality of the data. The results showed that data were normally distributed as absolute values of Skewness and Kurtosis did not exceed the allowed maximum (2.0 for univariate Skewness and 7.0 for univariate Kurtosis) as shown in Table 6. Finally, the Kolmogorov-Smirnov (K-S) tests were also applied to test the normality of the different items in each group due to the size of the sample being higher than 25. The confidence level chosen for the tests was 95%. Table 6 shows the K-S tests.

Table 4
Scores for practice assignment phases.

Score	Phase 1	Phase 2	Phase 3	Phase 4
Succeed	1	Phase 1 + 1	Phase 2 + 1	Phase 3 + 1
Not succeed	0	0	0	0
Not executed	–	–	–	–

Table 5
Cognitive and affective feedback and units of analyzes.

(a) Cognitive feedback (CF)	
CF1	Make the course objectives clearer and more understandable
CF2	Provide students appropriate and complementary information to increase their ability to complete their work
CF3	Organize and present the contents in a more orderly manner
CF4	Build on students' existing knowledge based on their level and needs
CF5	Enrich the knowledge presented with novel elements
CF6	Provide more support to practical aspects
CF7	Support students to deal with the final evaluation successfully
CF8	Be subtle enough not to interfere and affect the duration of the course negatively
CF9	Guide students to better communicate their individual results in the group
CF10	Help students complete the activity successfully
CF11	Ensure the accomplishment of the learning objectives according to the criteria set by the course
CF12	Help students acquire skills and attitudes
CF13	Enable students to better face their difficulties
CF14	Offer students possibilities to make the best decision in cases of doubt
CF15	Trigger and maintain students' interest in the activity and their learning
(b) Affective feedback (AF)	
AF1	Encourage students' proposals and initiatives
AF2	Do not hinder students' creative process
AF3	Create an appropriate emotional climate for the development of the upcoming learning activities
AF4	Foster an environment that encourages creativity
AF5	Provide students confidence for carrying out the activity
AF6	Inform students about the purpose and the objectives of the activity
AF7	Bring students to real-world tasks and achieve that they express in a clear way the previous knowledge, perceptions, ideas, and representations (informal knowledge) they have about the concepts they are going to learn a clear way the previous knowledge, perceptions, ideas, and representations (informal knowledge) they have about the concepts they are going to learn
AF8	Motivate students to think that the lesson goals are achievable
AF9	Arouse students' interest in the topics/contents to be addressed
(c) Motivation (M)	
M1	I think I am a good student
M2	I am sure I can do an excellent job on the problems and tasks
M3	I think I will receive a good grade in this class because my study skills are excellent
M4	I know that I will be able to learn the material for this class
M5	I prefer class work that is challenging so I can learn new things
M6	I like what I am learning in this class because it is useful for me to know
M7	Understanding this subject is important to me because I think I will be able to use what I learn in this class in other classes
(d) Self-regulation (SR)	
SR1	I work on practice exercises and answer end of chapter questions even when I do not have to
SR2	Even when study materials are dull and uninteresting, I keep working until I finish
SR3	Before I begin studying, I think about the things I will need to do to learn
SR4	I often find that I have been reading for class but do not know what it is all about
SR5	When I am reading, I stop once in a while and go over what I have read
SR6	I work hard to get a good grade even when I do not like a class
(e) Metacognitive reasoning (MR)	
Self-reflection	
MRSR1	Make students reflect on the critical factors that influenced the realization of their learning activity
MRSR2	Make students think whether the type of feedback received during the learning activity was really helpful
MRSR3	Make students think about the information that would have been most appropriate to support their conceptual and personal change better
MRSR4	Make students meditate on alternative aspects that could have led them to take different decisions
Conceptual change (what students learned, i.e., what has changed with respect to their initial beliefs/knowledge)	
MRCC1	Make students think more critically about what they have learned in this course
MRCC2	Enable students to meditate that certain changes (in their knowledge and skills) evidently occurred with respect to what they initially thought or knew
MRCC3	Make students remember when these changes occurred
MRCC4	Make students think about what these changes are due to
MRCC5	Allow students to consider the aspects they are still confused about
MRCC6	Make students reflect on what they want to know more about
Personal Growth and Understanding (how students learned, i.e., what led them to change their initial beliefs)	
MRPGU1	Make students reflect on the actions they took to change their initial points of view
MRPGU2	Let students remember what difficulties they have encountered that made it harder for them to achieve the desired changes
MRPGU3	Enable students to meditate on how their perception was finally altered
MRPGU4	Enable students to think about how their comprehension changed
MRPGU5	Let students imagine how they are going to tackle their next work more efficiently

Note. CF = Cognitive Feedback; AF = Affective Feedback; M = Motivation; SR = Self-Regulation; MRSR = Self-Reflection of Metacognitive Reasoning; MRCC = Conceptual Change of Metacognitive Reasoning; MRPGU = Personal Growth and Understanding of Metacognitive Reasoning.

Table 6
Multivariate normality of data and the Kolmogorov–Smirnov test.

Variable/Item	CG Skewness	Kurtosis	Min-Max	p-value (*)	EG Skewness	Kurtosis	Min-Max	p-value (*)
Learning performance	0.46	−1.28	0–4	< 0.001	0.28	−1.35	0–4	< 0.001
Cognitive feedback (CF)								
CF1	−1.64	5.14	0–5	< 0.001	−1.033	0.885	0–5	< 0.001
CF2	−1.33	3.43	0–5	< 0.001	−0.908	0.464	0–5	< 0.001
CF3	−1.24	4.63	0–5	< 0.001	−1.309	1.186	0–5	< 0.001
CF4	−0.89	1.50	1–5	< 0.001	−0.821	0.256	0–5	< 0.001
CF5	−1.07	1.71	1–5	< 0.001	−0.846	−0.017	0–5	< 0.001
CF6	−0.16	−0.35	1–5	< 0.001	−1.090	0.910	0–5	< 0.001
CF7	−0.40	−0.54	1–5	< 0.001	−0.903	0.273	0–5	< 0.001
CF8	−0.97	0.73	1–5	< 0.001	−1.380	2.320	0–5	< 0.001
CF9	−0.56	0.32	1–5	< 0.001	−0.871	0.330	0–5	< 0.001
CF10	−1.04	1.77	0–5	< 0.001	−0.956	0.409	0–5	< 0.001
CF11	−1.08	2.62	0–5	< 0.001	−0.795	0.164	0–5	< 0.001
CF12	−0.77	0.81	0–5	< 0.001	−0.647	−0.238	0–5	< 0.001
CF13	−0.20	−0.80	2–5	< 0.001	−0.843	0.338	0–5	< 0.001
CF14	−0.60	0.52	1–5	< 0.001	−0.893	0.376	0–5	< 0.001
CF15	−0.64	−0.25	1–5	< 0.001	−0.948	0.456	0–5	< 0.001
Affective feedback (AF)								
AF1	−0.720	1.810	5–0	< 0.001	−0.750	0.752	0–5	< 0.001
AF2	0.978	0.728	4–1	< 0.001	−0.085	−0.484	0–5	< 0.001
AF3	−0.083	−0.682	3–2	< 0.001	−0.963	0.506	0–5	< 0.001
AF4	−0.529	1.120	5–0	< 0.001	−1.052	1.171	0–5	< 0.001
AF5	−0.532	0.023	4–1	< 0.001	−0.761	0.605	0–5	< 0.001
AF6	−0.674	0.023	3–2	< 0.001	−1.073	1.126	0–5	< 0.001
AF7	−0.362	0.052	4–1	< 0.001	−0.789	0.120	0–5	< 0.001
AF8	−0.722	0.568	4–1	< 0.001	−1.023	0.681	0–5	< 0.001
AF9	−0.452	−0.126	4–1	< 0.001	−0.809	0.459	0–5	< 0.001
Motivation (M)								
M1	−1.143	3.580	0–5	< 0.001	−0.317	−0.118	2–5	< 0.001
M2	.074	−0.955	3–5	< 0.001	−0.406	0.682	2–5	< 0.001
M3	−0.053	0.582	1–5	< 0.001	−0.749	2.054	0–5	< 0.001
M4	−1.578	3.978	0–5	< 0.001	−0.637	1.098	2–5	< 0.001
M5	−0.638	0.424	2–5	< 0.001	−1.011	1.810	1–5	< 0.001
M6	−1.082	1.497	1–5	< 0.001	−0.927	1.077	1–5	< 0.001
M7	−0.472	−0.451	1–5	< 0.001	−0.633	0.452	1–5	< 0.001
Self-regulation (SR)								
SR1	−0.189	−0.317	0–5	< 0.001	−0.124	−0.755	1–5	< 0.001
SR2	−1.101	1.283	1–5	< 0.001	−0.856	0.264	1–5	< 0.001
SR3	−0.652	−0.075	1–5	< 0.001	−1.040	1.713	1–5	< 0.001
SR4	0.169	−0.851	1–5	< 0.001	−0.158	−0.515	0–5	< 0.001
SR5	−0.887	0.854	1–5	< 0.001	−1.091	2.715	1–5	< 0.001
SR6	−0.948	1.044	1–5	< 0.001	−1.031	1.240	1–5	< 0.001
Metacognitive reasoning (MR)								
MRSR1	−0.362	−1.356	0–5	< 0.001	−0.676	−0.793	0–5	< 0.001
MRSR2	−0.455	−1.271	0–5	< 0.001	−0.662	−0.829	0–5	< 0.001
MRSR3	−0.777	−0.636	0–5	< 0.001	−0.764	−0.478	0–5	< 0.001
MRSR4	−0.863	−0.492	0–5	< 0.001	−0.681	−0.556	0–5	< 0.001
MRCC1	−0.305	−0.407	2–5	< 0.001	−0.880	0.828	0–5	< 0.001
MRCC2	−1.039	2.670	0–5	< 0.001	−1.047	0.699	0–5	< 0.001
MRCC3	−1.020	2.430	0–5	< 0.001	−1.011	1.250	0–5	< 0.001
MRCC4	−1.265	3.675	0–5	< 0.001	−1.041	1.279	0–5	< 0.001
MRCC5	−0.583	0.572	0–5	< 0.001	−0.760	0.393	0–5	< 0.001
MRCC6	−0.769	1.380	0–5	< 0.001	−1.209	1.506	0–5	< 0.001
MRPGU1	−0.866	2.230	0–5	< 0.001	−1.003	1.071	0–5	< 0.001
MRPGU2	−1.194	2.674	0–5	< 0.001	−1.053	0.840	0–5	< 0.001
MRPGU3	−1.153	2.205	0–5	< 0.001	−0.989	1.203	0–5	< 0.001
MRPGU4	−1.053	2.495	0–5	< 0.001	−1.051	1.367	0–5	< 0.001
MRPGU5	−0.422	0.233	1–5	< 0.001	−0.805	0.410	0–5	< 0.001

Note. CF = Cognitive Feedback; AF = Affective Feedback; M = Motivation; SR = Self-Regulation; MRSR = Self-Reflection of Metacognitive Reasoning; MRCC = Conceptual Change of Metacognitive Reasoning; MRPGU = Personal Growth and Understanding of Metacognitive Reasoning; * The Kolmogorov-Smirnov Test was used to verify the normality of the sample.

2.4. Data analysis techniques

Descriptive and inferential statistics were used to find relationships between the variables and units of the analysis. Because normality was not met in the K-S tests, the non-parametric Mann-Whitney U test was chosen to perform a comparison between the results of the two groups, specifically in LP, M, and SR. This value has been highlighted in orange when it is significant ($p < 0.05$) at a significant level of 5 %. Last, the analysis between the independent variables and the set of items of MR was executed by calculating Pearson's correlation coefficient to present an overall view of the relationship. In addition, a multivariate analysis, specifically factor analysis, was conducted to summarize the relationship and identify common factors among variables and unit of analysis.

3. Results

This section presents the analysis performed with the data collected in the quasi-experiment.

3.1. Descriptive statistic measures and the nonparametric Mann-Whitney U test

Tables 7 and 8 show the mean ($\bar{X}$), standard deviation (SD), median (Mdn), interquartile range (P75-P25), and p-value of the nonparametric contrast (its significance). Regarding the independent variables, there were significant differences between the two groups on almost all the items, except three. For CF, CF6 (U= 4155, $p = 0.08$) and CF8 (U= 4246.5, $p = 0.14$), and for AF, AF2 (U= 4233, $p = 0.13$).

Table 7
Descriptive statistic measures and the nonparametric Mann–Whitney U test of the independent variables.

Item	CG			EG			Mann–Whitney U	
	X̄ (SD)	Mdn (IR)	Min-Max	X̄ (SD)	Mdn (IR)	Min-Max	UMW	p-value
Cognitive Feedback (CF)								
CF1	4.04(0.87)	4(1)	0-5	3.23(1.22)	3(1)	0-5	2799	.00
CF2	3.77(0.96)	4(1)	0-5	3.02(1.29)	3(1)	0-5	3087.5	.00
CF3	4.04(0.82)	4(1)	0-5	3.27(1.27)	4(1)	0-5	3091.5	.00
CF4	4.01(0.8)	4(1)	1-5	3.05(1.32)	3(1.5)	0-5	2672.5	.00
CF5	4.01(0.88)	4(1)	1-5	3.2(1.4)	4(1)	0-5	3176.5	.00
CF6	3.76(0.89)	4(1)	1-5	3.36(1.26)	4(1)	0-5	4155	.09
CF7	3.8(0.98)	4(2)	1-5	3.17(1.31)	3(1)	0-5	3591.5	.00
CF8	4.12(0.9)	4(1)	1-5	3.86(1.15)	4(2)	0-5	4246.5	.14
CF9	3.91(0.85)	4(2)	1-5	3.25(1.28)	4(1)	0-5	3432.5	.00
CF10	3.89(0.99)	4(2)	0-5	3.15(1.25)	3(1)	0-5	3155.5	.00
CF11	3.87(0.9)	4(1)	0-5	3.04(1.24)	3(1.5)	0-5	2914.5	.00
CF12	3.83(1.01)	4(2)	0-5	3.03(1.34)	3(2)	0-5	3194	.00
CF13	3.82(0.88)	4(2)	2-5	3.08(1.24)	3(1)	0-5	3248.5	.00
CF14	3.86(0.84)	4(1)	1-5	3.13(1.28)	3(1)	0-5	3232.5	.00
CF15	3.75(1.07)	4(2)	1-5	3.21(1.27)	3(1)	0-5	3663.5	.00
Affective Feedback (AF)								
AF1	3.81(0.91)	4(1)	5-0	3(1.15)	3(1)	0-5	2857.5	.00
AF2	1.83(0.89)	2(1)	4-1	1.99(1.05)	2(2)	0-5	4233	.14
AF3	3.88(0.76)	4(1)	3-2	2.84(1.28)	3(1)	0-5	2440.5	.00
AF4	3.62(0.96)	4(1)	5-0	3.06(1.2)	3(1)	0-5	3634.5	.00
AF5	3.83(0.9)	4(1)	4-1	3.06(1.18)	3(1)	0-5	3012.5	.00
AF6	4.21(0.75)	4(1)	3-2	3.33(1.25)	4(1)	0-5	2738	.00
AF7	3.35(0.86)	3(1)	4-1	2.75(1.27)	3(2)	0-5	3543.5	.00
AF8	3.91(0.87)	4(2)	4-1	3.12(1.27)	3(1)	0-5	3025.5	.00
AF9	3.76(0.91)	4(1)	4-1	3.04(1.23)	3(1)	0-5	3205	.00

Note. CG = Control Group; EG = Experimental Group; SD = Standard Deviation; IR =

Note.CG = Control Group; EG = Experimental Group; SD = Standard Deviation; IR = Interquartile Range; UMW = Nonparametric Mann-Whitney U Test; CF = Cognitive Feedback; AF = Affective Feedback.

Table 8
Descriptive statistic measures and the nonparametric Mann–Whitney U test of the dependent variable and units analyzes.

Item	CG			EG			Mann–Whitney U	
	X̄ (SD)	Mdn (IR)	Min-Max	X̄ (SD)	Mdn (IR)	Min-Max	UMW	p-value
M1	3.78 (.83)	4 (1)	0-5	3.92 (.74)	4 (1)	2-5	4453.00	.34
M2	3.94 (.7)	4 (1)	3-5	3.97 (.65)	4 (0)	2-5	4653.00	.68
M3	3.23 (.85)	3 (1)	1-5	3.47 (.88)	3 (1)	0-5	3941.50	.02
M4	4 (.92)	4 (1)	0-5	4.04 (.68)	4 (0)	2-5	4715.00	.81
M5	4.03 (.76)	4 (1)	2-5	4.14 (.79)	4 (1)	1-5	4360.50	.23
M6	3.96 (.9)	4 (1)	1-5	4.06 (.85)	4 (1)	1-5	4531.50	.47
M7	3.8 (.98)	4 (2)	1-5	3.95 (.9)	4 (2)	1-5	4421.00	.32
Self-Regulation (SR)								
SR1	3.09 (1.13)	3 (2)	0-5	3.36 (1.06)	3 (1)	1-5	4188.00	.11
SR2	3.88 (.92)	4 (0)	1-5	3.9 (.95)	4 (1)	1-5	4716.50	.82
SR3	3.55 (1.03)	4 (1)	1-5	3.95 (.86)	4 (1)	1-5	3780.50	.01
SR4	2.87 (1.16)	3 (2)	1-5	3.01 (1.15)	3 (2)	0-5	4421.50	.33
SR5	3.84 (.86)	4 (0)	1-5	4.03 (.74)	4 (0)	1-5	4239.50	.11
SR6	4.07 (.86)	4 (1)	1-5	4.16 (.84)	4 (1)	1-5	4494.50	.41
Metacognitive Reasoning (MR)								
MRSR1	2.47 (3)	1.81 (4)	0-5	2.63 (1.57)	3 (3)	0-5	4660.00	.72
MRSR2	2.64 (3)	1.83 (4)	0-5	2.81 (1.66)	3 (2.5)	0-5	4614.00	.63
MRSR3	2.93 (3)	1.69 (1)	0-5	2.8 (1.54)	3 (1.5)	0-5	4404.50	.30
MRSR4	2.98 (3)	1.66 (1)	0-5	2.76 (1.55)	3 (2)	0-5	4202.50	.12
MRCC1	3.89 (4)	.81 (1)	2-5	2.95 (1.16)	3 (1)	0-5	2507.00	.00
MRCC2	3.82 (4)	.89 (1)	0-5	3.23 (1.31)	3 (1)	0-5	3590.00	.00
MRCC3	3.52 (4)	.98 (1)	0-5	3.07 (1.19)	3 (1)	0-5	3740.00	.00
MRCC4	3.69 (4)	.94 (1)	0-5	3.11 (1.16)	3 (1)	0-5	3362.50	.00
MRCC5	3.44 (4)	.99 (1)	0-5	2.98 (1.2)	3 (2)	0-5	3798.00	.01
MRCC6	3.7 (4)	.95 (1)	0-5	3.26 (1.19)	3 (1)	0-5	3860.00	.01
MRPGU1	3.72 (4)	.92 (1)	0-5	3.13 (1.22)	3 (1)	0-5	3462.00	.00
MRPGU2	3.73 (4)	.94 (1)	0-5	3.12 (1.27)	3 (1)	0-5	3420.00	.00
MRPGU3	3.51 (4)	1.09 (1)	0-5	2.98 (1.19)	3 (1)	0-5	3446.00	.00
MRPGU4	3.62 (4)	.92 (1)	0-5	2.98 (1.14)	3 (1)	0-5	3140.50	.00
MRPGU5	3.83 (4)	.85 (1)	1-5	3.08 (1.26)	3 (1)	0-5	3163.00	.00

Note. CG = Control Group; EG = Experimental Group; SD = Standard Deviation; IR =

Note. CG = Control Group; EG = Experimental Group; SD = Standard Deviation; IR = Interquartile Range; UMW = Nonparametric Mann-Whitney U Test; M = Motivation; SR = Self-Regulation; MRSR = Self-Reflection of Metacognitive Reasoning; MRCC = Conceptual Change of Metacognitive Reasoning; MRPGU = Personal Growth and Understanding of Metacognitive Reasoning.

In general, the overall results reject the hypothesis; however, there are several relationships of the variables and units of analysis that do align with the hypothesis. That is, the hypothesis is partially supported by the results.

3.2. Comparison of learning performance, motivation, and self-regulation (RQ1)

The Mann-Whitney U test was conducted to determine if there were differences in LP, M, and SR between students who received cognitive and affective chatbot feedback (EG) and those who received human teacher feedback (CG; see Table 8). For LR, the test revealed that the scores for the EG (Mdn = 2) were not significantly different from the CG (Mdn = 2), U= 4530, $p = 0.48$. For M, there were no significant differences between the two groups on most of the items: M1 (U= 4453.0, $p = 0.33$), M2 (U= 4653.0, $p = 0.68$), M4

(U= 4880.0, p = 0.81), M5 (U= 4360.5, p = 0.22), M6 (U= 4531.5, p = 0.46), and M7 (U= 4421.0, p = 0.31). However, a significant difference was found for M3 (U= 3941.5, p = 0.02). For SR, similar patterns were observed with no significant differences for most of the items: SR1 (U= 4188.0, p = 0.11), SR2 (U= 4716.5, p = 0.82), SR4 (U= 4421.5, p = 0.32), SR5 (U= 4239.5, p = 0.11), and SR6 (U= 4494.5, p = 0.41). Nevertheless, a significant difference was noted for SR3 (U= 3780.5, p = 0.00).

3.3. Relationship between cognitive and affective chatbot feedback, and metacognitive reasoning (RQ3)

This subsection presents the bivariate and multivariate analysis of the EG.

3.3.1. Bivariate analysis

Pearson's correlation coefficient analyses were conducted to examine the relationships between both cognitive and affective chatbot feedback, and students' MR. Due to the 360 combinations generated by all the items being a lot, some of them with weak, moderate, strong, or very strong relationships, we have highlighted in blue and green the items that have a strong and very strong correlation and statistical significance, respectively ($r \geq 0.60$, $p < 0.01$; see Tables 9 and 10). The white and yellow colors mean without and moderate ($0.25 \leq r < 0.60$) correlations, respectively. Ten relationships are in the top very strong correlation. There was a very strong, positive correlation between AF9 and MRPGU1, which was statistically significant (r= 0.788, $p < 0.01$); AF8 and MRPGU1 (r= 0.778, $p < 0.01$); AF9 and MRCC1 (r= 0.761, $p < 0.01$); AF9 and MRPGU5 (r= 0.757, $p < 0.01$); AF9 and MRPGU4 (r= 0.747, $p < 0.01$); CF1 and MRPGU4 (r= 0.741, $p < 0.01$); AF8 and MRPGU2 (r= 0.739, $p < 0.01$); AF8 and MRPGU4 (r= 0.735, $p < 0.01$); AF9 and MRPGU2 (r= 0.734, $p < 0.01$); AF4 and MRPGU1 (r= 0.733, $p < 0.01$). There was no strong or very strong, negative correlation with statistical significance ($r < -0.60$, $p < 0.01$).

3.3.2. Multivariate analysis

The multivariate analysis, specifically factor analysis, was conducted to explore the relationship between both CF and AF, and

Table 9
Pearson's correlation coefficients between cognitive chatbot feedback and metacognitive reasoning components.

Item	MRSR				MRCC						MRPGU				
	1	2	3	4	1	2	3	4	5	6	1	2	3	4	5
CF1	0.46**	0.49**	0.55**	0.55**	0.69**	0.58**	0.66**	0.66**	0.57**	0.58**	0.69**	0.72**	0.70**	0.74**	0.72**
CF2	0.38**	0.43**	0.46**	0.42**	0.60**	0.47**	0.52**	0.58**	0.40**	0.48**	0.53**	0.52**	0.52**	0.53**	0.55**
CF3	0.48**	0.45**	0.50**	0.47**	0.58**	0.44**	0.50**	0.49**	0.46**	0.49**	0.58**	0.58**	0.54**	0.60**	0.56**
CF4	0.43**	0.42**	0.51**	0.41**	0.59**	0.52**	0.60**	0.63**	0.40**	0.43**	0.63**	0.63**	0.61**	0.63**	0.67**
CF5	0.40**	0.45**	0.47**	0.44**	0.57**	0.44**	0.51**	0.51**	0.48**	0.45**	0.54**	0.52**	0.49**	0.51**	0.57**
CF6	0.36**	0.43**	0.49**	0.46**	0.61**	0.54**	0.60**	0.56**	0.51**	0.58**	0.66**	0.65**	0.63**	0.67**	0.68**
CF7	0.46**	0.50**	0.55**	0.50**	0.65**	0.53**	0.54**	0.55**	0.48**	0.54**	0.56**	0.56**	0.55**	0.63**	0.65**
CF8	0.18	0.22*	0.16	0.17	0.24*	0.27**	0.23*	0.21*	0.29**	0.27**	0.36**	0.29**	0.27**	0.28**	0.28**
CF9	0.39**	0.43**	0.49**	0.46**	0.67**	0.58**	0.55**	0.57**	0.46**	0.57**	0.65**	0.61**	0.58**	0.62**	0.61**
CF10	0.38**	0.43**	0.47**	0.46**	0.67**	0.59**	0.58**	0.62**	0.53**	0.55**	0.65**	0.65**	0.62**	0.65**	0.64**
CF11	0.43**	0.46**	0.50**	0.50**	0.68**	0.63**	0.64**	0.64**	0.50**	0.58**	0.72**	0.71**	0.69**	0.70**	0.69**
CF12	0.37**	0.40**	0.47**	0.41**	0.62**	0.57**	0.60**	0.62**	0.47**	0.47**	0.64**	0.61**	0.58**	0.58**	0.66**
CF13	0.42**	0.40**	0.48**	0.44**	0.64**	0.64**	0.64**	0.61**	0.44**	0.56**	0.70**	0.65**	0.64**	0.68**	0.69**
CF14	0.48**	0.45**	0.48**	0.49**	0.59**	0.54**	0.58**	0.50**	0.52**	0.54**	0.60**	0.62**	0.62**	0.63**	0.63**
CF15	0.45**	0.50**	0.53**	0.48**	0.67**	0.64**	0.64**	0.65**	0.54**	0.53**	0.69**	0.64**	0.64**	0.63**	0.68**

Note. CF = Cognitive Feedback; MRSR = Self-Reflection of Metacognitive Reasoning; MRCC = Conceptual Change of Metacognitive Reasoning; MRPGU = Personal Growth and Understanding of Metacognitive Reasoning; Green = very strong ($r \geq 0.70$); blue = strong ($0.60 \leq r < 0.70$); yellow = moderate ($25 \leq r < 0.60$); white = without correlations; * Correlation is significant at the 0.05 level (2-tailed); ** Correlation is significant at the 0.01 level (2-tailed).

Table 10
Pearson's correlation coefficients between affective chatbot feedback and metacognitive reasoning components.

Item	MRSR				MRCC						MRPGU				
	1	2	3	4	1	2	3	4	5	6	1	2	3	4	5
AF1	0.50**	0.54**	0.55**	0.49**	0.68**	0.60**	0.59**	0.60**	0.45**	0.49**	0.72**	0.63**	0.67**	0.68**	0.64**
AF2	0.22*	0.10	0.22*	0.17	0.13	0.01	0.08	0.10	0.35**	0.02	0.17	0.17	0.14	0.24*	0.20*
AF3	0.29**	0.37**	0.43**	0.41**	0.57**	0.46**	0.47**	0.57**	0.37**	0.30**	0.54**	0.44**	0.52**	0.54**	0.47**
AF4	0.42**	0.43**	0.45**	0.50**	0.65**	0.63**	0.57**	0.62**	0.49**	0.55**	0.73**	0.65**	0.65**	0.69**	0.64**
AF5	0.46**	0.45**	0.49**	0.42**	0.60**	0.54**	0.52**	0.55**	0.42**	0.51**	0.66**	0.61**	0.54**	0.63**	0.56**
AF6	0.43**	0.46**	0.50**	0.52**	0.62**	0.60**	0.64**	0.57**	0.60**	0.60**	0.72**	0.68**	0.65**	0.68**	0.64**
AF7	0.47**	0.45**	0.56**	0.47**	0.70**	0.55**	0.57**	0.54**	0.41**	0.52**	0.68**	0.66**	0.64**	0.69**	0.64**
AF8	0.50**	0.50**	0.54**	0.50**	0.71**	0.67**	0.65**	0.57**	0.53**	0.64**	0.77**	0.74**	0.71**	0.73**	0.72**
AF9	0.51**	0.56**	0.59**	0.53**	0.76**	0.66**	0.68**	0.61**	0.50**	0.61**	0.78**	0.73**	0.70**	0.74**	0.75**

Note. AF = Affective Feedback; MRSR = Self-Reflection of Metacognitive Reasoning; MRCC = Conceptual Change of Metacognitive Reasoning; MRPGU = Personal Growth and Understanding of Metacognitive Reasoning; Green = very strong ($r \geq 0.70$); blue = strong ($0.60 \leq r < 0.70$); yellow = moderate ($25 \leq r < 0.60$); white = without correlations; * Correlation is significant at the 0.05 level (2-tailed); ** Correlation is significant at the 0.01 level (2-tailed).

students' MR.

Between CF and MR, the internal consistency of the items was measured using Cronbach's alpha, with values higher than 0.9 suggesting an excellent measurement instrument. Cronbach's alpha yielded a value of 0.978 for the 30 items, indicating excellent internal consistency. The adequacy of the sample for factor analysis was assessed using the Kaiser–Meyer–Olkin (KMO) index, with values from 0.5 to 1 suggesting appropriateness. The KMO yielded a value of 0.939, indicating a suitable sample for Factor Analysis. Bartlett's test of sphericity tested the correlation matrix against the null hypothesis of no correlation. Bartlett's test of sphericity corroborated KMO findings, with a significant p-value (0.000), suggesting a correlation between CF and MR. Valid results are indicated by high test values and reliability below 0.05. Factors were extracted using the Principal Component Analysis method and the Varimax rotation method was applied. In this analysis, it was decided to keep three factors because the variability is high; the three factors explain 80.12 % of the data variability. Table 11 (a) shows the communalities of each item with three factors, that is, the variability of each item explained by common factors. Table 11 (b) shows the percentage of variability explained by each factor. Table 11 (c) shows the factorial multivariate analysis. For a better interpretation, only factor scores greater than 0.6 are displayed.

In the factor analysis for CF and MR, three factors emerged: Factor 1 comprised a range of CF items (CF9, CF10, CF7, CF11, CF2, CF5, CF15, CF13, CF12, CF3, CF4, CF14, CF1, and CF6), with the highest weights; Factor 2 included MR items related to MRCC and MRPGU (MRCC2, MRCC3, MRPGU1, MRPGU3, MRPGU2, MRPGU4, MRCC6, MRCC1, MRCC4, MRPGU5); Factor 3 highlighted CF items (CF9, CF10, CF7, and CF11) similar to Factor 1 but more focused.

Between AF and MR, the internal consistency of the items was measured using Cronbach's alpha. Cronbach's alpha yielded a value of 0.971 for the 24 items, indicating excellent internal consistency. The adequacy of the sample for factor analysis was assessed using the KMO index. The KMO yielded a value of 0.93 between AF and MR, indicating a suitable sample for Factor Analysis. Bartlett's test of sphericity corroborated KMO findings, with significant p-values (0.000), suggesting a correlation between the variable and unit of analysis. Factors were extracted using the Principal Component Analysis method and the Varimax rotation method was applied. In this analysis, it was decided to keep three factors because the variability is high; the three factors explain 79.93 % of the data variability. Table 12 (a) shows the communalities of each item with three factors, that is, the variability of each item explained by common factors. Table 12 (b) shows the percentage of variability explained by each factor. Table 12 (c) shows the factorial multivariate analysis. For a better interpretation, only factor scores greater than 0.6 are displayed.

Table 11
Communalities, variability and factorial multivariate analysis between cognitive chatbot feedback and metacognitive reasoning.

(a) Communalities			(b) Variability			(c) Factorial Multivariate Analysis			
Item	Initial	Extraction	Total	% of variance	% accumulated	Item	Factors		
							1	2	3
CF1	1	0.792	18.375	65.624	65.624	CF9	0.849		
CF2	1	0.751	2.614	9.335	74.959	CF10	0.835		
CF3	1	0.747	1.445	5.16	80.12	CF7	0.825		
CF4	1	0.76				CF11	0.816		
CF5	1	0.734				CF2	0.813		
CF6	1	0.706				CF5	0.8		
CF7	1	0.824				CF15	0.797		
CF9	1	0.856				CF13	0.796		
CF10	1	0.858				CF12	0.789		
CF11	1	0.884				CF3	0.785		
CF12	1	0.776				CF4	0.78		
CF13	1	0.842				CF14	0.738		
CF14	1	0.713				CF1	0.722		
CF15	1	0.832				CF6	0.707		
MRCC1	1	0.789				MRCC2		0.816	
MRCC2	1	0.796				MRCC3		0.781	
MRCC3	1	0.798				MRPGU1		0.779	
MRCC4	1	0.688				MRPGU3		0.771	
MRCC6	1	0.682				MRPGU2		0.751	
MRPG1	1	0.835				MRPGU4		0.743	
MRPG2	1	0.812				MRCC6		0.74	
MRPG3	1	0.835				MRCC1		0.709	
MRPG4	1	0.863				MRCC4		0.698	
MRPG5	1	0.788				MRPGU5		0.694	
MRSR1	1	0.809				CF9			0.869
MRSR2	1	0.914				CF10			0.836
MRSR3	1	0.903				CF7			0.833
MRSR4	1	0.846				CF11			0.812

Note. CF = Cognitive Feedback; MRCC = Conceptual Change of Metacognitive Reasoning; MRPGU = Personal Growth and Understanding of Metacognitive Reasoning.

Table 12
Communalities, variability and factorial multivariate analysis between affective chatbot feedback and metacognitive reasoning.

(a) Communalities			(b) Variability			(c) Factorial Multivariate Analysis			
Item	Initial	Extraction	Total	% of variance	% accumulated	Item	Factors		
							1	2	3
AF1	1	0.737	14.04	66.856	66.856	MRCC2	0.807		
AF4	1	0.692	1.67	7.953	74.809	MRCC3	0.803		
AF5	1	0.792	1.076	5.124	79.933	MRCC6	0.754		
AF6	1	0.778				MRCC4	0.749		
AF7	1	0.716				MRPGU3	0.698		
AF8	1	0.834				MRCC1	0.681		
AF9	1	0.78				MRPGU1	0.67		
MRCC1	1	0.798				MRPGU2	0.664		
MRCC2	1	0.814				MRPGU4	0.652		
MRCC3	1	0.829				MRPGU5	0.652		
MRCC4	1	0.717				AF5		0.835	
MRCC6	1	0.711				AF6		0.775	
MRPG1	1	0.849				AF8		0.773	
MRPG2	1	0.798				AF1		0.735	
MRPG3	1	0.816				AF7		0.734	
MRPG4	1	0.853				AF4		0.691	
MRPG5	1	0.775				AF9		0.685	
MRSR1	1	0.816				MRSR2			0.881
MRSR2	1	0.919				MRSR3			0.854
MRSR3	1	0.913				MRSR1			0.838
MRSR4	1	0.847				MRSR4			0.825

Note. AF = Affective Feedback; MRSR = Self-Reflection of Metacognitive Reasoning; MRCC = Conceptual Change of Metacognitive Reasoning; MRPGU = Personal Growth and Understanding of Metacognitive Reasoning.

For AF and MR, the analysis revealed: Factor 1 focused on MRCC and MRPGU (MRCC2, MRCC3, MRCC6, MRCC4, MRPGU3, MRCC1, MRPGU1, MRPGU2, MRPGU4, and MRPGU5) with high weights; Factor 2 encompassed AF items (AF5, AF6, AF8, AF1, AF7, AF4, and AF9); Factor 3 highlighted MRSR items (MRSR2, MRSR3, MRSR1, and MRSR4).

4. Discussion

This section discusses the results. Each subsection is addressed with a RQ, variables, and units of analysis mentioned in the hypothesis.

4.1. RQ1. Has both the cognitive and affective chatbot feedback significantly increased students' learning performance compared to human teacher feedback?

The findings suggest that the introduction of both cognitive and affective feedback via a chatbot does not significantly differ in terms of impacting student learning performance compared to traditional human teacher feedback. These results indicate that while the implementation of advanced feedback mechanisms through empathic chatbots is innovative, it may not necessarily enhance learning performance more than the results of human teacher feedback. Although studies in other domains have found significant differences in learning performance (e.g., [34,36,37,43]), in the domain of computer competencies development there is no clear enhancement in learning performance fostered by the empathic chatbot, at least with the way the student processed the feedback presented in Table 5.

4.2. RQ2. To what extent has both the cognitive and affective chatbot feedback enhanced students' motivation and self-regulation for learning in comparison to human teacher feedback?

The results indicate that the use of cognitive and affective chatbot feedback did not significantly enhance most aspects of students' motivation and self-regulation compared to traditional human teacher feedback. However, these students' processing of the cognitive and affective chatbot feedback obtained similar results as the human teacher feedback, and significant differences observed in the self-efficacy factor of motivation, "I think I will receive a good grade in this class because my study skills are excellent" (M3), and self-regulation factor, "before I begin studying, I think about the things I will need to do to learn" (SR3), suggest that specific aspects of motivation and self-regulation may be differentially impacted by the type of empathic feedback received. First, although the finding that including an empathic chatbot does not impact learner motivation is similar to that presented by Kumar [36], we discovered that aspects of self-efficacy can be positively affected using this agent. Second, these findings point to the potential nuanced effects of chatbot feedback on certain dimensions of student self-regulation, warranting further exploration to understand the implications of these differences.

4.3. RQ3. Is there a significant relationship between both the cognitive and affective chatbot feedback types, and students' metacognitive reasoning?

The findings suggest a significant relationship (top strong) between thirteen cognitive and seven affective chatbot feedback types, with conceptual change, and personal growth and understanding components. For cognitive chatbot feedback, "Make the course objectives clearer and more understandable" (CF1) is strongly related to "Enable students to think about how their comprehension changed" (MRPGU4). The other cognitive feedback types are 2–4, 6, 7, and 9–15, which are listed in Table 5. For affective chatbot feedback, "Arouse students' interest in the topics/contents to be addressed" (AF9) is strongly related to "Make students think more critically about what they have learned in this course" (MRCC1), "Make students reflect on the actions they took to change their initial points of view" (MRPGU1), "Let students imagine how they are going to tackle their next work more efficiently" (MRPGU5), "Enable students to think about how their comprehension changed" (MRPGU4), and "Let students remember what difficulties they have encountered that made it harder for them to achieve the desired changes" (MRPGU2). "Motivate students to think that the lesson goals are achievable" (AF8) is strongly related to "Make students reflect on the actions they took to change their initial points of view" (MRPGU1), "Let students remember what difficulties they have encountered that made it harder for them to achieve the desired changes" (MRPGU2), and "Enable students to think about how their comprehension changed" (MRPGU4). "Foster an environment that encourages creativity" (AF4) is strongly related to "Make students reflect on the actions they took to change their initial points of view" (MRPGU1). The other affective feedback types are 1, and 5–7, which are listed in Table 5.

The presence of distinct items of student processing of empathic chatbot feedback suggests that cognitive and affective chatbot feedback types uniquely contribute to metacognitive reasoning. The strong weighting of cognitive chatbot feedback types in Factors 1 and 3 in the CF analysis indicates a pronounced influence of these on metacognitive reasoning. This supports the hypothesis that cognitive chatbot feedback is crucial in fostering metacognitive processes related to Conceptual Change and Personal Growth and Understanding [52,53]. The emergence of affective feedback types in the AF analysis, particularly in Factor 2, underscores the importance of these on metacognitive reasoning. This aligns with the view that emotional and affective responses play a role in metacognitive processes, especially in aspects of Self-Reflection [51].

5. Conclusions

This section highlights the main findings, limitations, and discusses directions for future research.

5.1. Findings and limitations

The main contribution is the analysis of student processing of cognitive and affective chatbot feedback, which based on this quasi-experimental study within the AIoT framework, provides relevant insights into its impact on learning performance, motivation, self-regulation, and metacognitive reasoning. First, the empathic chatbot feedback has equivalent results to the human teacher feedback in learning performance, motivation, and self-regulation. Second, the empathic chatbot feedback types have significantly better results than the human teacher feedback in aspects of motivation and self-regulation; specifically, fostering students' positive thinking about the upcoming results due to their confidence in the competencies developed, and fostering the students' planning about what they need to do to learn, respectively. Second, thirteen cognitive (1–4, 6, 7, 9–15) and seven affective (1, 4–9) chatbot feedback types contribute greatly to students' metacognitive reasoning (see Table 5, sections a and b). In this regard, empathic chatbot feedback facilitates the student's learning process, orchestrating students' motivation and self-regulation at a level similar to that of the human teacher feedback; in addition, specific types of cognitive and affective chatbot feedback are crucial in fostering their metacognitive reasoning strongly. These findings mean that DSLab-Bot can assist in a specific teacher function, providing feedback, which is one component of teaching tasks, meaning that the empathic chatbot can achieve an efficient and productive symbiosis with the human teacher functions.

There are four main limitations in the study. First, the results presented were based on students' perceptions collected utilizing a questionnaire, as this instrument was not very intrusive compared to other tools like image or voice recognition. In this regard, the findings were based only on information that may not have captured the experiment's full effect. Second, the study tried to isolate the feedback source and types that were considered the only variables that were modified; however, in online teaching and learning, several variables influence the learning process that could have changed results in the participants (e.g., students external and/or internal factors, teacher performance, etc.). In addition, it is necessary to interpret the findings in terms of the features of DSLab-Bot, which was designed with a focus on textual feedback neglecting others (e.g., multimodal interaction). Third, the study only evaluated quantitatively the effectiveness of two scenarios, empathic chatbot and human teacher feedback; however, an evaluation of another scenario in which the agent's empathic capability was disabled and qualitative data collection from all scenarios would demonstrate additional insight into the impact of the empathy-based model of agent behavior. Last, bearing in mind that the aim was to evaluate an entire panoramic and first approximation on several variables and units of analysis, it is likely that some of them will require an individualized report.

5.2. Directions for future research

Two main lines of future research are derived from this study, regardless of the replication in other contexts and addressing limitations. First, a study on how to regulate the students' emotions based on real-time analysis of student processing of emphatic chatbot feedback is needed to reorientate or reduce emotions that do not support learning. Although these negative emotional states could add to the hypothetical positive results of other variables or units of analysis. For instance, how a feedback type that has a positive effect on learning performance can be redirected through students' emotion regulation to also foster the conceptual change of metacognitive reasoning? Second, further research is needed on the relationship between empathic feedback and learning performance, in our case the computer competence domains. That is, what empathic feedback types are more appropriate to foster the development of cognitive, skill-based, or affective outcomes?

CRediT authorship contribution statement

Elvis Ortega-Ochoa: Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **José Quiroga Pérez:** Writing – review & editing, Software, Resources, Investigation, Formal analysis, Data curation. **Marta Arguedas:** Writing – review & editing, Supervision, Formal analysis. **Thanasis Daradoumis:** Writing – review & editing, Supervision. **Joan Manuel Marquès Puig:** Supervision.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Elvis Ortega-Ochoa reports financial support was provided by Universitat Oberta de Catalunya. Elvis Ortega-Ochoa reports a relationship with Universitat Oberta de Catalunya that includes: funding grants.

Data availability

Data will be made available on request.

References

[1] Organisation for Economic Co-operation and Development, Education At a Glance 2022: OECD Indicators, OECD Publishing, 2022, https://doi.org/10.1787/3197152b-en.
[2] B.L. Marcolin, D.R. Compeau, M.C. Munro, S.L. Huff, Assessing user competence: conceptualization and measurement, Inform. Syst. Res. 11 (1) (2000) 37–60, https://doi.org/10.1287/isre.11.1.37.11782.
[3] K. Pelletier, M. McCormack, J. Reeves, J. Robert, N. Arbino, M. Al-Freih, C. Dickson-Deane, C. Guevara, L. Koster, M. Sánchez-Mendiola, L. Skallerup, J. Stine, EDUCAUSE Horizon Report, Teaching and Learning Edition, EDUCAUSE, 2022.
[4] W. Huang, K.F. Hew, L.K. Fryer, Chatbots for language learning—Are they really useful? A systematic review of chatbot-supported language learning, J. Comput. Assist. Learn. 38 (1) (2021) 237–257, https://doi.org/10.1111/jcal.12610.
[5] M.A. Kuhail, N. Alturki, S. Alramlawi, K. Alhejori, Interacting with educational chatbots: a systematic review, Educ. Inf. Technol. (Dordr) 28 (2022) 973–1018, https://doi.org/10.1007/s10639-022-11177-3.
[6] C.W. Okonkwo, A. Ade-Ibijola, Chatbots applications in education: a systematic review, Comput. Educ.: Artif. Intell. 2 (2021) 100033, https://doi.org/10.1016/j.caeai.2021.100033.
[7] G. Bilquise, S. Ibrahim, K. Shaalan, Emotionally intelligent chatbots: a systematic literature review, Hum. Behav. Emerg. Technol. (9601630) (2022) 1–23, https://doi.org/10.1155/2022/9601630.
[8] E. Ortega-Ochoa, M. Arguedas, T. Daradoumis, Empathic pedagogical conversational agents: a systematic literature review, Brit. J. Educ. Technol. 00 (2023) 1–24, https://doi.org/10.1111/bjet.13413.
[9] M. Arguedas, T. Daradoumis, Analysing the role of a pedagogical agent in psychological and cognitive preparatory activities, J. Comput. Assist. Learn. 37 (2021) 1167–1180, https://doi.org/10.1111/jcal.12556.
[10] S. Jimenez, R. Juárez-Ramírez, V.H. Castillo, A. Ramírez-Noriega, Integrating affective learning into intelligent tutoring systems, Univers. Access. Inf. Soc. 17 (2018) 679–692, https://doi.org/10.1007/s10209-017-0524-1.
[11] A.C. Graesser, H. Li, C. Forsyth, Learning by communicating in natural language with conversational agents, Curr. Dir. Psychol. Sci. 23 (5) (2014) 374–380, https://doi.org/10.1177/0963721414540680.
[12] D. Pérez-Marín, Review of the practical applications of pedagogic conversational agents to be used in school and university classrooms, Digital 2021 (1) (2021) 18–33, https://doi.org/10.3390/digital1010002.
[13] A.M. Mzahm, M.S. Ahmad, A.Y.C. Tang, Enhancing the Internet of Things (IoT) via the concept of agent of things (AoT), J. Netw. Innov. Comput. 2 (2014) (2014) 101–110. https://www.mirlabs.net/jnic/secured/Volume2-Issue1/Paper11/JNIC_Paper11.pdf.
[14] M. Wu, T.-J. Lu, F.-Y. Ling, J. Sun, H.-Y. Du, Research on the architecture of Internet of Things, in: D. Wen, R. Wang, Y. Yie (Eds.), ICACTE 2010 3rd International Conference on Advanced Computer Theory and Engineering, IEEE, 2010, pp. V5.484–V5.487, https://doi.org/10.1109/ICACTE.2010.5579493.
[15] M. Zouai, O. Kazar, G. Ortiz Bellot, B. Haba, N. Kabachi, M. Krishnamurhty, Ambiance intelligence approach using IoT and multi-agent system, Int. J. Distrib. Syst. Technolog. 10 (1) (2019) 37–55, https://doi.org/10.4018/IJDST.2019010104.
[16] S.-Y. Kuo, X.-R. Huang, L.-B. Chen, Smart ports: sustainable smart business port operation schemes based on the Artificial Intelligence of Things and blockchain technologies, IEEE Potent. 41 (6) (2022) 32–37, https://doi.org/10.1109/MPOT.2022.3198808.
[17] M. Rukhiran, N. Phaokla, P. Netinant, Adoption of environmental information chatbot services based on the internet of educational things in smart schools: structural equation modeling approach, Sustainability 14 (23) (2022) 1–32, https://doi.org/10.3390/su142315621.
[18] M.L. Hoffman, Empathy and Moral Development: Implications for Caring and Justice, Cambridge University Press, 2000, https://doi.org/10.1017/CBO9780511805851.
[19] F.B.M. de Waal, The 'Russian doll' model of empathy and imitation, in: S. Bråten (Ed.), On Being moved: From mirror Neurons to Empathy, John Benjamins Publishing Company, 2007, pp. 49–69, https://doi.org/10.1075/aicr.68.06waa.
[20] M.H. Davis, Measuring individual differences in empathy: evidence for a multidimensional approach, J. Pers. Soc. Psychol. 44 (1) (1983) 113–126, https://doi.org/10.1037/0022-3514.44.1.113.
[21] M.H. Davis, C. Luce, S.J. Kraus, The heritability of characteristics associated with dispositional empathy, J. Pers. 62 (3) (1994) 369–391, https://doi.org/10.1111/j.1467-6494.1994.tb00302.x.
[22] B.L. Omdahl, Cognitive Appraisal, Emotion, and Empathy, Psychology Press, 1995.
[23] K.R. Stueber, Rediscovering Empathy: Agency, Folk Psychology, and the Human Sciences, The MIT Press, 2006, https://doi.org/10.7551/mitpress/5833.001.0001.
[24] A.I. Goldman, Simulating Minds: The Philosophy, Psychology, and Neuroscience of Mindreading, Oxford University Press, 2006, https://doi.org/10.1093/0195138929.001.0001.
[25] A.I. Goldman, Two routes to empathy: insights from cognitive neuroscience, in: A. Coplan, P. Goldie (Eds.), Empathy: Philosophical and Psychological Perspectives, Oxford University Press, 2012, pp. 31–44, https://doi.org/10.1093/acprof:oso/9780199539956.003.0004.
[26] A. Coplan, P. Goldie, Empathy: Philosophical and Psychological Perspectives, Oxford University Press, 2011, https://doi.org/10.1093/acprof:oso/9780199539956.001.0001.
[27] F. de Vignemont, T. Singer, The empathic brain: how, when and why? Trends Cogn. Sci. (Regul. Ed.) 10 (10) (2006) 435–441, https://doi.org/10.1016/j.tics.2006.08.008.
[28] L. Hall, S. Woods, The importance of similarity in empathic interaction, in: C. Ghaoui (Ed.), Encyclopedia of Human Computer Interaction, Idea Group Reference, 2006, pp. 303–310, https://doi.org/10.4018/978-1-59140-562-7.
[29] J. Taverner, E. Vivancos, V. Botti, Towards a model of empathic pedagogical agent for educating children and teenagers on good practices in the use of social networks, in: A.P. Rocha, L. Steels, J. van den Herik (Eds.), *Proceedings of the 13th International Conference on Agents and Artificial Intelligence (ICAART 2021) - Volume 1* (pp. 439-445). 13th International Conference on Agents and Artificial Intelligence (ICAART 2021), SciTePress Digital Press, 2021, https://doi.org/10.5220/0010345504390445.
[30] Ö.N. Yalçın, S. DiPaola, Modeling empathy: building a link between affective and cognitive processes, Artif. Intell. Rev. 53 (2020) 2983–3006, https://doi.org/10.1007/s10462-019-09753-0.
[31] A.A. Lipnevich, E. Panadero, A review of feedback models and theories: descriptions, definitions, and conclusions, Front. Educ. (Lausanne) 6 (2021) 1–29, https://doi.org/10.3389/feduc.2021.720195.
[32] A.A. Lipnevich, D.A.G. Berg, J.K Smith, Toward a model of student response to feedback, in: G.T.L. Brown, L.R. Harris (Eds.), Handbook of Human and Social Conditions in Assessment, Routledge, 2016, pp. 169–185, https://doi.org/10.4324/9781315749136-12.
[33] A.A. Lipnevich, J.K Smith, Student - feedback interaction model: revised, Stud. Educ. Evaluat. 75 (2022) 1–11, https://doi.org/10.1016/j.stueduc.2022.101208.
[34] A. Oker, F. Pecune, C. Declercq, Virtual tutor and pupil interaction: a study of empathic feedback as extrinsic motivation for learning, Educ. Inf. Technol. (Dordr) 25 (2020) 3643–3658, https://doi.org/10.1007/s10639-020-10123-5.
[35] G. Błażejowska, Ł. Gruba, B. Indurkhya, A. Gunia, A study on the role of affective feedback in robot-assisted learning, Sensors 23 (3) (2023) 1–17, https://doi.org/10.3390/s23031181.
[36] J.A. Kumar, Educational chatbots for project-based learning: investigating learning outcomes for a team-based design course, Int. J. Educ. Technol. High. Educ. 18 (65) (2021) 1–28, https://doi.org/10.1186/s41239-021-00302-w.
[37] Z. Long, D. Luo, H. Gao, X. Hu, The effects of rejection sensitivity on confusion regulation during learning in multiagent intelligent tutoring system environments, Chairs, in: A.M. Sinatra, J.A. DeFalco (Eds.), *Approaches and Challenges in Team Tutoring Workshop* (pp. 77-86). 20th Artificial Intelligence in Education Conference (AIED 2019). CEUR Workshop Proceedings, 2019, https://ceur-ws.org/Vol-2501/paper9.pdf.
[38] M.R. Scholten, S.M. Kelders, J.E.W.C. Van Gemert-Pijnen, An empirical study of a pedagogical agent as an adjunct to an eHealth self-management intervention: what modalities does it need to successfully support and motivate users? Front. Psychol. 10 (2019) 1–14, https://doi.org/10.3389/fpsyg.2019.01063.

[39] S.K. D'Mello, B. Lehman, A Graesser, A motivationally supportive affect-sensitive AutoTutor, in: R. Calvo, S.K. D'Mello (Eds.), New Perspectives on Affect and Learning Technologies, Springer, 2011, pp. 113–126, https://doi.org/10.1007/978-1-4419-9625-1_9.
[40] E. Bevacqua, F. Eyben, D. Heylen, M. ter Maat, S. Pammi, C. Pelachaud, M. Schröder, B. Schuller, E. de Sevin, M. Wöllmer, Interacting with emotional virtual agents, in: A. Camurri, C. Costa (Eds.), Intelligent Technologies for Interactive Entertainment, Springer, 2012, pp. 243–245, https://doi.org/10.1007/978-3-642-30214-5_31.
[41] J. Robison, S. McQuiggan, J. Lester, Evaluating the consequences of affective feedback in intelligent tutoring systems, Chairs, in: J. Cohn, A. Nijholt, M. Pantic (Eds.), *Proceedings of the2009 3rd International Conference on Affective Computing and Intelligent Interaction and Workshops, ACII* (pp. 1-6). 2009 3rd International Conference on Affective Computing and Intelligent Interaction and Workshops, IEEE, 2009, https://doi.org/10.1109/ACII.2009.5349555.
[42] X. Mao, Z. Li, Implementing emotion-based user-aware E-learning, Chair, in: D.R. Olsen (Ed.), 2009, https://doi.org/10.1145/1520340.1520572.
[43] A. Munshi, R. Rajendran, J. Ocumpaugh, G. Biswas, R.S. Baker, L. Paquette, Modeling learners' cognitive and affective states to scaffold SRL in open-ended learning environments, Chairs, in: T. Mitrovic, J. Zhang (Eds.), *UMAP '18: Proceedings of the 26th Conference on User Modeling, Adaptation and Personalization* (pp. 131-138). UMAP '18: 26th Conference on User Modeling, Adaptation and Personalization, Association for Computing Machinery, 2018, https://doi.org/10.1145/3209219.3209241.
[44] P.R. Pintrich, E.V. De Groot, Motivational and self-regulated learning components of classroom academic performance, J. Educ. Psychol. 82 (1) (1990) 33–40, https://doi.org/10.1037/0022-0663.82.1.33.
[45] J. Hattie, H. Timperley, The power of feedback, Rev. Educ. Res. 77 (1) (2007) 81–112, https://doi.org/10.3102/003465430298487.
[46] P.R. Pintrich, A conceptual framework for assessing motivation and self-regulated learning in college students, Educ. Psychol. Rev. 16 (4) (2004) 385–407, https://doi.org/10.1007/s10648-004-0006-x.
[47] C.C. Chen, Self-regulated Learning Strategies and Achievement in an Introduction to Information Systems course, Information Technology, Learning, and Performance Journal 20 (1) (2002) 11–25. https://www.learntechlib.org/p/95111/.
[48] R.K Gable, Review of motivated strategies for learning questionnaire, in: J.C. Impara, B.S. Plake (Eds.), The Thirteenth Mental Measurements Yearbook, The University of Nebraska Press, 1998, pp. 681–682.
[49] R.T. Taylor, *Review of the Motivated Strategies For Learning Questionnaire (MSLQ) Using Reliability Generalization Techniques to Assess Scale Reliability* (Doctoral Dissertation), Auburn University, Alabama, 2012. http://hdl.handle.net/10415/3114.
[50] I. Molenaar, C.A.M. van Boxtel, P.J.C. Sleegers, Metacognitive scaffolding in an innovative learning arrangement, Instr. Sci. 39 (2011) 785–803, https://doi.org/10.1007/s11251-010-9154-1.
[51] F.G. Karaoğlan Yılmaz, Y.Z. Olpak, R. Yılmaz, The effect of the metacognitive support via pedagogical agent on self-regulation skills, J. Educ. Comput. Res. 56 (2) (2018) 159–180, https://doi.org/10.1177/0735633117707696.
[52] J. Boaler, Mathematical Mindsets: Unleashing Students' Potential through Creative Math, Inspiring Messages and Innovative Teaching, 2nd ed., Jossey-Bass/Wiley, 2016.
[53] A.S. Labuhn, B.J. Zimmerman, M. Hasselhorn, Enhancing students' self-regulation and mathematics performance: the influence of feedback and self-evaluative standards, Metacogn. Learn. 5 (2) (2010) 173–194, https://doi.org/10.1007/s11409-010-9056-2.
[54] J. Dewey, Experience and Education, Macmillan, 1938.
[55] J.M. Marquès Puig, T. Daradoumis, L. Calvet Liñan, M. Arguedas, Fruitful student interactions and perceived learning improvement in DSLab: a dynamic assessment tool for distributed programming, Brit. J. Educ. Technol. 51 (1) (2020) 53–70, https://doi.org/10.1111/bjet.12756.
[56] Grup Operatiu de Serveis per a l'Aprenentatge - Área de Tecnologia Educativa. (n.d.). *Plan Docente - Sistemas Distribuidos* [Unpublished Syllabus]. Universitat Oberta de Catalunya.
[57] J.R. Anderson, Cognitive Psychology and Its Implications, 9th ed., Worth Publishers, 2020.
[58] K. Kraiger, J.K. Ford, E. Salas, Application of cognitive, skill-based, and affective theories of learning outcomes to new methods of training evaluation, J. Appl. Psychol. 78 (2) (1993) 311–328, https://doi.org/10.1037/0021-9010.78.2.311.
[59] M. Alavi, D.E. Leidner, Research commentary: technology-mediated learning-a call for greater depth and breadth of research, Inform. Syst. Res. 12 (1) (2001) 1–10, https://doi.org/10.1287/isre.12.1.1.9720.
[60] M. Arguedas, F. Xhafa, L. Casillas, T. Daradoumis, A. Peña, S. Caballé, A model for providing emotion awareness and feedback using fuzzy logic in online learning, Soft. Comput. 22 (2018) 963–977, https://doi.org/10.1007/s00500-016-2399-0.
[61] Arguedas, M. (2016). FUZZYEMOSYS (U.S. Patent No. TXu 1-997-006). U.S. ISERN Patentes y Marcas.
[62] R. Plutchik, The nature of emotions, Am. Sci. 89 (4) (2001) 344–350, https://doi.org/10.1511/2001.28.344.
[63] A. Mehrabian, E O'Reilly, Analysis of personality measures in terms of basic dimensions of temperament, J. Pers. Soc. Psychol. 38 (3) (1980) 492–503, https://doi.org/10.1037/0022-3514.38.3.492.
[64] M.M. Bradley, P.J. Lang, Affective Norms for English words (ANEW): Instruction Manual and Affective Ratings, Technical Report C-1, The Center for Research in Psychophysiology, University of Florida, 1999.
[65] S.M. Mohammad, P.D. Turney, NRC Emotion Lexicon, National Research Council of Canada, 2013, https://doi.org/10.4224/21270984.
[66] American Educational Research Association, American Psychological Association, National Council on Measurement in Education, The Standards for Educational and Psychological Testing, American Educational Research Association, 2014.
[67] T. Daradoumis, J.M. Marquès Puig, M. Arguedas, L. Calvet Liñan, Enhancing students' beliefs regarding programming self-efficacy and intrinsic value of an online distributed Programming Environment, J. Comput. High. Educ. 34 (2022) 577–607, https://doi.org/10.1007/s12528-022-09310-9.