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Investigating the role Augmented Virtuality has in assessing collaboration in educational environments

A. A. Ali^{a,b}, J. C. Augusto^{a,b} and G. Dafoulas^b

^aResearch Group on Development of Intelligent Environments, Smart Spaces Lab, London, UK; ^bDepartment of Computer Science, Middlesex University, London, UK

ABSTRACT

This paper presents research on the role of Augmented Virtuality (AV) within collaborative educational environments. While AV remains a rather underexplored dimension in the Virtuality-Reality Continuum, this study lays the groundwork for its pedagogical integration, investigating how real-world data can enhance collaborative learning and offer valuable insights into students' collaborative interactions. The paper provides a background on current approaches to collaborative learning, particularly assessing collaboration to understand interactions, indicators and behaviours that indicate a possible degree of collaboration between students. The paper describes the iterative experimental studies conducted, aimed at assessing learners' states during learning activities, which played a key role in refining the initial requirements for the proposed framework, design and development of the system. The key results from the validation experiments with students and consultation with teaching practitioners are presented. The results from validation experiments showed a positive correlation between students' perceived collaboration levels and those calculated by the algorithm developed, indicating the potential for the framework proposed to promote student self-awareness and potentially more enhanced collaborative interactions. The scope of this study is to contribute as an intersection of AV technologies and education, providing a foundation for educational practitioners to create collaborative environments enriched by AV technologies.

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Introduction

The importance of collaboration and teamwork has been recognised as key skills in academic and professional achievements, which can be determined by several factors. To begin with, these skills are actively pursued by employers and organisations. According to a study conducted by Gray (2022), regarding the attributes employers seek in candidates' resumes, over 60% of participating employers regarded the capacity to solve problems and work effectively within teams as highly significant. This is also echoed in the Symonds (2022) report. Collaborative learning is described by

CONTACT A. A. Ali  a.a.ali@mdx.ac.uk  Research Group on Development of Intelligent Environments, Smart Spaces Lab, Middlesex University, The Burroughs, London NW4 4BT, UK

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(Smith and MacGregor (1992, p. 11) as “an umbrella term for a variety of educational approaches involving joint intellectual effort by students, or students and teachers together.” Moreover, collaborative learning provides an opportunity for developing communication skills, opinions, peer teaching and creativity, as explained by Osipov and Ziyatdinova (2015). Despite these advantages and emphasis on collaboration in both organisational and educational environments, the methods currently used for evaluating teamwork and assessing collaboration in educational settings may have shortcomings in appraising the domain-specific skills of diverse student populations and the proficiencies related to collaborative learning. As a result, these approaches could be viewed as falling short of providing real-time assistance and support for collaboration (Meijer et al., 2020).

Technology has been adopted to facilitate and enhance collaborative learning, particularly through Internet-based applications (Pun, 2012). These tools allow teams separated by geographical distances to communicate and interact with a shared objective, as Al-Rahmi et al. (2015) demonstrated. Immersive technologies situated along the Virtuality-Reality continuum defined by Milgram and Kishino (1994) have also been integrated into collaborative learning environments. Such environments have paved the way for more immersive interactions and learning experiences. Numerous institutions of higher education have embraced Virtual Learning Environments (VLEs), particularly for fostering collaborative education (Ali et al., 2019; Hamilton et al., 2021), demonstrating the potential of the technology to facilitate collaborative learning tasks.

Nonetheless, current frameworks available to educators have limitations in effectively incorporating these technologies within physically co-located collaborative educational environments.

Assessing collaboration

As a pedagogy, collaborative learning encompasses a range of activities in which students work together. Such activities include consensus building, which can take various forms such as group discussions, pair work and project-based learning. This study adopts collaborative learning in its broadest sense, which covers all learning scenarios involving group work where students cooperate to accomplish learning goals, as defined by Suthers and Seel (2012).

Computer-Supported Collaborative Learning (CSCL) is a pedagogical approach that specifically centres on how people learn collaboratively with the support of Information and Communications Technologies (ICT), as stated by Stahl et al. (2006).

In the context of collaborative learning, assessment is a challenging process that demands thorough consideration of both individual learners’ and groups’ achievements. Challenges are associated with a common assessment method where students collectively receive the same grades, scores, or feedback in group evaluation (Meijer et al., 2020). This approach may lead to construct validity issues, blurring the distinction between an individual students’ work and the group’s collective effort. This becomes particularly problematic when assessing student’s domain-specific abilities. Furthermore, such an approach limits the ability to address individual accountability, where empirical studies question the validity of group assessments. Bacon et al. (1998) found that the

collective average ability of individuals within a group is the most used predictor of a group's grade or score.

In recent years, there has been a noticeable shift in the focus of collaborative learning research, as reviewed by Yang (2023). This shift involves transitioning from electronic learning (e-learning) and web-based platforms to environments that integrate technologies spanning the Virtuality-Reality continuum as defined Milgram and Kishino (1994). The Virtuality-Reality continuum is a conceptual framework describing and classifying the range of experiences that blend the real and virtual worlds.

We have undertaken a literature mapping study exploring Mixed Reality (MR) environments that support collaborative education. Our research revealed that Augmented Virtuality (AV) remained an area with limited research within collaborative educational settings, particularly regarding assessment tasks, as discussed in Ali et al. (2019).

According to the Virtuality-Reality continuum by Milgram and Kishino (1994) presented in Figure 1, Augmented Reality (AR) and Augmented Virtuality (AV) are situated within the middle range of the spectrum, between the two extremes of a completely real environment and an entirely Virtual Reality (VR) environment¹.

AR primarily enhances the physical world with virtual elements, whereas AV starts from a virtual environment and integrates real-world data to enrich the experience. Although neither AR nor AV is entirely real or entirely virtual, AR incorporates more elements of the real world, while AV is more dominated by virtual content. This makes AV particularly valuable for collaborative learning scenarios, where virtual environments can be dynamically informed by real-world interactions and data, providing real-time, personalised¹ feedback based on student interactions.

Furthermore, this potential is illustrated in Vellingiri et al. (2023), where an educational tour utilising AV to instruct students in tree identification was created. In this study, an AV-guided tour enabled students to recognise trees. To achieve this, AV environments require at least one sensor to gather data from the environment, such as natural gestures, body language and movement tracking. This data is used to generate a real representation of the real world within the virtual setting. Sensors, in a broader sense, can capture a wide range of data useful within an educational context. For instance, eye-tracking sensors can observe the gaze patterns and attention spans of learners, thereby allowing educators to gain insights into their focus and level of engagement during the learning process, as explained by Wang et al. (2021). Furthermore, biometrics sensors can measure

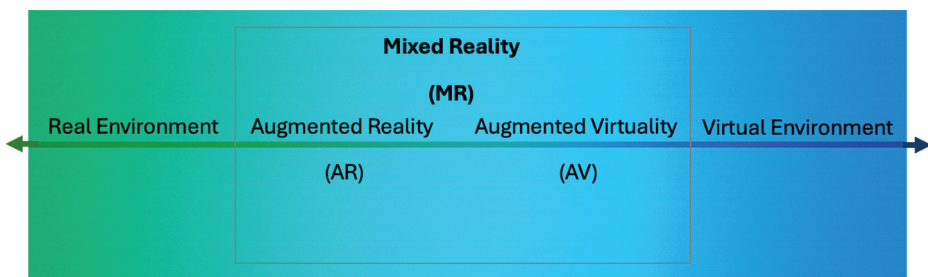


Figure 1. Virtuality-Reality continuum (recreated based on the original concept) inspired by Milgram and Kishino (1994).

heart rate and skin conductance, which can provide insight into learners' stress levels and emotional states, as explored by Francisti et al. (2020). AV has the potential to serve as a pedagogical tool by bringing real-world data obtained from sensors into virtual learning spaces to support CSEL goals such as shared understanding and reflective learning (Stahl et al., 2006). However, the selection of sensors and data collection approaches plays a crucial role in determining the use of the information gathered and its potential application in AV collaborative educational environments.

In the following sections, we examine measurable interactions, indicators, and behaviours associated with collaborative learning. Investigating these aspects will facilitate the creation of a framework that effectively leverages essential components of AV technology to develop an approach aligned with learner behaviours. This process aids in determining the most suitable data collection strategies.

Measurable interactions, indicators and behaviours of collaboration

First, collaborative interactions are described as synchronous, involving individuals working side-by-side. In this context, communication is expected to occur synchronously, with one or more participants listening or anticipating communication from other participants and promptly processing the received communication and reciprocating the process (Dillenbourg, 1999; Stahl et al., 2006). Measurable communication cues within collaborative educational environments, as identified by researchers, include metrics such as speech rates which can serve as an indicator of student participation.

Negrón and Jiménez (2008) found that analysing speech frequency and duration is useful for understanding group communication dynamics, where silent periods may indicate that students are developing ideas that are not ready for group sharing. Furthermore, Sondhi et al. (2015) suggest that voice characteristics, such as elevated pitch, can indicate potential moments of heightened stress. It is also essential not to discard the significance of the role of non-verbal communication, notably in face-to-face interactions. Gaze patterns offer insight into participants' focal points, revealing attention and conversation direction. Observing head movements and body postures indicate group communication involvement, but their interpretations vary due to contextual dependencies, introducing potential ambiguities.

Moreover, certain universal head movements can be analysed, such as "nodding to convey agreement or comprehension" or "side-to-side movement to indicate disagreement or incomprehension" (Negrón & Jiménez, 2008).

Second, collaborative interactions are described as symmetric, where participants work together towards a common goal. Achieving this requires students to establish a shared understanding (Dillenbourg, 1999). One common objective in assessing collaboration is to implement a task where the level of interaction with and manipulation of the artefact, materials, or the task itself serves as a measurable indicator of collaboration. Furthermore, the depth of dialogue or communication can provide insight into the strategy used to collaborate, as well as non-verbal cues like gaze, deictic gesture and proxemics. For instance, during a task, individuals often direct their gaze towards those involved, as observed by Lin (2015).

Finally, a collaborative process is also described from the perspective of cognitive load, encompassing the division between task-level and strategy-level tasks. This entails

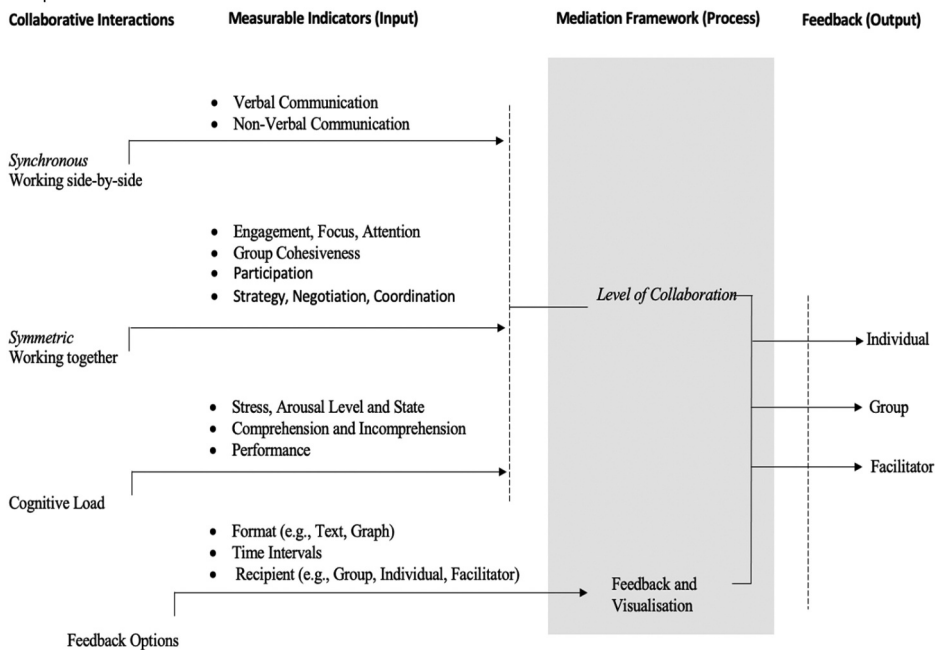


Figure 2. Proposed mediation framework.

interactions where negotiations and group self-explanation occur (Celepkolu & Boyer, 2018). The tasks require organisation and coordination among the group members for such interaction to occur. As stated by Kirschner et al. (2018), several other factors can also influence this dynamic, including the members' familiarity with the task, collaboration skills and familiarity with team members. Conventional cognitive load measurement involves questionnaires, examining roles and self-reported cues on material processing (Kirschner et al., 2018). Performance metrics like scores, reaction times, completion, and subjective evaluations are alternative methods. More direct indicators include physiological metrics such as heart rate, pupil dilatation, blink rate, electrodermal responses (e.g., Galvanic Skin Response [GSR]), and neuroimaging techniques (Dillenbourg & Betrancourt, 2006; Shi et al., 2007).

This paper presents a mediation framework (Figure 2) that underpins collaborative learning theories. It draws upon the definitions and characteristics of collaborative learning as described by Dillenbourg (1999) and CSCL as elaborated by Stahl et al. (2006). It is important to note that the proposed approach is not dependent on specific technologies or tools. Instead, it defines indicators of collaborative learning that suggest a level of collaboration, focusing on behaviours, interactions, and indicators of collaboration. It is informed by physiological research on behaviour and pedagogy that implies a degree of collaboration, drawing on insights from existing literature. The framework accommodates a wide range of sensors and data collection methods, which may be used as data input in AV applications for collaborative environments. Additionally, it aims to empower educational practitioners by offering the flexibility to target specific aspects of collaborative learning for feedback, mediation, support, and assessment purposes, thus possibly enhancing the impact in educational settings.

Materials and methods

The goal of this article is to gain a deeper understanding of how collaborative interactions can be identified within real-world environments. Specifically, the study explores the following Research Questions (RQs):

RQ 1 What are suitable measurable indicators to assess the level of collaboration in educational environments?

RQ 2 What data sources could be used to effectively assess collaboration in educational environments?

RQ 3 How does the students' perceived level of collaboration compare with the system-calculated level of collaboration?

RQ 4 What do educators perceive as valuable data interpretation for fostering collaborative learning environments?

Exploratory studies

In the first phase, research focused on exploring measurable indicators to assess the level of collaboration in educational environments (RQ1), specifically using sensor-generated data to evaluate teamwork and individual contributions among students, as presented in Dafoulas et al. (2018). Third-year Information Technology (IT) course students engaged in group projects were invited in the study. The studies were carried out over three iterations, following an iterative, user-centred methodology inspired by the approach described by Augusto (2014). Each iteration involved 40-to-50 students, where the participants were organised into groups of two to six individuals. The groups collaborated on various group scenarios, including consensus meetings, scrum also referred to as stand-up meetings, and group presentations.²

In each scenario, the data collection utilised various sensors (microphones for audio, Microsoft Kinect for facial images, and GSR sensors) Video recordings allowed post-experiment analysis, providing insights into students' behaviour and potential physiological states. Although the reliability of this information may be debated, when combined with learning performance data and temporal markers like activity completion time, it provided interesting insights into learners' interactions and behaviours during learning activities. This also enhanced understanding of the data sources, which could be used to effectively assess collaboration (RQ2).

An extension of this research investigated the use of additional physiological sensors, such as heart rate and voice fluctuation patterns (Dafoulas et al., 2018). Our exploratory research in this phase enabled researchers to gain insight into students' perceptions and experiences, shedding light on potential challenges associated with data collection in face-to-face collaborative learning settings. This understanding was the foundation for designing and developing a well-informed framework that aligns with students' preferences and requirements.

System architecture

The prototype system developed is based on the proposed framework, which comprises of three core algorithms that operate together. Figure 3 presents a system

3. Management Algorithm

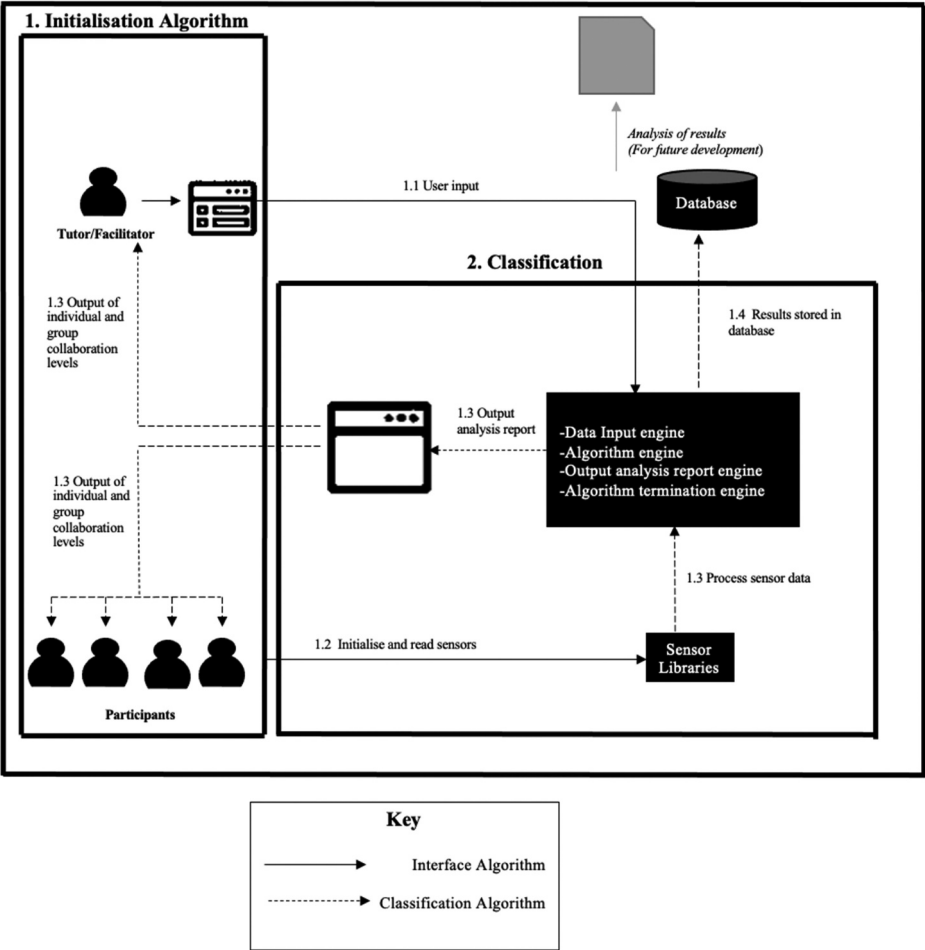


Figure 3. System architecture.

architecture diagram illustrating the data flow among the algorithms developed. Subsequently, the implementation of these algorithms in the prototype system is discussed.

Algorithm

Management Algorithm: This algorithm coordinates and integrates the overall data flow between the two main algorithms and serves as a control flow, invoking the Initialisation Algorithm to set up the system and gather initial data. It then passes the relevant data to the classification algorithm for computation and receives the output. Finally, it generates feedback based on the results and repeats the process until termination conditions are met. A detailed breakdown of these two algorithms can be accessed at <https://figshare.com/s/76906a407494fe1b78cc>. Furthermore, the Management Algorithm has potential

for future expansion, allowing for the incorporation of advanced data analysis capabilities and notifications.

The Management Algorithm contains the Initialisation and Classification algorithms.

ALGORITHM 1: Management Algorithm

Input:

Measurable collaborative indicators I, Collaborative interactions of interest L

Feedback recipient F, Feedback interval time FI

Activity duration AD, Number of participants AN

Process:

1. Call Initialisation Algorithm:

a. Input: I, L, AN

b. Output: Results of the Initialisation algorithm

2. Check the Initialisation algorithm termination condition

a. If the Initialisation algorithm is terminated, stop further processing.

3. Retrieve data for Classification Algorithm:

a. Input: Sensor data, Sensed Behaviors S, Dimensions D, Participant IDs (PID)

b. Output: Data for Classification Algorithm (S, D, PID)

4. Call Classification Algorithm:

a. Input: S, D, PID

b. Output: Computer measurable indicators II and collaborative interactions LI

5. Check Classification Termination Conditions:

a. If the Classification Algorithm is terminated, stop further processing.

6. Generate Feedback:

a. Input: II, LI, F, FI, AD

b. Output: Visual representation, report for F, and database storage.

7. Repeat or Terminate

a. If termination conditions are met (e.g., end of the activity) stop the process

b. If not, repeat from step 3.

Output:

Visual representation of computer measurable indicators II and collaborative interaction LI

Repeat generation for feedback recipient F at regular intervals.

Results are stored in the database for further analysis.

Initialisation Algorithm: This algorithm processes inputs from sensors using relevant libraries. It defines how these inputs should be interpreted and determines their contribution to the overall objective. Data sent and received in this algorithm is presented with a solid arrow in the diagram.

Classification Algorithm: This algorithm generates information for the tutor/facilitator by processing data from the activity inputted by the tutor/facilitator, combined with the output information from the Initialisation Algorithm (levels of group and individual collaboration). The primary objective of this algorithm is to identify instances where mediation by the tutor/facilitator is required to enhance group collaboration or to alert students about their collaboration levels. Data sent and received in this algorithm is presented with a dashed arrow in [Figure 3](#).

Implementation

Based on the framework, specific areas for investigation and application have been identified. These were considered suitable for the learning task in the validation study and implemented them as part of the algorithm.

For synchronous communication, verbal and non-verbal cues are assessed, with voice pitch, volume, and speech duration analysed using the PortAudio and Aubio Python libraries. Additionally, facial emotions and head movements are evaluated using the Open

Source Computer Vision (OpenCV) library. In the symmetric context, engagement, cohesiveness, participation, and coordination are measured through gaze changes, head movements, object movements, and speech duration. Cognitive load is identified by factors like blink rate, gaze changes, comprehension levels, and task performance metrics, such as completion time and tangible object movements. The system prototype, developed in Python, incorporates various Python libraries for data processing and analysis in each area.

System interface

The web interface presented in [Figure 4](#) serves as an interaction point for configuring and monitoring the collaborative activity management system. Users, typically facilitators or teachers, can input key parameters through the interface, including selecting measurable collaborative indicators (I) and collaborative interactions of interest (L). The system allows users to customise feedback by designating a specific recipient (F) and configuring temporal settings, such as feedback interval time (FI) and activity duration (AD). Additionally, users input the total number of participants (AN) and tailor preferences for sensed behaviours (S) and dimensions (D), ensuring that the algorithms receive relevant information.

The interface presented in [Figure 5](#) provides a visually intuitive display of overall computed measurable indicators (II) and collaborative interactions (LI), enhancing user



Measuring Collaboration

Facilitator Form

1

Activity

Type Of Activity:

Discussion

Number of Participants:

2

Duration Hours:

Duration Minutes:

Figure 4. System interface: activity data input screen.



Figure 5. System interface: overall collaboration screen.

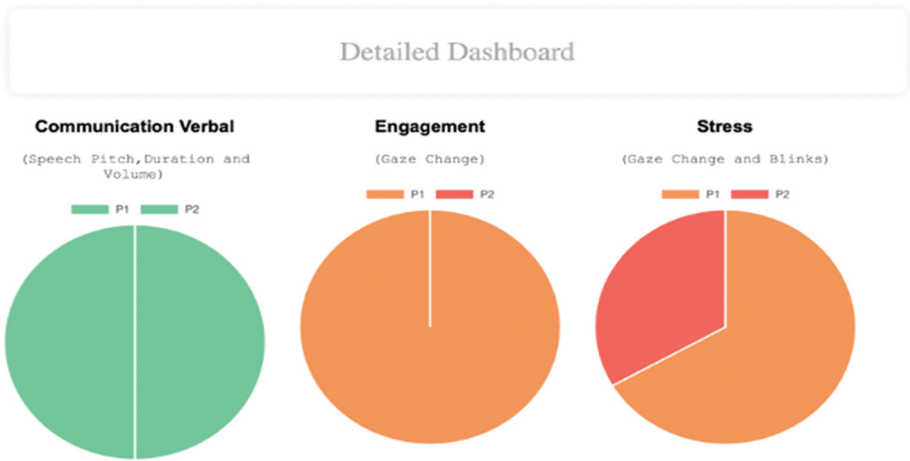


Figure 6. System interface details participant collaboration screen.

comprehension of group collaboration during the activity. Additionally, [Figure 6](#) facilitates the generation of detailed reports at regular intervals of computed sensed behaviours (S) for each participant, identified by their assigned participant identifications such as P1 for Participant 1.

Validation studies

In the second phase, the aim was to validate the framework, system and algorithms developed. Thirty-four computing students, divided into 15 groups of two to three members, participated in the study. All the students engaged in a collaborative learning task centred on applying theoretical knowledge in database design. Students were tasked



Figure 7. Validation studies setup.

with using Entity-Relationship Diagrams (ERD) to collectively solve a provided case study on a transparent physical surface, which tracked objects, as shown in [Figure 7](#). The choice of databases design for this learning task is based on its status as a core topic covered in most of the Computing Science and IT courses. Feedback on students' perceived level of collaboration and compare it with system-calculated level of collaboration was also gathered (RQ3).

In this phase, an online feedback consultation was also conducted, involving 11 educational professionals invited from various higher education institutes. The objective was to gather pedagogical feedback based on these professionals' experience and knowledge (RQ4). Participants were provided with a recorded presentation detailing the research project. This included a demonstration of the system developed and an explanation of the learning task for the study. Finally, participants completed a questionnaire. The Middlesex University ethical committee granted ethical approval for all the studies detailed.

Results

The exploratory studies served as an initial step in the research project, helping understanding students' perceptions and experiences. The results showed that most students who participated in the first phase demonstrated a positive perception of the data collection process, recognising the potential for more feedback. The students expressed a favourable attitude towards data collection and in its impact on their group performance. [Figure 8](#) shows that the majority of the students who participated held a positive outlook regarding the idea that

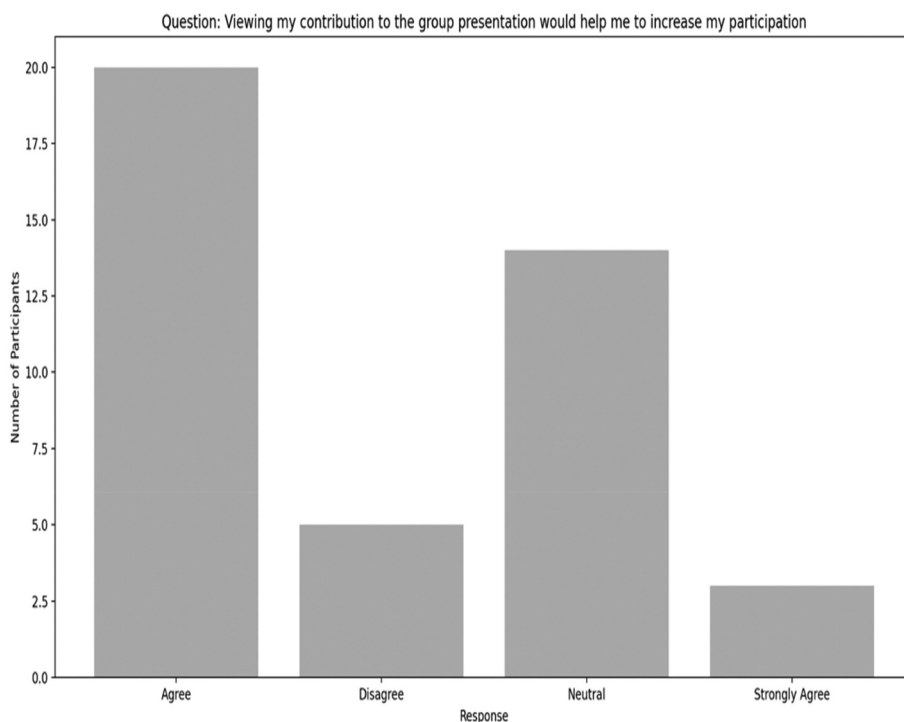


Figure 8. Question: “viewing my contribution to the group presentation and my participation”.

reviewing their contributions to a group presentation could enhance their participation. This positioning was consistent across the other settings in the study. However, students may vary in how they perceive the value of self-review, which may be influenced by their learning styles and personal preferences. While some may find the process empowering and enlightening, others uncertain about critiquing their contributions.

The exploratory studies helped define initial framework requirements and refine technical elements like sensor thresholds, placement, and room conditions.

In the validation studies, the students shared their concerns regarding group work, such as “There’s more stress in an assignment knowing other people rely on me alone, along with communication sometimes being an issue” and “really depends on who I’m in the group with and the level of their participation,” highlighting concerns related to free-riding behaviours among peers. Despite this, the students generally expressed an optimistic view regarding collecting data for more personalised feedback in group learning activities. Additionally, most participants perceived the data collection process as minimally distracting, as reflected by most responses. An in-depth quantitative analysis explored potential relationships within the collected data. The goal was to determine whether there was a relationship between the group’s collaboration score, calculated by the developed algorithm, and their average questionnaire responses to whether viewing their contributions during group meetings increased their participation.

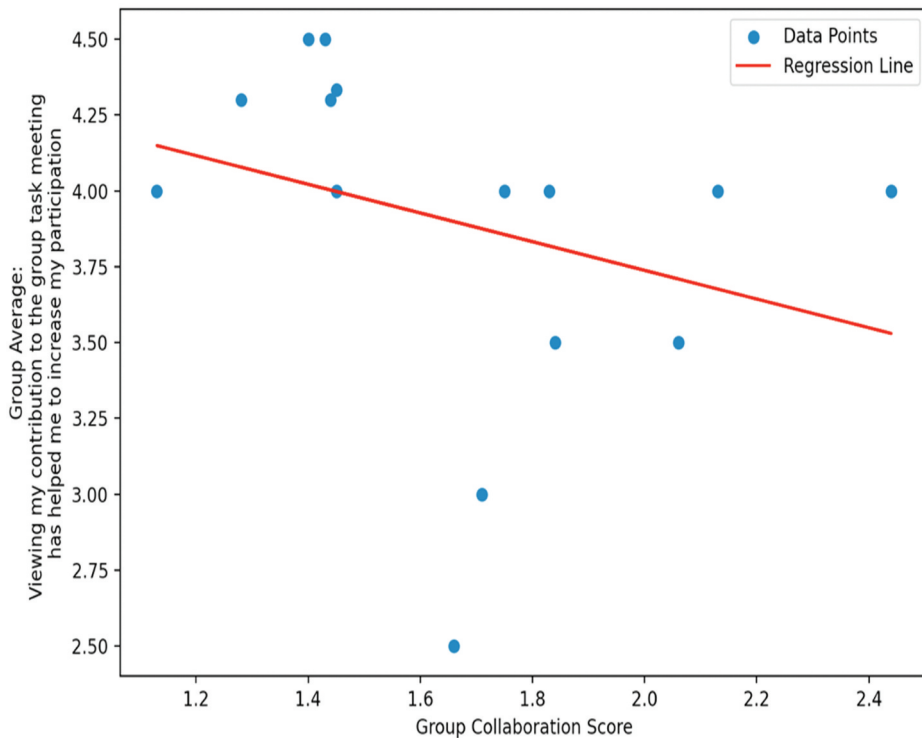


Figure 9. Regression graph on collaboration score and participation perception.

In this case, a score of one represents “strongly disagree”, while a score of five represents “strongly agree”. Figure 9 illustrates a weak negative relationship between the two variables, suggesting that various other factors may contribute to this outcome.

Figure 10 delves into the potential disparities between the objectively quantified collaborative behaviours and the self-reported behaviours of students.

This is further analysed through a comprehensive examination of the differences between the two variables, which is visually shown in Figure 11. Where a green discrepancy signifies that the perceived performance of a student aligns closely with the calculated performance, displaying a difference of less than 50%. A red indication in the visualisation draws attention to instances where a substantial discrepancy exists between the two variables. This discrepancy, reflected by a difference exceeding 50%, points to situations where students’ perceptions of their collaborative engagement significantly deviate from the quantified assessment.

The alignment presented in Figure 11 suggests that the students’ subjective evaluations of their collaborative behaviours closely correspond with the quantitative assessment generated by the algorithm. This small negative discrepancy between the calculated and perceived performance is consistent across most collaboration indicators.

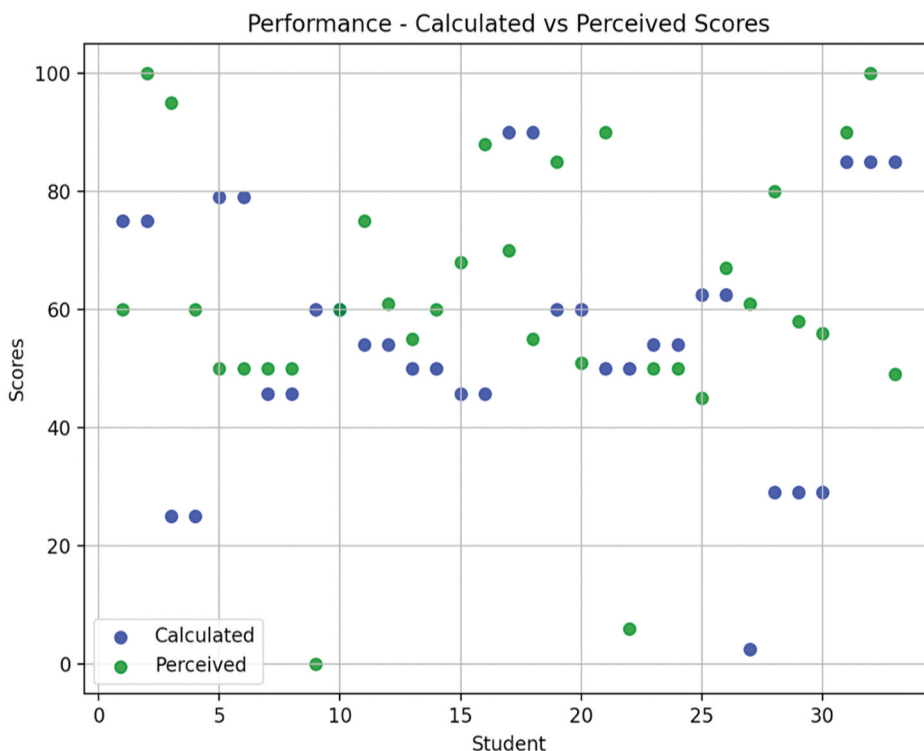


Figure 10. Calculated student performance vs. perceived performance by students.

Additionally, students reported that seeing their contributions helped to increase their participation (Figure 12), which aligns with expectations from the exploratory studies about the benefits of self-observation.

In summary, students provided several favourable comments, emphasising the importance of accessing their contribution data, gaining insights into their participation, and receiving feedback to enhance their collaborative learning task.

In the consultation process, a total of 11 education professionals with experience ranging from 3 to over 22 years in educational fields, including IT, Computing, User Experience (UX), Psychology, and Higher Education related to Learning and Teaching participated. During the consultation, participants indicated their preference for incorporating collaboration more strongly in learning activities than in teaching and assessment activities.

As shown in Figure 13, educators were asked about implementing the metrics proposed in the framework for assessing collaboration within their current practices. Their responses revealed a significant use of metrics such as verbal communication, participation, performance assessment, as well as the measurement of comprehension and incomprehension. However, metrics associated with non-verbal communication and stress/arousal levels were less frequently used. These findings suggest potential areas that could be explored further or reconsidered to ensure a comprehensive and well-rounded evaluation of collaboration in educational settings.

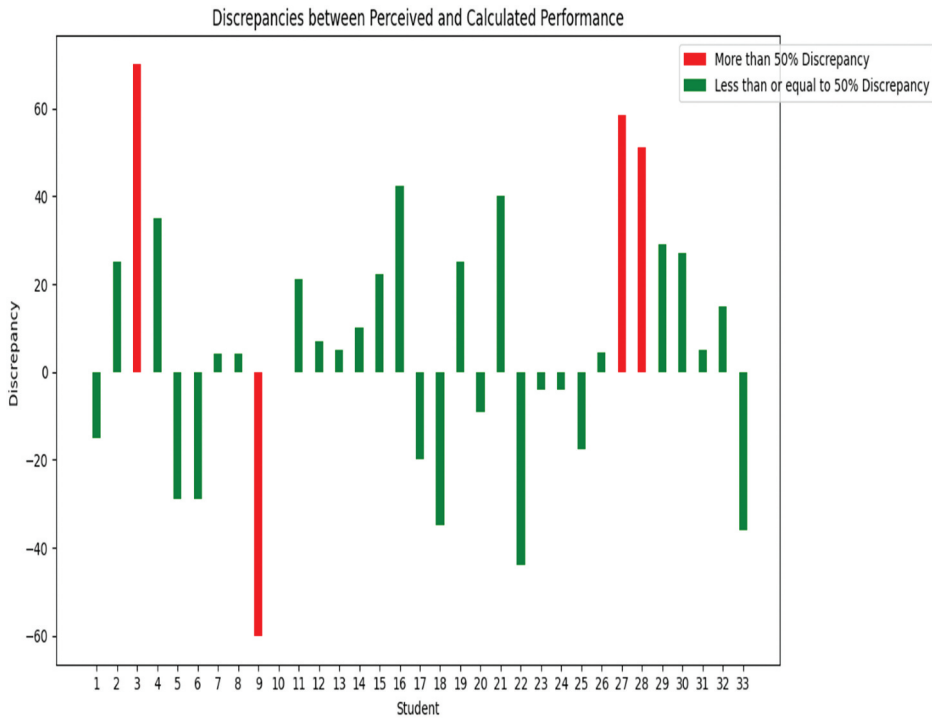


Figure 11. Discrepancy between perceived and calculated performance.

Sentiment analysis was performed on the educators' responses to the question, "Please explain how you think accessing live feedback of students' contributions and working on collaborative tasks would be helpful or not helpful to you as an educational professional." The findings revealed a notably even distribution of opinions and perspectives, with one-third of responses being positive, one-third neutral and one-third uncertain. It was observed there was potentially a shared recognition of the potential usefulness of gaining insights about students' participation in collaborative activities, which was accompanied by the understanding that such a mechanism could facilitate feedback, particularly when a user-friendly setup allows for immediate feedback. It is worth highlighting educators' concern that this approach should not unnecessarily extend the duration of learning tasks.

Additionally, the participants expressed agreement or partial agreement regarding the suitability of the input options within the prototype. They agreed that the prototype effectively presents the overall collaboration level of a group clearly and understandably as a means of mediation feedback for educators. However, concerns were raised regarding the practicality of implementing such a system, particularly regarding training and financial investment. There were also reservations on counterproductive effects of promoting a culture of authentic collaboration.

Discussion

The primary aim of this study was to explore the advantages of AV in using real-world data to support collaboration in educational settings (RQ1, RQ2). AV can offer a way to bridge

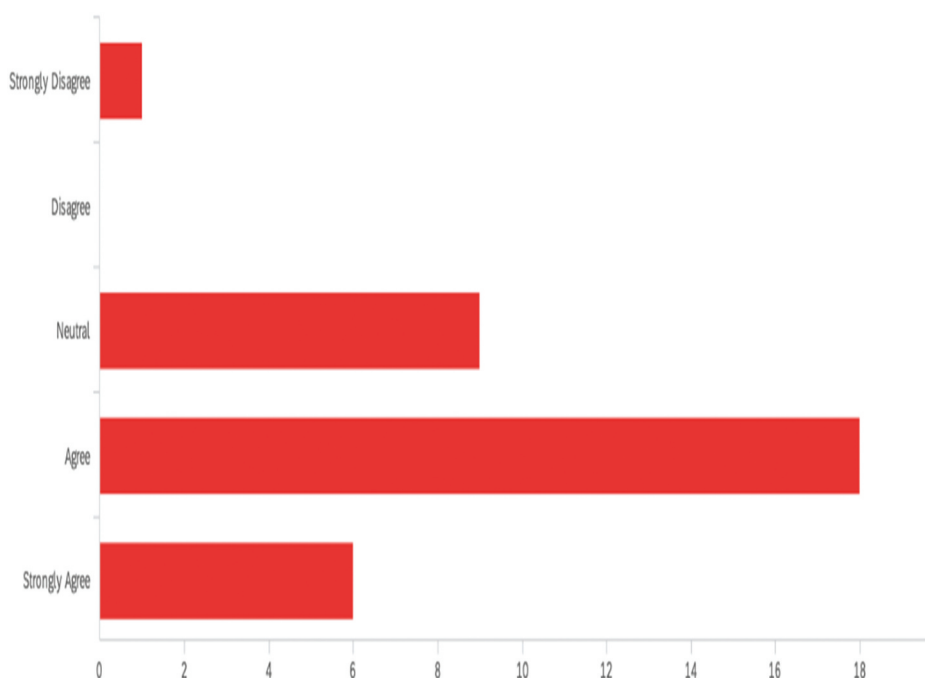


Figure 12. Question: “viewing my contribution to the group task meeting has helped me to increase my participation”.

physical interactions and virtual learning, making group dynamics visible and offering valuable insights for students and educators in CSCL environments. To develop the framework, we drew insights from exploratory studies and a pedagogical understanding of how to support collaborative interactions. We decided this was a fundamental step in utilising AV, as data extracted from the physical world constitutes a vital element in acquiring information, which subsequently be projected into virtual environments.

We conducted in-depth literature review on the technical, psychological, and pedagogical perspectives to clarify what indicators can be understood from the data collected and how they contribute to collaborative behaviours (RQ1). An example of this is the analysis of audio data, encompassing elements such as pitch, volume, and duration. This indicated possible stressful situation patterns in communication and coordination within the task context, which can offer contextual insights that can support key CSCL aims such as group awareness, reflection, and adjustments by learning themselves or through educators’ guidance.

The algorithm utilises average behaviours as a baseline to tackle the challenge of establishing collaboration thresholds. It compares each participant’s actions to the collective average behaviours of all participants, identifying deviations that signal potential alignment issues within the group (RQ2) to support student self-awareness and encourage improved collaboration or timely educator intervention.

The validation studies involved 34 students working in groups of two to three (RQ3). The tasks required physical object manipulation for more accurate task measurement. The post-task analysis of task sheets enabled comparison of individual and group task solutions, offering insights into student learning performance.

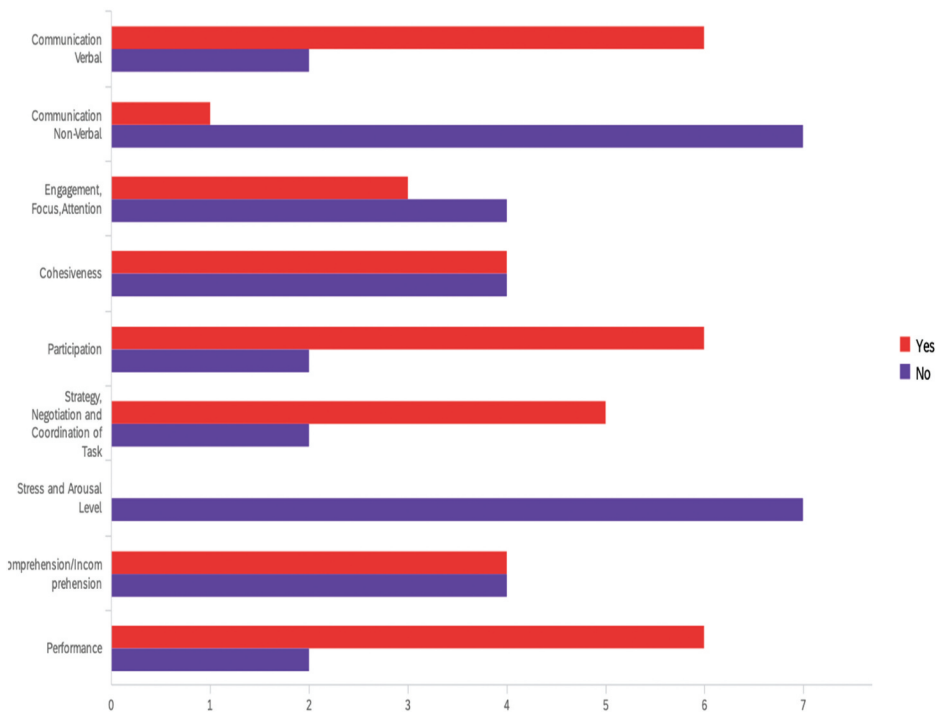


Figure 13. Question: “have you used any of the following metrics to assess collaboration?”.

Participant acceptance of data collection during learning activities significantly rose in validation studies, demonstrating a substantial shift in perception. Additionally, a positive correlation was noted between students’ perceived collaboration levels and those calculated by the algorithm, suggesting a sound understanding of their collaborative behaviours, possibly aided by task visualisations. However, a potential limitation lies in the algorithm’s reliance on accurate data collection, which is vulnerable to environmental factors such as lighting affecting facial expression detection and noise impacting audio accuracy.

A primary goal of this study was to propose a framework to support educators and facilitators in gaining a more comprehensive understanding of interactions in the collaborative learning environment and identify areas for improvement among students. As higher education institutions increasingly explore new technologies to enhance their teaching methods, the potential of MR technologies in education has shown promise. However, pedagogical aspects, such as learning objectives and assessment, remain underexplored, as stated by Kommeter and Ebner (2019) and Hamilton et al. (2021).

This lack of exploration challenges effectively utilising AV for educational purposes, especially within collaborative learning environments. To address these challenges, the research project developed a comprehensive framework to support educational professionals in designing collaborative educational environments that leverage data captured from both the learning environment and participant interactions (RQ4). By integrating the perspectives of these educational experts in the validation phase, we identified potential areas needing refinement in the framework to ensure seamless integration into diverse settings. Educators emphasised the importance of acknowledging cultural diversity and

avoiding exclusive reliance on UK-based norms in assessing collaboration. They expressed enthusiasm for real-time feedback as useful for context-specific insights. They also acknowledged the framework's potential to identify underperforming students, facilitating more effective support.

Our research focused on the less-explored dimension in the Virtuality Continuum: Augmented Virtuality. The emphasis was placed on understanding how data captured from the real environment may be utilised in collaborative educational environments. The framework supports collaborative learning goals by identifying key behaviours like communication, teamwork, and engagement. Furthermore, the integration of AV technology within this framework enables students to receive actionable feedback that reflects their measurable behaviours and performance in collaborative learning environments. It can be understood from the findings that integrating physical-world data into virtual settings can provide valuable feedback that can facilitate self-awareness and group understanding in relation to CSCL.

It is worth noting that our study explored only fragments of this technology. Future research may be directed towards understanding how the information may be effectively projected and embedded within the virtual environment, thereby fostering a more enhanced AV experience and interaction. There is also an opportunity for strengthening the validation through testing in a broader range of collaborative settings with larger student cohorts, as well as examining the correlation between teacher assessments and algorithmic evaluations.

In conclusion, this research offers an optimistic outlook and contributes to advancing collaborative learning and teacher feedback facilitation. The study signifies an initial step towards bridging the gap between AV technologies and education, as there is a lack of research and practical application in integrating AV technologies into educational environments. Furthermore, this study establishes a foundation to aid educational practitioners in building collaborative educational environments supported by AV technologies.

Note

1. While the terms "real" and "virtual" are used, as originally defined in. Virtuality-Reality Continuum. The different views about the separation of these concepts (Heim, 1998), are acknowledged. In which the boundaries between real and virtual can be argued to be blurred. However, for the purposes of this study, the distinction to differentiate between physical-world input ("real") and artificial virtual content("virtual") is maintained, which is necessary to support the conceptual positioning of this work.
2. Scrum meetings are short, structured sessions used to review progress and plan next steps in the project. In this study, the scrum meetings provided students with structure for coordinating and briefly discussing tasks collaboratively.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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