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Unpacking the Complexity: Why Current Feedback Systems Fail to Improve Learner Self-Regulation of Participation in Collaborative Activities

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Abstract

Even before the inception of the term *learning analytics*, researchers globally had been investigating the use of various feedback systems to support the self-regulation of participation and promote equitable contributions during collaborative learning activities. While some studies indicate positive effects for distinct subgroups of learners, a common finding is that the majority of learners do not modify their behaviour, even after repeated interventions. In this paper, we assessed one such system and, predictably, did not find measurable improvements in equitable participation. Informed by self-regulated learning theory, we conducted a mixed-methods study to explore the diverse paths that learners take in the self-regulation process initiated by the feedback. We found that the observed deviations from the expected path explain the difficulty in measuring a generalized effect. This study proposes a shift in research focus from merely improving the technological aspects of the system to a human- and pedagogical-centred redesign that takes special consideration of how learners understand and process feedback to self-regulate their participation.

Notes for Practice

- Research on collaborative learning analytics (CLA) tools designed to support the self-regulation of participation, aimed at preventing large differences in speaking time, shows that these tools are not always effective in achieving this goal. Some learners respond to the feedback provided and regulate their participation, while others show no change in behaviour.
- The impact of CLA tools on equitable participation is complex, influenced primarily by learners' cognitive, metacognitive, and affective processes. For instance, effectively using CLA tools to regulate speaking time requires learners to be willing to self-regulate, to be attentive to the tool's signals, and to be knowledgeable about strategies to adjust their own participation or to encourage participation among teammates.
- This study was conducted in a lab setting, limiting the ecological validity and scope of the findings. It is important to acknowledge the significant role that contextual factors present in real educational settings, such as the nature of the task, the team's composition, and the learning design, could have in the use and effect of CLA tools.

Keywords

Equitable participation, self-regulated learning, feedback systems

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1. Introduction

Collaborative learning analytics (CLA) is defined as the use of learning analytics tools as mediators in the process of computer supported collaborative learning (CSCL) (Wise et al., 2021). The most common form that CLA has taken is an informational display that surfaces several measured features about the collaboration (Hu & Chen, 2021).

The objective of surfacing this information could be to help learners improve the quality and effectiveness of the collaboration for learning (Wise et al., 2021) or to support the development of collaboration skills (Praharaj et al., 2018).

The ability to self-regulate participation in co-located collaborative activities in order to achieve participation equality has been a central research focus for these types of systems (Praharaj et al., 2021). The design and evaluation of the participation-focused CLA tools, which capture and present real-time data on individual participation levels, predate even the introduction of the term *learning analytics* (DiMicco et al., 2004). Initial research in this area was primarily disseminated through CSCL and computer-supported cooperative work (CSCW) venues (Wise et al., 2021). These systems are frequently cited as exemplars of learning analytics in physical spaces (Ochoa, 2022). It is important to note that participation is a low-level construct and is less important than other collaborative learning constructs, such as cognitive presence, knowledge sharing, or reflective thinking (Baanqud et al., 2020). The sustained interest in systems focused on the self-regulation of participation can be attributed to psychological, technological, and analytical reasons. Psychologically, the construct of self-regulated participation is straightforward and characterized by easily measurable behavioural indicators, such as the frequency and duration of verbal contributions (Strauß & Rummel, 2021). Technologically, these contributions can be simply and affordably measured using low-cost sensors like directional microphones or microphone arrays (Praharaj et al., 2021). Analytically, it is assumed that data on the extent or proportion of participation can be immediately used by learners to adjust their own engagement levels (Praharaj et al., 2018). Even though participation is a simple construct, large imbalances in it have been demonstrated to affect higher-level constructs such as knowledge co-construction (Vogel et al., 2023) and satisfaction with collaboration (Capdeferro & Romero, 2012), a point used by these systems to justify their usefulness.

However, as will be detailed in Section 2, Previous Works, these types of systems generally yield mixed results with respect to their ability to achieve equitable participation. Most studies report significant effects only for limited subsets of individuals and do not demonstrate broader, population-level impacts or improvements in equitable group participation—even in repeated interventions. These studies usually do not offer compelling explanations of why these results, and not others, are observed. We hypothesize that these inconclusive findings are not merely the result of technical design flaws in the feedback tools. Rather, they also arise from complex cognitive and metacognitive phenomena that occur once feedback is presented to learners. In their ground-breaking work linking feedback with self-regulated learning (SRL) theories, Butler and Winne (1995) suggest that learners engage in a cyclical internal regulatory process that encompasses task definition, goal setting, strategy selection, and adaptation. Each step of this process, including the perception of feedback, is influenced by the learners' beliefs and knowledge and, in turn, may alter those beliefs and knowledge. Under this more nuanced framework, it becomes evident that to fully understand the effects (or lack thereof) of feedback systems, we cannot treat learners' cognition as a black box that uniformly responds to stimuli. Instead, we must delve into the complexity associated with the varied ways learners perceive, interpret, and react to feedback, and explore how these variations explain observed behaviours. The relative simplicity and immediacy of CLA tools to support the self-regulation of participation, along with their uneven effects, make them a good context in which to study the specifics of the interplay between external learning analytics feedback and the internal regulation loop in a laboratory setting.

The current research aims to offer an initial examination of the different paths individuals follow in their self-regulatory processes when they are provided with speaking time information during co-located collaborative activities, and how this information is used to regulate (or not regulate) their participation. To achieve this objective, we developed a rudimentary system inspired by earlier feedback tools for collaborative activities and conducted a repeated-measures experiment that replicates the conditions of previous studies. The primary contribution of this work lies in our use of a mixed-methods approach to examine how learners interact with the feedback and to identify deviations from expected behaviour at various stages of the self-regulation process.

This paper is organized as follows: Section 2 provides a review of prior literature, including previous studies on tools to provide speaking-time feedback during collaborative activities and existing models to understand the internal processing of learning analytics information, especially those based on SRL. Section 3 outlines our conceptualization of the cognitive and metacognitive processes that occur in response to the provided feedback. Section 4 presents our research questions and delineates the design of both our tool and our study. Section 5 offers the results pertaining to the effectiveness of the system, while Section 6 seeks to unveil the underlying dynamics during the various steps in the learners' self-regulation process. Finally, Section 7 discusses these results in the context of prior works and their implications for the design of CLA systems.

2. Previous Works

To adequately support and position our study, this review of previous works is divided into two parts. First, we highlight the effectiveness problem of CLA tools designed to support the self-regulation of participation. In this part, the results of existing studies are reviewed, with an emphasis on their uneven effects. Second, we explore different conceptual models, specifically

SRL, which have been used to examine the cognitive and metacognitive processes involved in the consumption and use of learning analytics information and feedback.

2.1 Study of CLA Tools for the Self-Regulation of Participation

As mentioned in the introduction, CLA tools have focused primarily on providing feedback to learners about their participation levels during collaborative learning activities, with the goal of helping them self-regulate their participation. The main driver behind supporting this process is the prevention of large imbalances in participation, such as having learners who barely contribute and/or learners who dominate the collaboration. The justification for trying to achieve equal participation in collaborative learning activities is rooted in several studies that conclude that large imbalances in participation (used as a proxy for contribution) lead to suboptimal collaboration experiences (Vogel et al., 2023), lower learning outcomes (Choi & Hur, 2023), and dissatisfaction with the learning collaboration activity (Capdeferro & Romero, 2012). With this justification in mind, the stated goal of these CLA tools is to reduce inequality in participation patterns. The explicitly described or implicitly assumed mechanism by which these tools expect to achieve this goal is that by presenting real-time feedback about their own participation, learners will self-regulate their interventions. If a learner is over-participating, they are expected to give space to others; if a learner is under-participating, they are expected to intervene more in the collaboration. Accordingly, the usual evaluation of the effectiveness of these systems consists of comparing the equality of participation when groups use the tool versus when they do not, or between groups that use the tools and those that do not.

An analysis of the literature, supported by four surveys that covered co-located CLA tools (Praharaj et al., 2018, 2021; Hu & Chen, 2021; Schneider et al., 2021), revealed six distinct systems that provide speaking-time feedback to support the self-regulation of participation in face-to-face settings. These works are listed in chronological order of publication:

- **Second Messenger (DiMicco et al., 2004).** The tool featured a shared screen displaying individual speaking times. The authors conducted a controlled experiment with 92 participants. The study found that dominant speakers in the experimental group spoke significantly less when exposed to the system. Interestingly, a similar but less pronounced reduction was observed among dominant speakers in the control group. Additionally, under-participants in the control group spoke significantly more during the second task, whereas those in the experimental group did not.

- **Unnamed System (Kulyk et al., 2006).** The tool featured a projection over the discussion table. The study involved 40 participants. Each group participated in two sessions: one with the system and one without. The study found that the feedback information did not significantly affect the overall speaking time of participants. A following study (Terken & Sturm, 2010) found that only under-participants altered their behaviour significantly.

- **Conversation Clock (Bergstrom & Karahalios, 2007).** The tool featured concentric rings displaying speaking times. The study was conducted over three testing sessions and did not include a control group. The number of participants was not reported. Key findings indicate that above-average speakers reduced their turn length, while below-average speakers increased their number of turns. However, there was no analysis to suggest broader changes or improvements in equitable group participation.

- **Meeting Mediator (Kim et al., 2008).** The tool displayed speaking dominance information via a smartphone. The controlled study consisted of two sessions involving 144 participants. The primary findings revealed that the tool reduced both the amount of overlapping speech and turn length. However, there was no evidence to suggest changes in overall speaking time or improvements in equitable group participation.

- **Reflect (Bachour et al., 2010).** The tool displayed a bar chart on a table, showing individual speaking times. The controlled study was conducted in a single session and involved 72 participants. The experimental group viewed information on speaking time per participant, while the control group saw speaking time per topic. The study found no significant impact on equitable group participation between the two conditions. However, a significant effect was observed when considering only participants who believed in the importance of equal participation.

- **Unnamed System (Starr et al., 2018).** The tool displayed participation percentages on a tablet situated in the collaborative area. The study employed a 2×2 design, with access to the tool as one variable and an informational session about collaboration as the second. Conducted in a single session, the study involved 80 participants. While the study did not explicitly address equitable participation, it focused on the quality of collaboration, which is presumed to be an outcome of balanced participation. The findings revealed no significant differences between groups that viewed the visualization and those that did not. However, a measurable positive impact was observed in groups that participated in the informational session (control).

Based on the results presented in these papers, it is clear that feedback systems of this nature consistently fail to produce universally positive effects according to their goal of promoting equality in participation, despite variations in approaches, interfaces, and interventions. Some evidence suggests that dominant speakers are more likely to modify their behaviour; however, certain studies present contradictory findings, indicating that it is the under-participants who are more prone to change. Interestingly, repeated-measures studies with control groups also reveal behavioural shifts in dominant speakers, which can be attributed to factors such as group dynamics or task requirements. Moreover, ruling out the possibility that these results are artifacts of specific settings or experimental designs, studies conducted during online collaborations with participation feedback systems also yield mixed outcomes (Strauß & Rummel, 2021; Ochoa et al., 2023).

Given the straightforward nature of the feedback and the ease with which behavioural changes can be measured, these inconclusive results point to a more complex process between feedback reception and behavioural modification than initially anticipated. Existing research already highlights potential explanations, such as learners failing to pay attention to the feedback (Starr et al., 2018) or not valuing the concept of equal participation (Kulyk et al., 2006; Bachour et al., 2010). Another important conclusion from this review of previous works is that none of the studies focus on the learning effect that the tools have on the participants' ability to self-regulate their participation, focusing only on their immediate effect.

Our work aims to build upon the foundational ideas and methodologies of previous studies. We intend to move beyond the basic feedback stimulus–behavioural response paradigm and delve into the cognitive and metacognitive processes that occur within learners' minds and the effect of such tools on the development of learners' ability to self-regulate their participation. This deeper investigation will better explain why only certain subgroups, under specific circumstances, are influenced by the feedback.

2.2 Models to Understand the Use of Learning Analytics Information

Several in-depth empirical studies have been conducted in the learning analytics community to better understand and model how end users, predominantly instructors and learners, interpret learning analytics information and how this new understanding is used to make decisions and drive changes. The most developed models predominantly focus on how instructors process information provided by learning analytics dashboards (Wise & Jung, 2019; Li et al., 2021; Van Leeuwen et al., 2019; Van Es & Sherin, 2002; Molenaar & Knoop-van Campen, 2018). Although these models differ in the number and boundaries of their cognitive processes, they generally involve noticing and making sense of the information, using the information to make decisions about what needs to be done and how to do it, and, finally, enacting those actions. For example, the model proposed by Van Leeuwen and colleagues (2021) includes three main cognitive stages: (1) awareness of the information presented, (2) interpretation of the information in the pedagogical context, and (3) enactment of interpretation into pedagogical actions. The studies conducted under the guidance of these models have found that the use of learning analytics information is indeed mediated by internal cognitive and metacognitive processes (Wise & Jung, 2019; Van Leeuwen et al., 2019). While the general patterns of processes can be applied to the consumption of learning analytics information, these studies also found that the specific paths taken, decisions made, and actions enacted are unique to each individual, even when exposed to the same information (Wise & Jung, 2019; Li et al., 2021; Van Es & Sherin, 2002). These individual differences ultimately determine the effect that providing learning analytics has on the instructors' actions.

SRL is a relatively recent field of study that seeks to explain how learners set and adjust their own learning goals, select and enact learning strategies, and monitor and evaluate their learning outcomes (Panadero, 2017). While there are many competing theories of SRL, all focus on the internal cognitive and metacognitive processes, as well as learner actions, as the primary drivers behind any meaningful learning process. Given that learners are usually embedded in a learning process when they receive learning analytics information and feedback, it is natural to use SRL as the theoretical framework to understand the use and processing of this information and feedback. Moreover, the most agreed upon cognitive and metacognitive steps to process feedback in SRL (monitoring task progress, setting goals, selecting strategies, and adaptation) (Panadero et al., 2019) align well with the previously presented learning analytics frameworks for understanding analytics use. Providing evidence of this match, Jivet and colleagues (2020) found that learners' SRL skills and personal learning goals explain the differences in the use of different learning analytics dashboard elements for sense-making. In a subsequent study (Jivet et al., 2021), they explored this relationship further and found that it also affects the selection of feedback indicators in a configurable learning analytics dashboard.

However, while there is extensive literature on learning analytics interventions to support SRL processes in learners (Heikkinen et al., 2023), comparatively fewer and more fragmented studies exist on how learners use the SRL process to make sense of and use learning analytics information and feedback. Most of these studies focus on sense-making, covering roughly the monitoring and goal-setting steps of the SRL cycle. For instance, Wise and colleagues (2014) studied how learners focus their attention in a learning analytics tool about online discussion engagement. They found differences in what information was noticed by learners based on their initial motivation. Some learners paid attention only to active threads due to their interest in peer-generated information, while others looked only at abandoned threads out of curiosity about why they were not answered.

In another example, Aguilar (2018) studied how learners set their goals when responding to different types of visualizations. He found that learners set mastery goals when presented with self-focused graphs and set performance goals when presented with comparison-focused graphs. To our knowledge, there are no studies that deeply focus on how the strategy selection and adaptation steps affect the effectiveness of learning analytics feedback. Only one exploratory study by Corrin and De Barba (2014) found that even if learners successfully understand the feedback information and make a decision on how to proceed, they struggle to devise a plan to improve their situation.

The most exhaustive and complete analysis of how individuals use cognitive and metacognitive processes to process feedback information comes from the field of CSCL. The work of Strauß and Rummel (2023) analyzed how learners process feedback information about participation (measured in the number of words) in an online collaborative document. Due to its paradigm, CSCL primarily focuses on understanding how computers mediate collaborative learning processes rather than on the acquisition of specific collaboration skills. For example, the collaboration management cycle (Soller et al., 2005) is used to understand and classify the roles of tools in supporting collaboration processes. This framework, developed to explain how groups regulate themselves, includes five main steps: (1) collecting interaction data, (2) constructing a model of the interaction, (3) comparing the current state of the collaboration with its desired state, (4) advising/guiding the interaction, and (5) evaluating interaction assessment and diagnostics. While somewhat similar to the SRL cognitive and metacognitive processes, it is conceptually different because it focuses on the role of the computer system in supporting the collaboration process, not on the cognitive processes or actions of the learners. Nonetheless, the findings of this study are highly relevant to our present work. The authors found that merely having access to feedback does not guarantee the self-regulation of participation; learners need to actively engage with the feedback to truly benefit from it. Their review identified several mediating factors in this process, including the amount of time learners attend to the feedback, their ability to correctly interpret it, and the regulatory actions they implement based on their understanding.

2.3 Conclusions from Previous Works

From all of these previous studies, it is evident that the processes by which instructors and learners make sense of and use learning analytics information and feedback are not straightforward. The implicit assumption made by previous CLA tools—that just presenting feedback information to learners will lead to overall reduction in the inequality of participation—is not realistic (Lipnevich & Panadero, 2021). Therefore, the focus of our work will be on understanding the complex interplay between the CLA feedback and the various mental processes it initiates (or fails to initiate) in learners' minds. To do this, we will employ an SRL model, since we are interested in CLA tools not as a means to support the immediate self-regulation of participation, but as a scaffolding tool to help learners learn the skill of regulating their own participation in collaborative activities. We will conceptually approach the use of a CLA tool as a learning experience, where continuous, real-time feedback about participation levels is provided. Learners will use their SRL processes to make sense of the feedback, make decisions about how to act, alter their behaviour, and use the external feedback to monitor their progress. In doing so, our work will be among the first to attempt to provide a cohesive explanation of why CLA tools fail to have the desired effect across the learner population. Additionally, it will be the first to apply the SRL model to quantitatively and qualitatively examine the entire process of using learning analytics feedback, from perception to behavioural adaptation.

3. Conceptualizing an Individual's Response to the Participation Feedback

In conceptualizing learners' responses to the participation feedback, we focused on the interactions between the tool's signals and the individual, their thought processes, and their actions. This study examines how learners learn to self-regulate their participation in response to the light signals provided by our prototype CLA tool. This form of regulation, occurring at an individual level in response to individual-targeted signals, can primarily be considered self-regulation. While other forms of regulation, such as socially shared regulation (Järvelä & Hadwin, 2013) resulting from group interactions, may be present, they will be excluded from our conceptualization to highlight the effect of the CLA tool.

The theorized mechanism behind the effect of the reviewed CLA tools is the self-regulation of participation. There are several models to conceptualize learners' self-regulation processes (Panadero, 2017). The main criterion for selecting a model for this study was the inclusion of external feedback as a primary factor driving the self-regulation process. The SRL model developed by Winne and colleagues (Butler & Winne, 1995; Winne & Perry, 2000), which focuses on the intertwining dynamics of external feedback on learners' metacognitive activities, is particularly relevant to our context. This model is extensively cited across CSCL, learning analytics, and other areas of educational technology to describe how feedback-providing interventions impact learners' learning processes and behaviours. Leveraging these characteristics, this study will use Winne's model as a framework for conceptualizing learners' SRL process of how to self-regulate their participation in response to participation-level feedback.

In their approach to measuring SRL, Winne and Perry (2000) suggest focusing on a series of observable "transition events."

These events are key moments when learners move from one state to another in their learning process. For example, in their work, they illustrate this with a hypothetical scenario: if a learner remarks that a task is hard, it can be inferred that they have engaged in monitoring the task and have a certain standard for comparison. This method of observation allows researchers to measure metacognitive activities, which are typically unobservable, through these discernible transitions in behaviour. Using this method, Winne and his colleagues conceptualized SRL processes as a series of events that span four phases: defining the task, setting goals and making plans, employing tactics, and making adaptations. Each phase represents different behaviours exhibited by learners, shaped by the interplay between their metacognitive activities and the external feedback they receive.

3.1 External Feedback

The external feedback provided by CLA tools can be conceptualized in three main steps: sensing, analytics, and display (see Figure 1). The sensing step uses individual microphones or, most commonly, microphone arrays, to periodically detect who in the group is speaking. In the case of overlapping speech, some systems only report the loudest individual, while others can report a list of all individuals speaking. This information is then provided to the analytics step. In this step, the speaking time of each individual is calculated, and this value is used to calculate the desired metric. The metric could be simply the percentage of total speaking time corresponding to each individual, but more complex calculations can be performed at this step. Finally, the calculated metric is presented to the individual or the whole group in the display step. This information is usually presented visually in the form of some type of graph.

In the specific case of the present study, the sensing step was conducted with a microphone array that detected only one individual at each measurement sample. The analytics step transformed the percentage of total speech into five levels, from very low to very high. In the display step, that level was presented to the participants with a light signal directed at each individual. More details about the implementation of our prototype can be seen in Section 4.1.

3.2 Self-Regulation Process

Inspired by the notion of observable transition events and the four phases of SRL described by Winne's model (Winne & Perry, 2000), we conceptualize the learner's internal SRL process for learning how to self-regulate their participation in response to a CLA tool providing feedback about their participation level in four distinct phases (Figure 1):

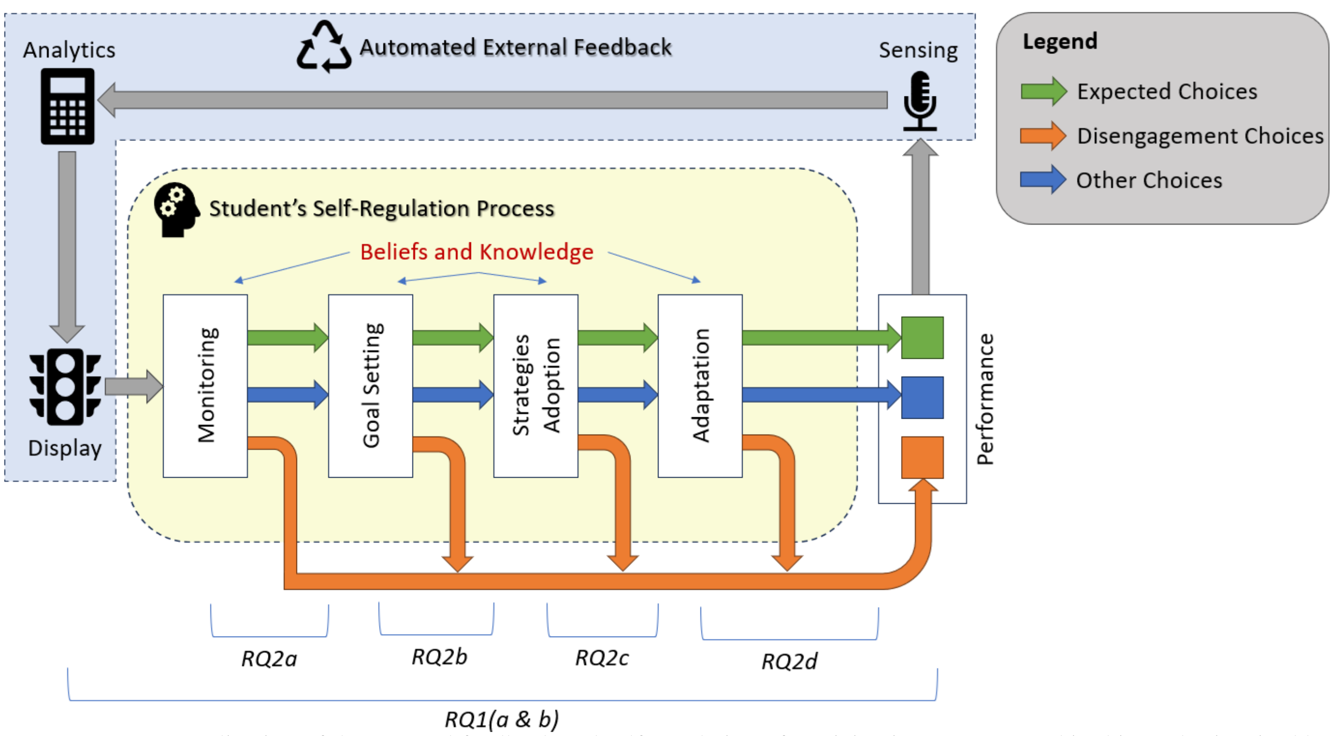


Figure 1. Conceptualization of the external feedback and self-regulation of participation process used in this study (inspired by Winne's SRL model; Butler & Winne, 1995; Winne & Perry, 2000). This image also summarizes the scope of the research questions.

- **Monitoring.** Monitoring is a critical entry point into the processes of SRL. It involves learners in two key activities: awareness of task information and interpretation of this information. In these activities, proposed by Winne's model (Butler & Winne, 1995), learners develop their understanding of a task based on two primary sources: the information about the task that is available in their environment and their own cognitive interpretation of this information. In our study, the presence of external feedback serves as environmental information. Participants are expected to use the feedback signal to monitor their level of participation by first becoming aware of the information presented and then interpreting what the signal means regarding their participation level.

- **Goal setting.** In Winne's model (Butler & Winne, 1995), goal setting is identified as a critical phase that builds on learners' initial task understanding and identified standards. This phase is characterized by its iterative nature: learners continuously monitor and revise their goals based on the outcomes of their efforts. Goal setting is also a complex process, influenced not only by the task itself but also by learners' pre-existing beliefs and knowledge. Therefore, goal setting in SRL is a nuanced process, intertwined with broader cognitive and emotional processes. In our study, after participants become aware of their participation level, it is expected that they will use this information to set a goal: participating more, less, or at the same level. This goal selection is expected to be influenced by their own understanding of what equitable participation is and their belief in the importance of equity in participation.

- **Strategies adoption.** The third phase in SRL, as noted by Winne and Perry (2000), involves choosing strategies to meet established goals. Effective strategy selection depends on learners' prior knowledge of the strategies, including their understanding of each strategy's purpose and appropriate application. Moreover, this phase is deeply influenced by learners' motivational and emotional factors, such as self-efficacy, expectations of outcomes, and motivational beliefs. In our study, if the goal selected by participants involves changing their current participation level, they should decide which strategy to use to do so. For instance, a participant who recognizes that they are speaking excessively may choose to invite others to provide their own opinion. The selection of participation strategies is subject to the participants' knowledge and comfort in using those strategies.

- **Behavioural adaptation.** The final phase in our process is conceptualized as behavioural adaptation. This phase is overt and observable, emerging from the internal cognitive processes undertaken in earlier stages. It demonstrates how well the strategies have been internalized and applied, aligning with the concept of "behavioural products" as outlined by Winne and Perry (2000). In our study, behavioural adaptation is represented by changes in participants' speaking time and their actual interaction behaviours, such as inviting others to speak. However, successful behavioural adaptation depends not only on the selection of a participation modulation strategy but also on how well it is implemented. It is expected that in participants who regulate their participation in response to the CLA signal, a clear SRL path can be traced, from becoming aware of the signal, to understanding its meaning, to setting appropriate goals, to adopting an effective strategy.

While these steps are common to every SRL process, the choices and decisions each student makes at each stage are idiosyncratic, depending on their beliefs, motivations, and prior knowledge. The next subsection will create a classification schema to help us analyze these choices from the perspective of the CLA tool's objectives.

3.3 Choices and Behaviour

We conceptualize three possible choices that participants might make at each of these four phases. In Figure 1, green arrows represent the expected self-regulation choices that would prevent individual learners from over- or under-participating, leading to more balanced participation in the group. The rationale for calling these choices "expected" is that they align with the system's desired effect of supporting individuals in learning how to regulate their participation. From the point of view of the CLA tool, students who follow the expected choices will have a positive outcome, maintaining a balanced participation level with the rest of the group. For instance, consider a scenario where a learner who consistently speaks more than their peers receives a visual signal indicating excessive speaking time. Upon noticing this signal, the learner understands that they have exceeded a reasonable share of the conversation. Recognizing this, they decide to speak less and instead ask their teammates for their opinions. By adopting this questioning strategy and actively inviting input from others, the learner not only reduces their own speaking time but also fosters a more balanced discussion within the group. This scenario represents a successful use of the feedback information to achieve the intended goal of the tool.

As previously mentioned, the choices made in the self-regulation process are heavily influenced by the learners' beliefs and pre-existing knowledge, introducing variability in how they respond. Students can and do make different choices than those "expected" by the tools' designers. This is supported by theory and empirical evidence from the evaluation of previous CLA tools. We have labelled these decisions as "other choices" (depicted in blue in Figure 1). For example, a student who has been over-participating receives a signal indicating excessive speaking time. They correctly interpret this signal, but they decide that this is not a problem and their strategy for regulation will be to keep talking until they finish their idea, even if that takes a while. As a result, the collaboration activity ends with the mentioned student excessively dominating the conversation. These types of decisions keep the students within the SRL process but on a path not desired or anticipated by the designers of the CLA tools, and their outcomes are considered negative from the perspective of the tool's effectiveness.

Finally, some of these unexpected choices could even lead to stopping the SRL process initiated by the CLA tools' signals. These choices are referred to as "disengagement" and are represented by orange arrows in Figure 1. For example, an over-participating student receives a signal indicating that they are doing so. Upon receiving and interpreting the signal, the student considers that the system is misjudging their participation and decides to ignore the feedback completely, continuing to dominate the collaboration. If students stop at any phase of the SRL process started by the signal without moving to the next, this is interpreted not only as a negative result from the perspective of the tool but also as a failure of the feedback system.

The existence of different paths in the response of students to the participation feedback is an intuitive conclusion that arises from using SRL as a basis to conceptualize this response. However, these different paths have not been used to explain the results of previous CLA tools reviewed in Section 2.1 and have only been modelled by a handful of learning analytics works compiled in Section 2.2. The subsequent sections of our study will focus on identifying the specific choices that take students through these different paths, particularly disengagement and other unexpected choices. We aim to achieve this through a combination of quantitative analysis of behaviour and qualitative analysis of participant experiences.

4. Research Design and Methodology

To investigate in detail the choices made by learners at each step, we began by constructing and testing a real-time participation feedback system. This reconstruction was necessary because all previous systems were research prototypes and are no longer available. This reconstruction is heavily inspired by these previous systems and is designed to support learners in developing the skill to self-regulate their participation. The first objective of this replication study is to corroborate previous quantitative findings by answering the following research question:

RQ1: Does the use of a participation feedback system improve participation equality within collaborative groups in a laboratory setting?

Concurrently with this evaluation, we conducted a mixed-methods study to examine the various stages of the self-regulatory processes to understand how learners' choices deviate from those expected by the current design of this type of system (indicated in blue in Figure 1) or result in disengagement from subsequent steps in the self-regulatory process initiated by the provided feedback (marked in orange in Figure 1). This study aims to address the following questions:

RQ2: How is the information presented by the system used at different stages of the self-regulation process?

- **RQ2a:** Do learners use the information provided to monitor their level of participation?
- **RQ2b:** What goals to self-regulate their participation do learners set based on their interpretation of the feedback signal?
- **RQ2c:** What strategies do learners adopt to self-regulate their participation in response to the feedback signal?
- **RQ2d:** What actual adaptations in participation are observed in the learners' behaviour?

The following subsections detail the technical design of the feedback system, describe the setup of the controlled laboratory experiment to collect data, and explain how the data was pre-processed before being analyzed to answer the previously stated research questions.

4.1 Feedback System

The feedback system was designed to follow the same principles as previous systems without copying the interface of any particular system. We did this to evaluate these general principles rather than their specific implementations. The design decisions made, such as the way to display the feedback signal, are not presented as optimal solutions but as a possible permutation of previous systems. The insights gained from the present study are expected to provide guidelines for designing better feedback systems to develop and support self-regulated participation.

The feedback system developed for this project incorporates a microphone array that captures both a beam-formed audio signal and the direction of arrival (DOA) of the predominant sound, measured in degrees. This data is relayed to straightforward analytics software that samples both the sound and the DOA angle every 100 ms. The sound data is then processed by a voice activity detection algorithm to determine whether it is speech or silence. If classified as speech, a simple mathematical function is employed to assign the DOA degree to the arc regions corresponding to the learners' positions around the table. The software

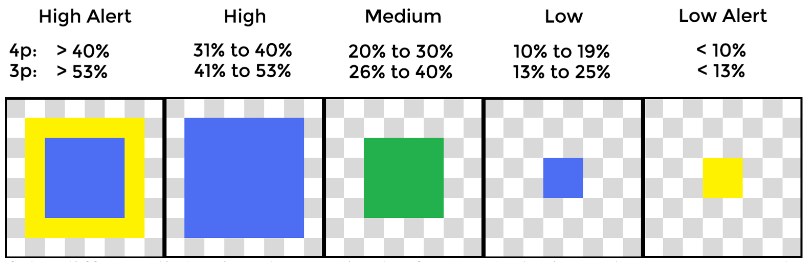


Figure 2. Visualization of the different light signals used in the feedback device. The percentages that trigger different signals depend on the number of participants around the table (4p: four, 3p: three)

uses this sample to compute the cumulative amount of talking per learner in real time, initializing not from zero, but from a state of equal participation. These cumulative amounts are subsequently converted into a signal displayed via a curved LED array situated on the device's surface.

The LED array has 32×8 LEDs divided into four 8×8 regions for each learner. Each region displays one of five signals—high alert, high, medium, low, and low alert—as illustrated in Figure 2. These coloured squares depict speaking activity levels, with size indicating talking percentage and colour signifying balance (green), imbalance (blue), or alert (yellow). We selected these colours (green, blue, and yellow) because they are easily identifiable colours, recognizable even by individuals with deuteranomaly or deuteranopia, the most common types of colourblindness. In cases where an individual cannot identify the colours, the size of the square is used as a secondary feature. Changes in signals are determined by each learner's percentage of accumulated speech and the number of participants present. Detailed descriptions of both hardware and software are available in a public repository[1].

4.2 Experimental Design

To evaluate the feedback system's effect on the self-regulation of participation, the acquisition of that skill, and ultimately the equality of participation, we designed and conducted a randomized, repeated-measures, laboratory-based study. While many other research approaches, such as design-based research (DBR) (Hoadley, 1994), could also be valid to explore the presented research questions, we decided on a traditional controlled experiment approach. Our main objective was not to create a better tool than those that came previously, but to better understand why those tools failed to achieve their objectives and to acquire deeper knowledge about the mechanisms behind using learning analytics feedback to learn to self-regulate participation.

After deciding on the methodological approach, choosing the setting was the most crucial decision. Although a real learning scenario would have provided ecological validity and introduced pedagogically relevant factors, we opted for a laboratory setting due to three considerations: methodological, to replicate previous studies accurately; ethical, because the tool's benefits are not conclusively proven, making its introduction into real learning processes unjustifiable; and technical, since the current technology for detecting speaking participants is not resilient to external noise.

The second most important decision for this experimental design was determining the sample size. We used the G*Power statistical software (Faul et al., 2009) to find that at least 16 groups were needed to detect a medium effect size in the main tests conducted to verify the effectiveness of the tool (ANOVA with repeated within- and between-subject measurements, effect size $(f) \geq 0.25$, two groups, four measurements, statistical power $\geq 80\%$, error probability $= 0.05$, measurement correlation $= 0.7$). This number was a reasonable target for the scope of our study and available resources.

Following IRB-approved consent procedures, we recruited 56 volunteers aged 18 to 38 to engage in four weekly discussion sessions, each lasting 45 minutes. Depending on scheduling availability, participants were assigned to three- or four-person groups. A total of 15 groups (one less than initially desired) were formed with the recruited participants. Randomly, seven of these groups were used as control, while eight were exposed to the signal lights. Participants were compensated $100 for their involvement. Despite the withdrawal of 12 participants, adjustments were made to ensure that no group had fewer than three participants. The experiment was conducted from April to June 2023.

All groups participated in four collaboration sessions, spaced at least one week apart. During session 1, both the experimental and control groups participated in a collaborative activity while their participation was recorded. None of the groups were exposed to feedback about their participation. This first session served as a baseline for the behaviour of both control and experimental groups. During sessions 2 and 3, only the experimental groups received feedback about their participation in the form of signal lights, while the control groups did not. Data about participation was recorded for both conditions. Unlike previous experiments with CLA tools, session 4 removed the feedback signal from the experimental group to assess the learning effect of the feedback. The structure of the experiment is detailed in Figure 3. While the experimental group was

[1] Github repository: https://github.com/xaoch/CollaborationLights

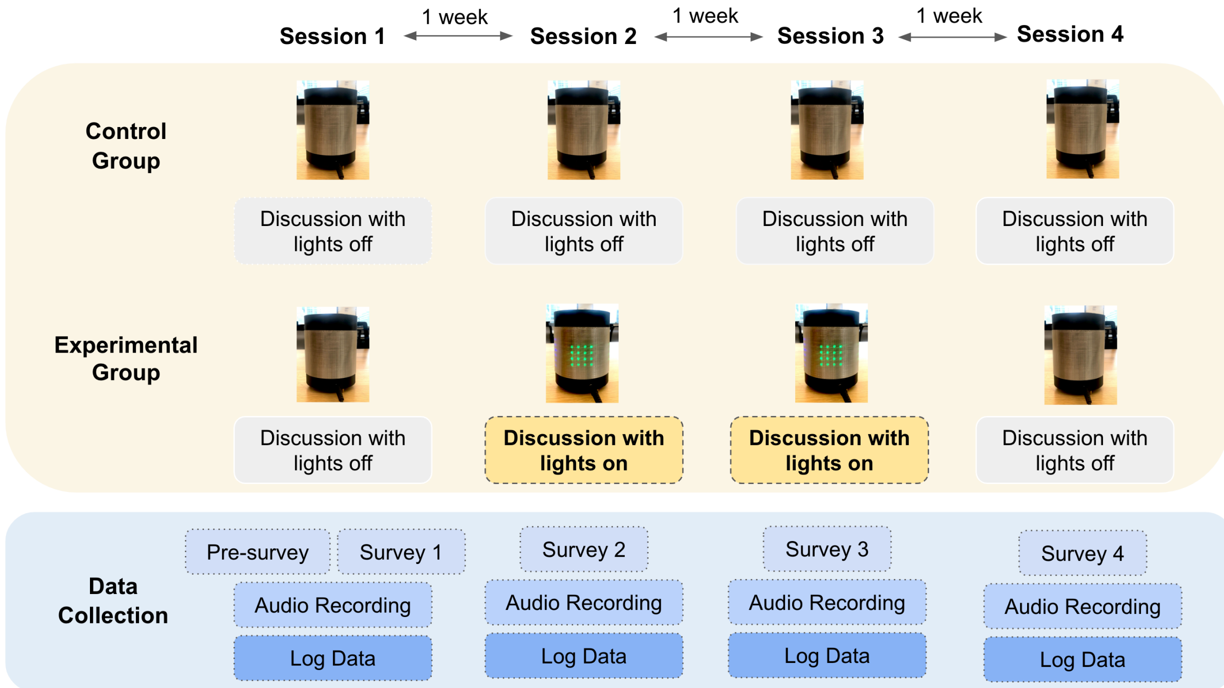


Figure 3. Experimental design and data collection.

only exposed to the lights twice, it is expected that these two exposures could be enough to detect reaction patterns to the signal. This expectation is based on the immediacy of the feedback (real time) and the short time needed to deploy corrective actions (measured on the order of seconds or minutes). The withdrawal of the light during the last session could allow for the observation of the immediate learning effect that the engagement of the SRL process would have on the acquisition of the skills to self-regulate their participation.

For all groups and sessions, participants were welcomed by a member of the research team. At the first session, everyone was randomly assigned a number from 1 to 4 (or 1 to 3 in the case of three-person groups) and directed to sit according to their number. The device was positioned at the centre of the table, displaying numbers 1 to 4 on each side when not in use. Participants were asked to sit on the side facing their assigned number and to maintain the same seating arrangement for the subsequent three sessions.

Following the seating arrangement, the researcher explained the goals and procedures of the experiment. We mentioned that this is a study on how people regulate their participation during collaboration and emphasized the importance of equality in participation before each session began. In sessions 2 and 3 for the experimental groups, we explained the operation of the feedback device and the meaning of the different light signals. To aid understanding, we used slides with photos to demonstrate different scenarios, indicating participation levels through three colours and shapes: green for the desired level of participation, blue for slight deviations from the desired level, and yellow as an alert for extreme deviations. Additionally, the size of the square displayed on the device corresponded to the duration of speaking time, with larger squares indicating more speaking time. We explained that the tool would monitor and display each participant's contribution to the group discussion. We emphasized that ideally, each person should aim for 25% participation (in the case of a four-person group) or 33% participation (in the case of a three-person group), which corresponded to a green medium-sized square.

The researcher then introduced the day's discussion topic. At each session, each participant received a printed handout of a commonly used hypothetical survival challenge, similar to the Survival on the Moon collaboration task (Pell, 2024). In such tasks, participants are asked to rank essential items needed to survive in a hostile environment such as the moon or the desert. The handouts had tables with two columns labelled "Individual Choices" and "Group Choices." Initially, participants were instructed to think independently and put their choices in the "Individual Choices" column. Once ready, they discussed as a group and, after reaching a consensus, recorded their agreed-upon decisions in the "Group Choices" column.

4.3 Data Collection and Preprocessing

During the experiment, data including audio, DOA logs, and survey responses was collected. Participants' voices were recorded, and log files noted which learner was talking every 100 ms. A pre-study survey gathered participants' demographics, English proficiency, comfort in discussions, beliefs about equal participation, and Big Five Inventory (BFI) personality test results (John et al., 1991). Post-session surveys gathered insights into their collaborative experiences and perceptions, and experimental groups were additionally queried about their interactions with and influences of the device, including the impact of visual displays on their behaviours. The questions of the pre- and post-session surveys can be reviewed in the Open Science Framework (OSF) repository[2].

Some of the raw data needed to be pre-processed in order to be used in the analysis:

- **Audio data.** The audio captured during the collaborative activities was converted into a transcript. We applied an automated speech recognition algorithm based on the WhisperX neural model (Bain et al., 2023). WhisperX achieves human-level performance in medium-quality audio like that captured during the sessions.
- **DOA data.** The data about who was talking at each time was trimmed to include only the active collaboration period.
- **Survey data.** The identifiers were aligned with the DOA data given the participants' positions per session.

4.4 Qualitative Coding

To explore how participants in experimental conditions used signal information in self-regulation processes, we conducted a qualitative analysis of responses to the survey's open-ended questions about their collaboration experience and the impact of the device on their behaviour. The question about the impact of the device was asked in the survey for experimental groups at the end of sessions 2 and 3. We adopted the qualitative content analysis coding method, which is commonly applied for analyzing open-ended responses (Jackson & Trochim, 2002; Kurasaki, 2000). Our analytical process was structured into three distinct phases:

- **Phase 1: Annotating.** Initially, we annotated the data for potential themes through a line-by-line examination. A researcher segmented each response into sentences or phrases that contain only one concept and then summarized them in one to five words.
- **Phase 2: Sorting.** Annotations were compiled and representative quotes extracted. Then, through theoretical sorting (Holton, 2007), we grouped similar annotations into 12 codes and 19 sub-codes. For example, the "expected strategies" code included four sub-codes: "talk more efficiently," "active listening," "invite others," and "collaborate more."
- **Phase 3: Developing a coding scheme.** In this phase, codes were aligned with SRL processes. We categorized them into four thematic areas: monitoring, goal setting, strategy adoption, and behavioural adaptation. A second researcher reviewed the initial codes and their definitions and refined the coding scheme into eight codes and 16 sub-codes.

To ascertain the reliability of our coding scheme, we computed the inter-rater reliability. A random 20% subset of the data was independently coded by a different team researcher using all identified codes and sub-codes from Phase 3. The computed weighted Cohen's kappa was 0.93, signifying substantial agreement and thus underscoring the reliability of our coding scheme across different raters.

5. System Effectiveness Results

The evaluation of the feedback system began with a general efficacy examination, reflecting methods used in previous systems. This evaluation model, rooted in behaviourist principles, applies stimuli, in this case, light signals, to experimental groups to observe expected behavioural changes in participants—namely, adjustments in speaking time to achieve balanced participation, compared to control groups without light signals.

5.1 Initial Measurements

To facilitate the contextualization of the subsequent analysis, various measurements were obtained:

- **Statistical sensitivity.** Using the sensitivity calculation of the G*Power software (Faul et al., 2009), the actual values for the number of groups (15) and the measured repeated measurement correlation (0.6) were used to determine the minimum effect size detectable by the experiment. The obtained value, $f = 0.28$, can still be considered a medium effect and does not deviate significantly from the designed 0.25.

[2] OSF repository: https://osf.io/zq58r/?view_only=33697d82b90540119974142e1a63af7b

- **System technical accuracy.** The system's accuracy in identifying the speaking learner was assessed using 100 random measurements from all 56 sessions, compared against judgments by two human coders. The system showed 94% average accuracy, with a Cohen's kappa of 0.95 between human coders, indicating substantial agreement. Most discrepancies arose during simultaneous talking.

- **Baseline distribution.** The initial distribution of participation levels was assessed using the first session's DOA log data. The levels found in the population were 5% low alert, 9% low, 45% middle, 25% high, and 16% high alert. A χ^2 test $[(4, N = 55) = 4.5, p = 0.35]$ showed no significant differences in distribution between experimental conditions, suggesting uniformity in participation levels across experimental and control groups.

- **Session duration.** The sessions, having no set time limits, varied in duration. Average duration decreased over sessions, from 18.5 min in session 1 to 7.3 min in session 4. ANOVA tests indicated significant differences $[F(3,53) = 8.57, p < 0.001]$ due to the session sequence, but not due to experimental condition $[F(1,55) = 1.4, p = 0.24]$. The decrease in duration is likely due to increased task familiarity and potential disengagement. These implications are considered in subsequent relevant analyses.

Given these preliminary confirmations of the data's validity, we will now proceed to analyze the impact of the feedback on participation equality.

5.2 System Effectiveness

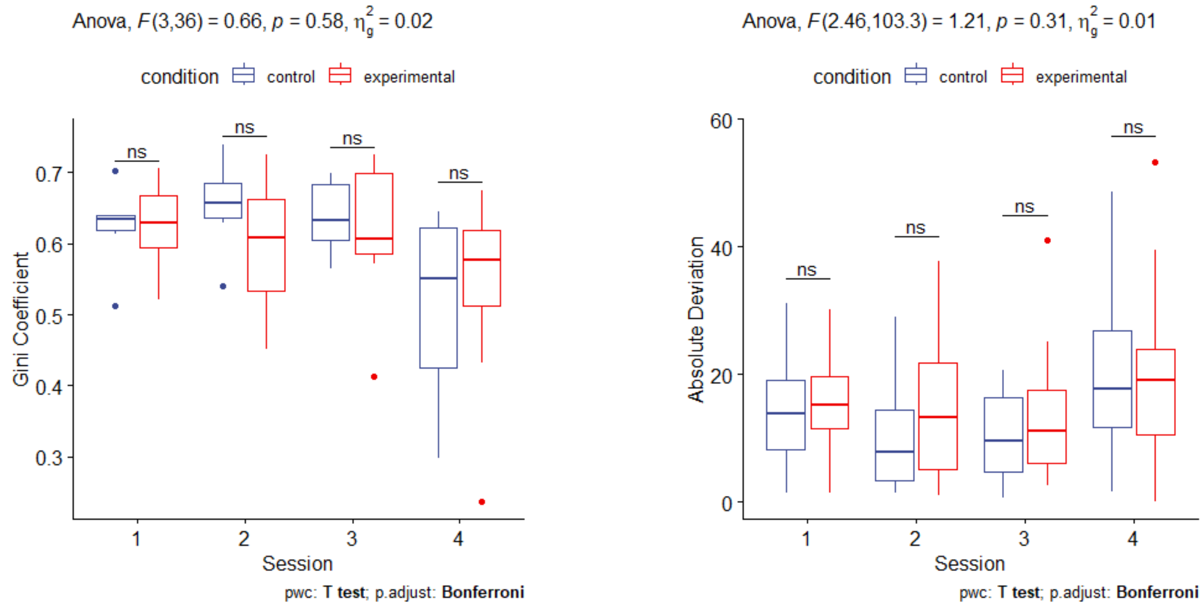
To evaluate if the feedback system influenced participation equality, we calculated individual contribution percentages per session. This involved dividing the number of instances a learner was identified as the speaker by the total number of 100 ms speaking instances during the activity. Using these percentages, the Gini coefficient (Dorfman, 1979) was then computed for each group and session to assess participation equality (Reinig & Mejias, 2014). The Gini coefficient is a statistical measure commonly used to quantify income inequality in economics, but it can also effectively measure inequality in other contexts, such as participation in group collaboration. The Gini coefficient ranges from 0 to 1, where 0 indicates perfect equality (everyone participates equally) and 1 means extreme inequality (one person dominates while others do not participate). For more realistic values, if in a group of four participants, one of them speaks 50% of the time and the others equally, the Gini coefficient will be approximately 0.25. If one participant speaks 75% of the time, and there is one participant who does not speak, the Gini coefficient will be approximately 0.62. The Gini coefficient is not sensitive to the number of individuals, making its results comparable across sessions, regardless of whether they had three or four participants.

The first hypothesis suggests that groups exposed to light signals will have more balanced participation than groups not exposed, within the same session. The second hypothesis posits a learning effect in the last session, leading to more balance in experimental groups than in control groups, even without exposure to signals. The null hypothesis assumes no difference between groups in any session.

To verify these hypotheses, a mixed ANOVA was used, examining the Gini coefficients across sessions (within subjects) and conditions (between subjects). All prerequisites for mixed ANOVA were met. Further pairwise t-tests with Bonferroni correction were performed to explore differences between conditions across sessions. Figure 4a displays the statistical analysis results. The mixed ANOVA $[F(3,36) = 0.66, p = 0.58]$ showed no significant interaction between conditions and sessions, and the effect of the condition alone was non-significant $[F(1,12) = 0.095, p = 0.76]$. Correspondingly, the pairwise t-test found no significant difference between conditions in each session (marked as "ns" in Figure 4a). High Gini coefficients in the first session indicate notable participation inequality in both groups, maintaining statistically through all sessions. Thus, the data suggests the null hypothesis cannot be rejected, indicating that the light signals from the feedback system don't significantly impact participation equality.

We also measured each individual's absolute deviation from ideal participation over time. We calculated this by subtracting each individual's participation percentage in each session from the ideal participation percentage, given the number of participants (25% for four, 33% for three). This analysis included only the 44 participants who completed all sessions. A mixed ANOVA was again employed to investigate the interaction between sessions (within-subject variable) and experimental conditions (between-subject variable), satisfying all requisite conditions for this analysis. Further, pairwise t-tests with Bonferroni correction were conducted to uncover direct differences. Figure 4b shows that the mixed ANOVA found no interaction between within-subject and between-subject variables $[F(2.46, 103.3) = 1.21, p = 0.31]$, and examining only the experimental condition also yielded no significant effect $[F(1,42) = 0.445, p = 0.51]$. Subsequent pairwise t-tests confirmed no significant effect. The persistent average absolute deviation from ideal equal participation, ranging between 10% and 20%, reveals minimal variation across sessions; thus, the null hypothesis is not rejected.

This study aligns with previous research in showing no generalized effect of the feedback system's light signals on participation behaviour at both group and individual levels (RQ1). This non-effect isn't due to already equitable participation,



(a) Group analysis (Gini coefficient). **(b)** Individual analysis (absolute deviation).

Figure 4. Results of the mixed ANOVA test and pairwise t-test with Bonferroni correction on the differences in (a) group Gini coefficients and (b) individual absolute deviation per session and experimental condition. No significant effect was found at either group or individual level.

given the consistently high Gini coefficient values, nor to a limited number of groups, as findings persist when analyzing individual members. Variations in group dynamics in the control group also outweigh any changes in the experimental group. Given the system's simplicity and the lack of positive results despite repeated exposure and measurement, it's clear that the complexity is in participants' perception, interpretation, and use of the information, not in the external analytics and feedback loop (Figure 1). The next section will explore a mixed-methods analysis to illuminate participants' internal cognitive and metacognitive processes.

6. Analysis of the Self-Regulation Process

After identifying no general effect within the experimental groups, we seek to understand why. We explore the complexities in the self-regulation process initiated by the feedback signals. The goal of this mixed-methods study is to gain insights to explain the observed outcomes, not necessarily to validate a hypothesis. This analysis is structured around the steps in our adaptation of the Butler and Winne framework (Butler & Winne, 1995) (Figure 1). We first explore whether the light signals enhance participants' awareness of their participation levels. Next, we identify the goals participants set and the strategies they employ in response to this awareness. Lastly, we observe how these goals and strategies are reflected in participants' behaviours. A summary of the different paths followed by the participants can be seen in Figure 5.

6.1 Awareness of the Task

To begin the self-regulatory process, it is crucial for learners to notice and make use of the light signals from our system. To understand how well learners perceived these signals, we asked the experimental group in our study to report on the frequency with which they paid attention to these signals. This was done through post-surveys conducted in sessions 2 and 3. In session 2, observations were 18% rarely, 54% sometimes, 21% often, and 7% always; in session 3 they were 19% rarely, 44% sometimes, 30% often, and 7% always, with no "Never" responses. A χ^2 test $[\chi^2(4) = 0.60, p = 0.96]$ showed no difference between sessions, indicating that around two thirds of the learners paid attention to the lights only sometimes or rarely. While this result may appear to indicate a problem with the specific design of the feedback system, this phenomenon was also found in studies of previous systems with completely different visualization approaches that also measure this variable (DiMicco et al., 2004; Bachour et al., 2010). This consistent disregard of the feedback signal points to deeper factors than just the way the signal is presented.

To evaluate the signals' impact on participants' awareness, both control and experimental participants assessed their participation levels using percentage ranges at the end of each session. The analysis converted ordinal scales to numerical

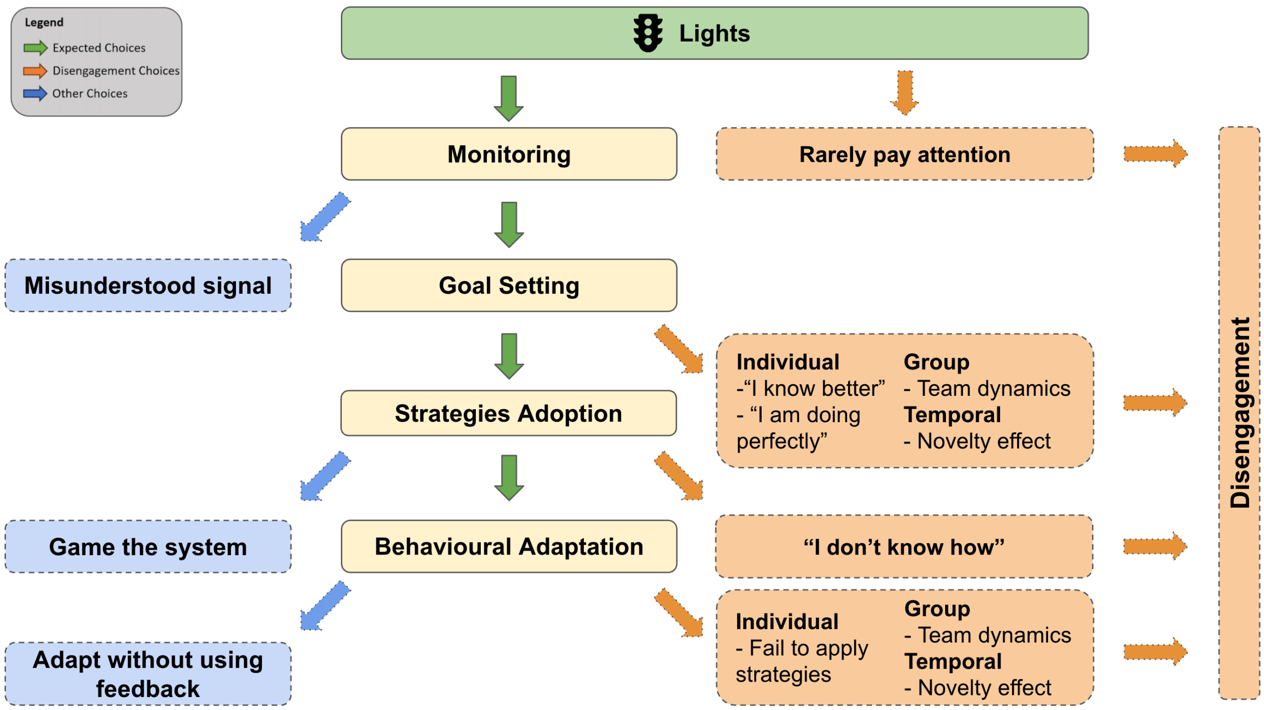


Figure 5. Summary of disengagement and other choices found during the study.

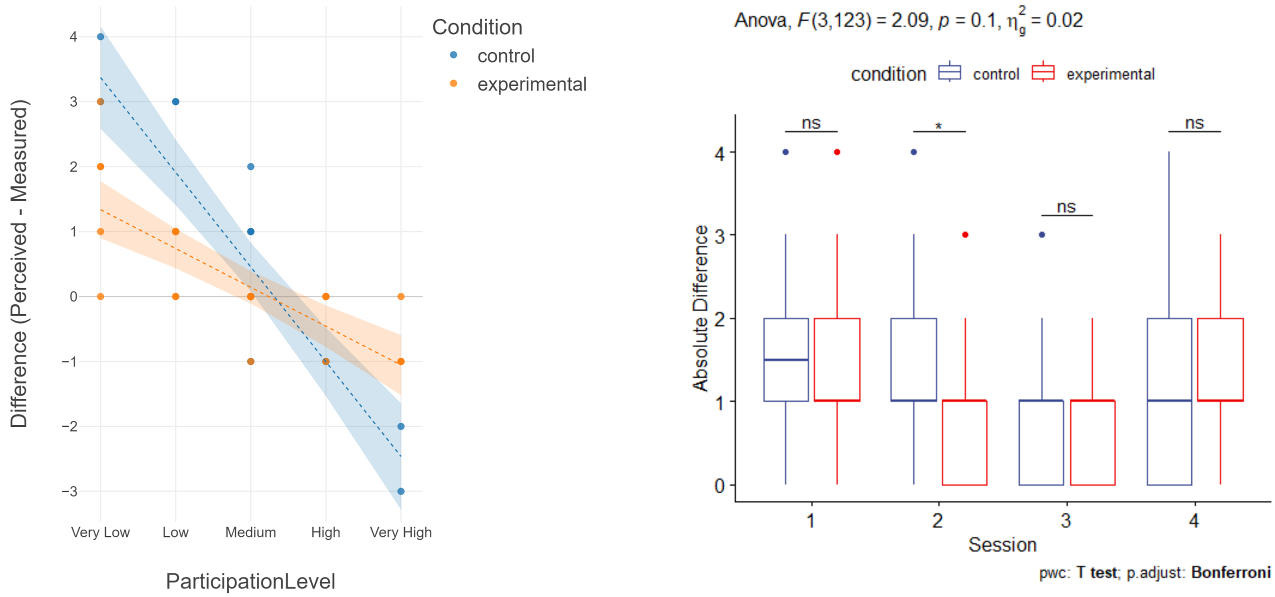
values between 1 and 5, and the absolute difference between participant estimates and device measurements was calculated. Most participants assessed their participation as middle range in the first session, causing larger absolute differences for under-participants (participants that receive a final signal of low or low alert) and over-participants (participants that received a final signal of high or high alert) in both conditions. However, in the second session, the experimental group's difference decreased, while the control group remained unchanged (see Figure 6a).

A mixed ANOVA found no overall interaction between session and condition [$F(3,123) = 2.09, p = 0.1$]. However, the main effect of the variable session was significant [$F(3,123) = 6.43, p < 0.001$], warranting further investigation through pairwise tests. t-tests (with p-values corrected using the Bonferroni method) found that the difference between perceived and actual participation was significantly lower for the experimental groups ($M = 0.70, SD = 0.78$) than for the control groups ($M = 1.38, SD = 1.20$) during session 2 ($p = 0.022$). The differences were not significant in session 3 or 4 (see Figure 6b). These results corroborate the visual analysis.

We also compared estimation differences in the experimental group between individuals reporting low attention (rarely or sometimes) to the lights and those reporting high attention (often and always) in sessions 2 and 3. A t-test [$t(22.26) = -2.6, p = 0.016$] revealed a significant difference in estimation accuracy in favour of the high-attention participants, but only in session 2.

Finally, all participants were also asked to estimate the contribution of their teammates in the surveys at the end of each session. A paired t-test [$t(54) = 1.88, p = 0.033$] showed that individuals more accurately judged others' participation than their own in the first session. The accuracy in estimating others' participation revealed no significant difference between those exposed and not exposed to the feedback signal in any session, implying that the enhanced awareness affects only self-participation estimation. In sessions 2 and 3, the self-estimation in the experimental groups became numerically more accurate than the estimation of others, while the statistical difference persisted for the control group.

Addressing RQ2a, the results suggest that light signals do enhance participants' awareness of their speaking time. Participants who reported looking at the signals more frequently had a lower discrepancy between their perceived and actual levels of participation. Interestingly, despite accurate reporting by the system, misperceptions of participation levels existed in the experimental group, likely stemming from a choice to ignore the system's feedback. This could hinder the initiation of the self-regulation process, explaining why some individuals may not respond to the feedback as expected.



(a) Difference between perceived and measured (Session 2). **(b)** Mixed ANOVA and pairwise t-tests.

Figure 6. Analysis of awareness of the task. Graph (a) represents the difference between perceived participation and measured participation for experimental and control groups in session 2, showing a more accurate perception by the experimental group. Graph (b) is the result of the mixed ANOVA and pairwise t-tests. The pairwise t-tests show that the difference between perception and reality was significantly lower in the experimental groups, but only in session 2.

6.2 Setting Goals

In our analysis of the goal-setting stage of self-regulation, we focused on understanding the decisions learners made after becoming aware of their participation levels. In the post-surveys following sessions 2 and 3 for the experimental groups, we included an optional open-ended question: "Can you indicate on one or more occasions that the light influenced your behaviour?" We applied qualitative coding to 38 responses, paying particular attention to those that mentioned their behavioural goals. As outlined in Section 3, the goals we expected to see were either "speaking more" or "speaking less." Among the 38 responses, "speaking more" and "speaking less" were identified as goals three and six times, respectively. Additionally, seven responses were either "No" or "Not this time," which we coded as "no decision."

Following this analysis, we conducted a comprehensive review of additional data related to these participants. This included their performance over time, their estimates of peers' speaking times, their responses in pre-surveys, and even the performance and responses of their team members. Our objective was to uncover potential variables influencing their goal-setting behaviours, such as prior knowledge, motivation, and the impact of social behaviours from others. By integrating all this information, we were able to discern the following decisions made by the learners.

6.2.1 Expected Choices

Over-participators aimed to speak less, and under-participators intended to speak more, reflecting changes in light signals, evidenced by statements like, "In the end, when I saw my light become smaller, I tried my best to speak more" (S22) and "I tried talking less after seeing the status of my light." (S50).

6.2.2 Disengagement Choices

Seven out of 38 respondents indicated that the lights didn't influence their behaviour with replies such as "not particularly" (S54) or "not in this session" (S53). To understand why participants chose to disengage, we first examined their pre-survey responses. This analysis unexpectedly showed no clear patterns: participants all valued equal participation, with no consistent differences in their English proficiency, comfort in discussions, or personality traits. However, a more nuanced understanding emerged when we integrated information from post-surveys, session transcripts, and log data, including data from team members. This holistic analysis revealed several key factors influencing participants' decisions to disengage.

At the individual level we observed the following factors:

- **I know better.** Some participants manifested confidence in their own judgment, feeling that their assessment was superior to the system's. For instance, S5 explained, "It did not influence me anymore this time. I just spoke, following my own feelings.”

- **I am doing perfectly.** Some participants, like S54, believed that their level of participation was already appropriate: “Not particularly, I was always speaking the right amount,” indicating a choice to disengage from the light signals.

At the group level, we observed these factors:

- **Team dynamics.** Three participants from the same group reported no influence from the lights in session 3. These participants also mentioned that they had invited an under-participating team member to contribute in session 2. The consistent low participation of the invited member may have led them to stop their inclusion efforts by session 3, contributing to disengagement choices.

At the temporal level, these factors revealed themselves:

- **Novelty effect.** In session 3, over one third (seven out of 18) reported no influence from the lights, with none reporting this in session 2. Some even specifically mentioned “not really this time” (S41) or “not in this session” (S53), indicating their awareness of their behaviour evolving across sessions. It is unsurprising that among these seven participants, five mentioned a decrease in how often they looked at the light signals from session 2 to 3. Collectively, these pieces of evidence suggest the possibility of a novelty effect in session 2 that waned by session 3.

6.2.3 Other Choices

In terms of behavioural change, we observed some unexpected alterations in response to the feedback system. For example, S5, an under-participant, reported, “I saw it was blue and tried to speak less.” This reveals a misinterpretation of the small blue light signal, leading to an incorrect adjustment in their participation.

6.2.4 Implications for Research Question 2b

In answer to RQ2b, the expected goal—adjusting speaking according to signals—is not the sole or predominant choice. A nuanced exploration revealed diverse goals and degrees of engagement with the self-regulation process initiated by the lights, clarifying the lack of expected generalized behavioural changes.

6.3 Strategies

In analyzing strategy adoption, we applied the same analysis procedure as before. Our initial focus was on the qualitative coding of responses categorized as “strategy,” identifying 13 out of 38 in this category. We then conducted a detailed cross-reference with other data sources for these participants, including transcript analysis, performance tracking over time, responses to survey questions, and team members’ data. This comprehensive method provided clear insights into the strategies learners chose and their underlying reasons.

6.3.1 Expected Choices

Several strategies were discerned from the participants’ responses:

- **Active listening.** Three learners explicitly mentioned employing this strategy. For instance, S19 stated, “I tried actively listening more and asking my group about their opinions when I noticed my light indicated that I was speaking too much.” Transcript analysis confirmed these behaviours. Notably, S19 used affirming phrases like “You are right,” while S11 frequently asked questions for clarification.

- **Talking more efficiently.** This was explicitly mentioned by two learners who aimed to communicate more succinctly, as expressed by S18, “Talked more efficiently when I was in the blue.” Pre-survey responses revealed that learners using this strategy generally had lower English-speaking confidence.

6.3.2 Disengagement Choices

There were instances where participants had intentions to change but lacked strategies. For instance, S41 indicated that “The light made me feel like I needed to speak more, even though I didn’t have much to add as my point was already conveyed.” This observation highlights that a simple feedback system may not universally provide actionable guidance, suggesting a need for complementary training.

6.3.3 Other Choices

Some learners aimed to attain the correct light signal rather than making meaningful contributions. S5 indicated, “When I don’t get enough light, I positively try to speak more even just casually chatting,” revealing a focus on manipulating the system’s simplicity rather than engaging genuinely.

6.3.4 Implications for Research Question 2c

In response to RQ2c, this exploration of strategies reveals a more complex situation than first presumed. The choice of strategy is significantly shaped by an individual's pre-existing knowledge and abilities in communication. While some participants employ sophisticated strategies like active listening, others, despite recognizing a need for adjustment, seem to be at a loss regarding which approach to adopt. Those without a clear path for enhancement may either withdraw from the self-regulation process or resort to simply trying to manipulate the system. These insights cast additional light on the possible reasons for the lack of general effectiveness of the feedback system.

6.4 Behavioural Adaptations

In our individual-level analysis of the experimental group, only seven out of 24 participants achieved the intended behavioural adaptation goals of maintaining medium participation levels in sessions 2, 3, and 4. Further examination of various data sources revealed diverse patterns and reasons behind adapting (or not adapting) their behaviours.

6.4.1 Expected Choices

Among the seven participants who met the self-regulation goals, six consistently made expected choices guided by the light signals. For instance, S39, who initially participated less, achieved medium-level participation in later sessions, responding effectively to a low signal with better speaking time management and active listening.

6.4.2 Disengagement Choices

In the experimental groups, among those participants who did not exhibit the expected behaviour (14 out of 24), we identified the following disengagement choices:

- **Failure to invite others.** In our individual-level analysis, six participants reported inviting others to speak more during discussions. Yet, those invited did not show increased speaking time. Transcript review revealed that while questions were asked, they were general and not specifically directed at the less active members. This suggests that the group's efforts to include quieter members did not effectively boost their participation.
- **Team dynamics.** At the team level, team dynamics plays a crucial role. For instance, S22, who usually participated less, mentioned that they tried to increase their speaking when seeing the light signal but found it challenging. A deeper look into their team revealed that one member dominated the discussions. This member, despite being highly active, expressed dissatisfaction with team collaboration and was hesitant to work with the team again. This suggests that dominant members might be speaking more, possibly to fill in for quieter members like S22, rather than out of a genuine desire to contribute. Such imbalances illustrate the complexity of team dynamics and its significant impact on individual participation.
- **Novelty effect.** Temporally, a novelty effect was observed. Participants like S5 and S16 increased their participation to medium levels in session 2, responding to a low light signal, but returned to lower participation in later sessions. Their survey responses indicated diminishing engagement over time; they initially tried to speak more in session 2, but by session 3, they either followed their instincts or remained aware without active change. This pattern might reflect either brief attention to the light signals in session 2 or a struggle to develop lasting strategies for behavioural change.

These disengagement choices provide insights into the varied reasons participants might not align with the expected behaviour, highlighting the complexities of individual responses and group dynamics in the presence of feedback systems.

6.4.3 Other Choices

Interestingly, one participant, S53, deviated from the anticipated path. Initially an under-participant, they achieved medium levels in the subsequent sessions but reported the light signal as not useful in session 3, rarely observing the lights. This indicates that while S53 moved away from relying on the light signals, they might have employed another self-regulation mechanism. Supporting this idea, six out of 20 control group participants also successfully self-regulated their participation by session 4 without light signals.

6.4.4 Implications for Research Question 2d

In response to RQ2d, this reveals a spectrum of behaviours. While some participants in the experimental group indeed modified their participation according to the expectations, this wasn't the predominant behaviour. The light signals, in most cases, didn't cause a measurable impact on the participants' behaviours. However, it's crucial to note that this lack of widespread impact does not indicate the feedback system's failure, as evidenced by those participants who effectively leveraged the signals to hone their self-regulation in participation. The diversity in responses underscores the pivotal role of individual attention, knowledge, motivations, and beliefs in not only initiating the self-regulation process triggered by the light signals but also maintaining adherence to this process to enact tangible changes in participation behaviour. The varied responses emphasize the intrinsic complexity and individualized nature of behavioural adaptation in interactive environments.

7. Discussion

In this section, we summarize the findings of our study, discuss their implications, and propose directions for future designs. Additionally, we acknowledge the limitations of our research and consider how they may influence the interpretation and application of our results.

7.1 Implication of Findings

In the first part of our study, our repeated-measurement randomized control trial conducted in a laboratory setting failed to detect improvements in participation equality and self-regulation of participation, as well as a durable learning effect on the self-regulation of participation. This finding aligns with those discussed in Section 2, where prior studies also did not discover changes in equality levels (Kulyk et al., 2006; Bergstrom & Karahalios, 2007; Kim et al., 2008; Starr et al., 2018), or identified alterations in speaking time exclusively for specific subsets of the population (DiMicco et al., 2004; Bachour et al., 2010). While we did not observe significant differences in the behaviour of the control group (DiMicco et al., 2004), a numerical examination of our data (Figure 4a) indicates considerable variability in behaviour even among participants who did not receive the light. This variability is likely attributable to other mechanisms of self-regulation or the inherent variability of group dynamics.

Our answer to RQ1 is, therefore, by no means surprising, but confirmatory. In this respect, our study serves as an additional data point reinforcing the conclusion that the effect of these types of systems is uneven among participants. Given that our system was based on the same principles but employed different technologies than previous systems, an important implicit contribution of the response to RQ1 is the possibility that the basic premises and assumptions on which these types of systems operate may be flawed. With this premise in mind, redesigning systems does not necessarily involve improving technical aspects such as the type of measurement, analytics, or signal display. We propose that any meaningful redesign should be informed by a deeper understanding of the cognitive processes that occur between presenting information to learners and observing changes in their participation behaviour. For instance, instead of merely trying to increase the attention learners pay to the feedback signal by changing how this signal is presented (a technical change), a more effective approach would be to identify the cognitive and metacognitive barriers that prevent learners from picking up and using the signal. These issues should be addressed with a combination of pedagogical and technological changes to the intervention as a whole. The second part of our analysis was a first step toward identifying these barriers.

By attempting to triangulate occurrences within participants' cognitive and metacognitive processes using the various data sources captured in our experiment, we have uncovered several paths that significantly deviate from the expected behaviours. We found that the initial step to self-regulate participation—gaining awareness of one's own speaking time—is aided by paying attention to the feedback signals, a discovery also made by Bachour and colleagues (2010). For the feedback to be effective, learners need to pay regular attention to the signal, a behaviour exhibited by only one third of the exposed participants in our study. It is important to note that this lack of attention is due not to problems with the visibility of the signal but to the willigness of the participants to use the signal during the collaboration activity. For example, we observed the role of a novelty effect in participants' attention, with participants reporting more attention to the signal in session 2 than in session 3. Confirming the role of students' beliefs and motivation, Bachour and colleagues (2010) found their feedback to be significantly effective only for participants who believed that equal participation was desirable. Also, Strauß and Rummel (2023) found that different groups held different ideas about the optimal distribution of participation time. However, we did not identify a correlation between this specific belief and awareness or any other self-regulation step. Further research is essential to unravel the specific modulators of attention to participation feedback.

Regarding the second step—goal setting—we discovered that participants' choices do not necessarily align with the objectives of the feedback system. Participants who disengaged decided either that they did not see the need to change or that their assessment of their contribution was more accurate than what the system presented. Choices to disengage due to a lack of belief in the system's accuracy were briefly noted by DiMicco and colleagues (2004) and Ochoa and colleagues (2023). We did not encounter open mistrust of the system. Instead, we found participants who were confident that their contribution was either sufficient or necessary. Once again, we observe that the path taken in this specific self-regulation process is heavily influenced by individual motivations and beliefs.

The selection of strategies also provided insights into the reasons why learners disengage from the feedback. Learners may either lack knowledge of available strategies to regulate their participation or lack the skills needed to translate their chosen strategies into effective actions. While this is a novel finding for this type of system, it is a known point of failure in SRL processes (Pedrotti & Nistor, 2019; Patel et al., 2015). Addressing this issue requires direct instruction or guided practice.

This prompts us to reconsider the role of these feedback systems: they are not standalone solutions but components of a more comprehensive educational intervention.

Finally, an analysis of the actual adaptations revealed the great variety of paths taken by participants, and how motivational factors (novelty effect), individual factors (failure to apply strategies), or group factors (team dynamics) derail them from the expected paths. However, this analysis also shows that these types of systems can and do work as intended when their goals align with those of the self-regulation process of the participants (Bachour et al., 2010).

A comprehensive response to RQ2 is intricate and multifaceted, and our investigations have merely begun to unravel its complexities. Beyond these initial findings, the unique contribution of this study to the learning analytics community lies in proposing new avenues for better evaluating and redesigning these systems. Instead of focusing on measuring the immediate effect of the external feedback loop on the regulation of participation, our study emphasizes the importance of understanding the SRL processes triggered by external feedback. These processes, in turn, affect not only the immediate regulation but also its acquisition as a durable skill. This shift underscores the importance of exploring the intricate interplay between individual cognitive and metacognitive processes and external feedback stimuli, highlighting the necessity to delve deeper into the internal mechanisms that mediate behavioural adaptation in the presence of learning analytics information.

7.2 Limitations

The findings presented should be understood in light of the study's limitations. Here, we discuss the most important limitations and their effect on the interpretation of the study's findings:

- The controlled experiment was conducted in a laboratory, with participants, not real learners, and as such, it cannot be considered an ecologically valid setting. In this study, contextual and social factors such as motivation, time constraints, familiarity among participants, and even noise levels are not similar to those found in a typical learning experience. Furthermore, various contextual factors such as learning design, teacher expectations, and assessment requirements could also influence learner motivation and beliefs. The discovered paths followed by participants and their rationale, especially for awareness, goal setting, and strategy selection, should be considered as a sample of what is expected to be a more diverse set in real learners.

- The synthetic nature of the collaborative activity could also have tinted the results. This effect was demonstrated by the decreasing amount of time invested in later sessions. While the use of synthetic activities was also a limitation of previous studies and, as such, does not affect the confirmatory nature of the answer to RQ1, it impacts the answers to RQ2. This effect mainly reduces the motivation to engage with the feedback signal and limits the range of self-regulation paths that could be observed.

- The limited exposure to the feedback signal—during only two sessions—may not have been sufficient for participants to learn how to self-regulate their participation and adapt their participation behaviours on their own. The findings concerning the fourth session of the experiment should be considered as an initial exploration into measuring a learning effect in these types of systems.

- As an experimental study focused on "what went wrong," this work cannot offer direct guidelines on how to improve these systems. It mainly highlights issues that are important to address. More design-oriented studies, such as a DBR study that explores the interplay between pedagogical and technological factors and individual factors, could offer more valuable insights in this respect.

As stated before, the purpose of this study was to start unpacking the mostly overlooked complexity of what appear to be simple feedback systems for collaboration. Fully unravelling this complexity requires much more than just one study, or even just one research approach. As such, the findings of this work should be interpreted not as definitive answers but as conversation starters for interested researchers.

8. Conclusions and Further Research

This investigation is an initial step toward deeply understanding the complexities of the SRL process triggered by the feedback provided by CLA tools designed to support the self-regulation of participation. The uneven effectiveness of these types of systems in achieving equality in participation, observed in previous studies, was corroborated. More important, through a mixed-methods examination of the paths followed by participants in their internal SRL process, our findings provide a plausible explanation for why these feedback systems appear to be ineffective for a substantial segment of the participants.

Due to the context in which this experiment was conducted, the paths found, both expected and unexpected, are only a sample of those that should be present in a real learning environment. In such an authentic environment, additional pedagogical, motivational, and social factors will add complexity to the internal SRL process but could also provide solutions to improve the effectiveness of the intervention beyond technical approaches. Further research for the redesign of these systems should be human-centred and take a holistic pedagogical, technological, and social approach.

Perhaps the most general insight from this study for the broader learning analytics community is the recognition that the study of feedback systems should not stop at the point of delivery. While the effectiveness of such systems depends on their technical qualities, such as accuracy, visibility, and clarity, this work exemplifies that how individual students interpret and process that feedback ultimately determines if the system will fulfill its purpose. The cultivation of feedback literacy (Carless & Boud, 2018) among learners and the bolstering of their SRL processes post-feedback delivery (Heikkinen et al., 2023) emerge as intriguing and potentially more fruitful paths of exploration and research. The exploration of these avenues could pave the way for more holistic, integrative approaches in learning analytics, focusing on the learner's journey and experiences.

Declaration of Conflicting Interest

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