Investigating the Relationship between Learners' Metacognitive Strategies and the Use of Conversational AI

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Abstract

Recent trends indicate a decline in student learning outcomes; however, the use of metacognitive strategies can enhance them. In turn, collaborative learning can increase metacognitive strategy frequency. This study investigated what metacognitive strategies students display when collaborating with and without Clair, a conversational agent, and whether learners were more aware of metacognitive strategies after working with Clair. This study aimed to gain insights into designing AI to better support students' metacognitive strategies and ultimately enhance learning outcomes. The research questions thus were to explore learners' metacognitive strategies without AI support, and their metacognitive strategies in interactions with AI. Thirty participants (N = 30), recruited through a convenience sample, completed the study in the online Go-Lab environment. Participants were asked to fill in a pre- and post-intervention questionnaire measuring metacognitive awareness and engaged in two peer discussions, first without and then with Clair. Qualitative analysis assessed Metacognitive Strategy use across both discussions, while quantitative analysis measured differences in Metacognitive Awareness. The key findings were that Monitoring was the most frequently used strategy in both conditions, a slight decrease in overall strategy frequency was observed with Clair and a significant increase in Planning awareness post-intervention was found via the Metacognitive Awareness Inventory. This research did not find sufficient evidence to support Clair's impact as a teaching support tool, as Clair did not seem to positively impact metacognitive strategy frequency in learners. Future research should explore modifying Clair to include more strategic prompts, explore longer sessions and additional data collection methods (e.g.: think-aloud or retrospective protocols) to better capture strategy usage.

Keywords: conversational agent, clair, metacognitive strategies, metacognitive awareness, collaborative learning, education

Introduction

In recent years, students increasingly showcased unsatisfying learning results. Overall, the Dutch Program for International Student Assessment (PISA) results from 2022 show that 15-year-old students in the Netherlands need to improve in natural sciences as well as reading skills, as 25% of students achieve dissatisfactory results in natural sciences and 33.3% dissatisfactory results in reading skills (PISA, 2022). Thus, a better understanding of how to help students regulate their own learning progress and give them tools to do so plays an important role in the learning progress of students. Research suggests that regulating one's cognitive processes, by using metacognitive strategies, improves problem-solving and writing abilities (Moshman and Schraw, 1995; Balloo et al., 2020). Facilitating the usage of metacognitive strategies is therefore desirable to achieve better learning outcomes (Bannert et al., 2015; OECD, 2019).

Metacognition is the process of thinking about thinking, so reflecting on, understanding and controlling one's learning is called metacognition (Schraw & Dennison, 1994). It is a broad mental concept that commonly is divided into metacognitive knowledge and metacognitive strategies, the regulation of cognition (Veenman, 2013, Schraw & Dennison, 1994).

Metacognitive strategies refer to the active regulation of one's cognitive processes, which includes planning, monitoring and evaluating (Clarebout et al., 2013; Veenman, 2013). However, there is controversy on the interchangeability of terms for metacognitive strategies, as no unified definition seems to be established yet (Azevedo, 2020). Furthermore, there is an ongoing discussion on how to establish a comprehensive definition of metacognitive strategies if it is supposed to be inclusive in all aspects, such as different learning environments (e.g., VR, AI) and incorporating different concepts, for example, conscious versus automatic metacognitive processes (Azevedo, 2020).

Recent developments in AI have brought forth the use of generative and conversational AI, the latter focusing on improving human-to-machine interaction by using natural language processing (NLP) (Nucci, 2025). Clair (Collaborative Learning Agent for Interactive Reasoning) is a conversational agent that can be used to create prompts to encourage productive collaborative learning, specifically in group discussions (de Araujo et al., 2024). As a potential teaching tool possibly facilitating metacognitive strategies, it will be investigated in the current study.

Conversational AI is becoming a more frequently used tool, especially in higher education (Venter et al., 2024). Currently, AI is mainly used in research as opposed to in teaching, though a multitude of advantages can be gained by using AI in research and teaching (Venter et al., 2024). Teachers are restricted by limited time and availability for each student, so having conversational AI as a tool to act as a tutor or discussion partner could offer students support outside of the traditional classroom (Schofield et al., 1994; Holstein et al., 2019). However, the effect of using conversational AI on learning outcomes differs depending on which AI is used (Zhang & Pan, 2025). It is therefore important to consider each AI agent individually for its hypothesised effectiveness in increasing metacognition.

Using conversational AI that is tailored to educational goals such as self-regulation as seen in metacognitive strategies, AI can be used to monitor and evaluate one's learning (Chang et al. 2023). While self-regulation is a different theory, metacognitive strategies are an important component of the feedback loop of self-regulated learning, which leads to some overlap in research (Leopold & Leutner, 2015). This feedback loop consists of planning, monitoring and judging ones working progress, thus good metacognitive strategy skills are crucial for effective self-regulation. A shared understanding and policy of conversational AI that could be used in educational settings needs to be developed, so that the benefits of conversational AI as a tool to enhance metacognition in students and ultimately better learning outcomes can be achieved (Venter et al., 2024; Chang et al., 2023).

Previous research has investigated how metacognition can be enhanced through collaborative learning and how different conversational agents can facilitate better discussions between learners (Azevedo, 2020; Chang et al., 2023; Çini et al., 2023). However, little is known about the effectiveness of collaborative AI, such as Clair, in the usage of metacognitive strategies specifically. In light of this, the study aims to investigate the relationship between metacognitive strategies of learners and their use of conversational AI, by analysing the types of metacognitive strategies learners display when interacting with conversational AI. Metacognitive strategies, collaborative learning and the collaborative learning agent Clair will be discussed in more detail.

Theoretical Background

Metacognitive Strategies

Schraw and Dennison (1994) developed a comprehensive questionnaire to measure metacognitive awareness, called Metacognitive Awareness Inventory (MAI). Metacognitive awareness describes a student's awareness of their metacognitive knowledge and strategies (Çini et al., 2023). First, the strategy of *Planning* involves setting goals, allocating resources such as time spent on a task prior to starting it and planning the learning process. The second strategy is *Information Management*, which includes skills and strategies used to efficiently process information. It can include strategies such as organizing, elaborating or summarizing. Thirdly, *Monitoring* consists of assessing one's learning and the strategy used. Schraw and Dennison (1994) added a fourth strategy called *Debugging*, which includes strategies used to correct comprehension and performance errors. Lastly, *Evaluation* as a metacognitive strategy includes analysing one's performance and strategy effectiveness after a learning session.

Moshman and Schraw's (1995) research elaborates on three essential metacognitive strategies, namely *Planning*, *Monitoring* and *Evaluation*. They defined *Planning* in the same manner as when measuring the metacognitive awareness mentioned above. In particular, older, more experienced learners, specifically regulate their learning *before* they start a task. *Monitoring* is explained as one's online awareness of comprehension and task performance, so, for example, periodic self-testing. Finally, *Evaluation* includes the appraising of the products and regulatory processes of one's learning, thus re-evaluating one's goals and conclusions.

Likely due to the unclear definition of metacognitive strategies mentioned, some researchers did not divide monitoring and debugging, therefore monitoring sometimes includes consistently regulating their learning when difficulties occur (Sobocinski et al., 2023). According to Sobocinski et al. (2023), metacognitive monitoring can be captured via think-aloud protocols, which require verbalization of one's thought process from the learner while working on a task. However, they caution that possibly not all metacognitive monitoring processes are verbalised and other metacognitive strategies, such as planning might not be captured. While Sobocinski et al. (2023) worked with VR environments, not AI, their findings showed that by integrating measures such as cognitive load in the learning environment, personalised support for learners' self-regulated learning needs is possible. According to Zimmerman (2013), students with better self-regulation use strategies such as goal setting, monitoring their learning, and evaluating their

progress based on personal feedback to faster gain good learning outcomes and stay motivated to learn. While his focus is self-regulated learning, there is an overlap in the description of terms with metacognitive strategies. Metacognition itself is not directly observable as it is an internal process. Nevertheless, it can be measured by analysing the metacognitive strategies that learners display and through, for example, communication with others (Çini, 2024, p.30). Therefore, it is important to analyse what metacognitive strategies students use when working with AI and if it can better facilitate the usage of metacognitive strategies, especially because students can struggle to recognize the need to use more metacognitive strategies (Azevedo, 2020).

For university students, the importance of using metacognitive strategies only increases and it is expected that they seek help on their own (Schworm & Gruber, 2011). However, according to Schworm and Gruber (2011), many students fail to seek help independently. They found that a simple tool such as giving prompts can encourage the students to seek help and thus learn more efficiently and ultimately receive better learning outcomes. When help-seeking was achieved, more active discussions, critical reflection and other learning strategies could be observed. On the other hand, help-seeking alone is not enough to achieve desirable learning outcomes (Azevedo et al., 2004). Students who use a multitude of metacognitive strategies achieved better learning results than students who mainly asked for help but did not actively monitor their learning progress. Examples of effective learning strategies could be planning one's learning by creating sub-goals, planning time and effort put into tasks, activating prior knowledge and monitoring one's understanding (Azevedo et al., 2004). As the number of university students increased by 75.900 students from 2016 to 2022, there is arguably also a growing need for students to effectively use metacognitive strategies in order to develop their independent learning (Statista, 2023).

Benefits of Collaborative Learning

In collaborative learning, students work together towards a common goal, however, they largely need to plan and structure their work progress themselves (Major, 2020). In other words, collaborative learning requires more metacognitive awareness than other less flexibly structured group environments. According to Major (2020), there are three essential features of collaborative learning. First, discussions need to be structured to some extent, like a clear end goal by the end of the discussion or prompts while discussing. Second, active participation from

each student throughout the discussion is expected. Third, an effect on the learning outcome must be recognizable.

Metacognitive awareness can exist on different levels, namely at an individual level, at a social level and at an environmental level (Çini et al., 2023). The individual level consists of the already discussed metacognitive awareness one needs for successful self-regulated learning. At the social level, learners interact with each other through written and spoken language or facial expressions. Lastly, the environmental level describes the interaction with a learning environment, such as feedback or prompts. Successful collaboration depends on learners' individual metacognitive awareness and if they're able to transfer metacognitive strategies to working with the group (Järvelä et al., 2013). In other words, learners with better self-regulation could better support other group members and thus work more efficiently in collaborative learning.

However, at a social level, a group is considered one agent, thus the metacognitive awareness of the whole group as one is measured (Çini et al., 2023). Groups regulate their collaboration by using metacognitive strategies like planning, monitoring and evaluating their learning progress together (Näykki et al. 2017). Collaboration seems to facilitate metacognitive awareness, as students working in collaboration have a better understanding of how they should work on a task (Çini et al., 2023). Collaborative learning thus seems to be twofold: the individual's metacognitive awareness impacts the successful group work and collaborating facilitates the use of metacognitive strategies in turn.

Collaborative learning enhances the knowledge-gaining process and understanding of the learning material by learners discussing current understanding and developing new ideas (Çini et al., 2023). Feedback is a common form of interaction within a learning environment and enables the learners to evaluate their learning progress (Çini et al., 2023). Additionally, receiving feedback on one's learning progress can increase one's accuracy of self-judgement on performance (Papadopoulos et al., 2021). Students have that exchange when working in groups, but a long-term goal in the development of conversational AI is to create a learning environment that encourages students to access metacognitive skills effectively by acting as an additional team member or tutor, that prompts students to use metacognitive strategies but more insight into the effectiveness of specific AI is needed (de Araujo et al., 2024; Edwards et al., 2024).

Conversational Agents in Collaborative Learning (Clair)

Clair (collaborative learning agent for interactive reasoning) is a conversational AI that can be used to create prompts to encourage productive collaborative learning, specifically in group discussions (de Araujo et al., 2024). The prompts used by Clair were developed using the Academic Productive Talk framework (APT) and are based on Michaels and O'Conners's (2015) Four Goals of Productive Discussion (FGPD) (Michaels & O'Conners, 2015; de Araujo et al., 2024). The FGPD are designed to guide discussions efficiently in a learning environment and consists of:

(1) Helping individual students share their own thoughts

(2) Helping students orient to and listen carefully to one another

(3) Helping students deepen their reasoning

(4) Helping students engage with others' reasoning

The eight APT talk moves Clair uses were developed to help students achieve the FGPD goals (de Araujo et al., 2024). Namely, Clair's talk moves are "*Recapping*", "*Add-on*", "*Rephrasing*", "*Agree/Disagree*", "*Linking contributions*", "*Building on prior knowledge*", "*Example*", and "*Expand reasoning*". According to de Araujo et al. (2024), Clair can facilitate the use of some FGPD goals, such as elaboration and engaging with each other's reasoning. Additionally, the presence of Clair led to more active group discussions (de Araujo et al., 2024). Clair can therefore be considered an effective conversational AI in collaborative learning and can act as a tutor in giving prompts. It is important to note that the APT framework is specifically designed to enhance productive dialogue, not to elicit metacognitive strategies (de Araujo et al., 2024). Therefore, while there is evidence for the positive impact Clair has on facilitating FGPD goals, which metacognitive strategies as defined by Schraw & Moshman's (1995) metacognitive regulation components students use due to Clair's presence are less researched. A better understanding of whether Clair, with its current design using the APT framework, is a useful tool for enhancing students' metacognitive strategy usage is needed. This can be gained by researching which metacognitive strategies learners use in a collaborative learning environment while being prompted by an AI.

Current Study

There seems to be little available research on what specific metacognitive strategies student learners display when interacting with conversational AI. While previous studies show a

positive effect of collaborative learning on metacognitive awareness, the impact of feedback on self-judgment, and the effectiveness of Clair on productive group discussions, what metacognitive strategies are used is less clear. This study therefore aims to research what metacognitive strategies students display when collaborating with and without Clair. Additionally, as the literature suggests using multiple metacognitive strategies facilitates better learning outcomes, and effective group discussions prompt using metacognitive strategies, this study will research if learners are indeed more aware of metacognitive strategies they can use after working with Clair. By doing so, this study aims at gaining insight into designing AI to better support student's metacognitive strategies and ultimately enhance learning outcomes. The following research questions were addressed:

RQ 1: What metacognitive strategies do learners employ in peer discussions without conversational AI to regulate their learning progress?
RQ 2: What metacognitive strategies do learners employ when interacting with conversational agents to regulate their learning progress?

Method

Participants

Participants (N = 30; M_age = 23.23, SD = 2.02) were recruited through convenience sampling, using the University of Twente's online subject pool (Sona) and direct outreach via WhatsApp and in-person invitations. The data collection of this study consisted of 17 Males and 13 Females. (Highest level of education = High school = 11, MBO/Abitur = 3, HBO/Applied Sciences = 2, Bachelor = 11, Master = 3, PhD/Doctorate = 0). Participants came from diverse national backgrounds, including Dutch (n = 18), German (n = 4), and others (e.g., Norwegian, Chinese, Japanese). The experiment was carried out online in March and April 2025, using Microsoft Teams Meetings and the Twente Go-Lab system (de Jong et al., 2021). Informed consent was asked for at the beginning of the Go-Lab environment. Informed consent was acquired from all participants. The discussion tasks were completed in dyads (n = 15), to which participants with anonymous usernames were randomly assigned. The eligibility criteria to participate in the study were that they had to be at least 18 years old, have access to a working laptop or computer, be proficient in written English and be a student at the University of Twente.

While two students misreported their current occupation as pupil and part-time worker, their occupation was verified to meet inclusion criteria. The study was approved by the ethics committee of the University of Twente (nr. 250328).

Design

This study employed a within-subject mixed-methods design. Each dyad worked on two tasks: one without the AI agent Clair and one with Clair. The primary dependent variable was students' metacognitive strategy awareness, measured before and after the interaction with Clair. Quantitative changes were analysed using pre- and post-MAI scores, and qualitative analysis focused on strategy usage observed in chat interactions.

Materials

Go-Lab

This research was conducted in Go-Lab (de Jong et al., 2021), an online learning system where teachers can create their own inquiry-based learning environment (ILS). The participants could sign up for a timeslot in the Sona System or were manually scheduled by the researcher. They needed a laptop or computer to join the Teams Meeting, where they received the link to the Go-Lab environment. The Go-Lab environment included a collaboration tool, a chat box, a consent form, a pre- and post-study questionnaire, preparation material, and a demographic questionnaire.

Metacognitive Awareness Inventory (MAI). The Metacognitive Awareness Inventory (MAI; Schraw & Dennison, 1994) consists of two parts. To measure students' metacognitive awareness of metacognitive strategies, only the part regarding the regulation of cognition was used. The questionnaire had a total of 35 items, to which participants responded positively or negatively. The questions included 5 subcategories: *Planning*, *Information Management Strategies*, *Monitoring*, *Debugging Strategies*, and *Evaluation*. An example of an item in *Planning* is: "I think about what I really need to learn before I begin a task". An example of an item in *Information Management Strategy* is: "I slow down when I encounter important information". An example of an item in *Monitoring* is: "I ask myself periodically if I am meeting my goals". An example of an item in *Debugging Strategies* is: "I ask others for help when I don't understand something". An example of an item in *Evaluation* is: "I know how well I did once I finish a task". The construct validity was assessed with a factor analysis and was found to be good, with a variance of 78%. The coefficient alphas for items loading on each factor reached

.91, indicating a high degree of internal consistency. The coefficient alpha for the regulation of cognition reached .88 (Schraw & Dennison, 1994).

Preparation Material. All students were presented with the same preparation material created for this study, which was related to the topic of climate change. It consisted of background information about climate change, a short text about waste management, ocean pollution and its environmental impact, an approximately 3-minute video about ocean pollution, and a knowledge quiz containing 4 multiple choice questions regarding information from the text and video.

Discussion Topics. The Go-Lab environment included two collaborative discussion phases. Phase 1 (see Figure 1 for Discussion 1) without Clair and Phase 2 (see Figure 2 for Discussion 2) with Clair. Each Discussion Topic was created based on the Preparation Material created for this study and examples of pre-existing ILS (Pauli, 2025). One ILS was selected and used as an example to create Discussion Topics, which were built based on the ARCS model of motivation, focused on *attention*, *relevance*, *confidence*, and *satisfaction* (Keller, 2010). The resulting Cases included realistic examples and clearly defined tasks and goals, achievable within the time given.

Figure 1

Case Task for Discussion Topic 1

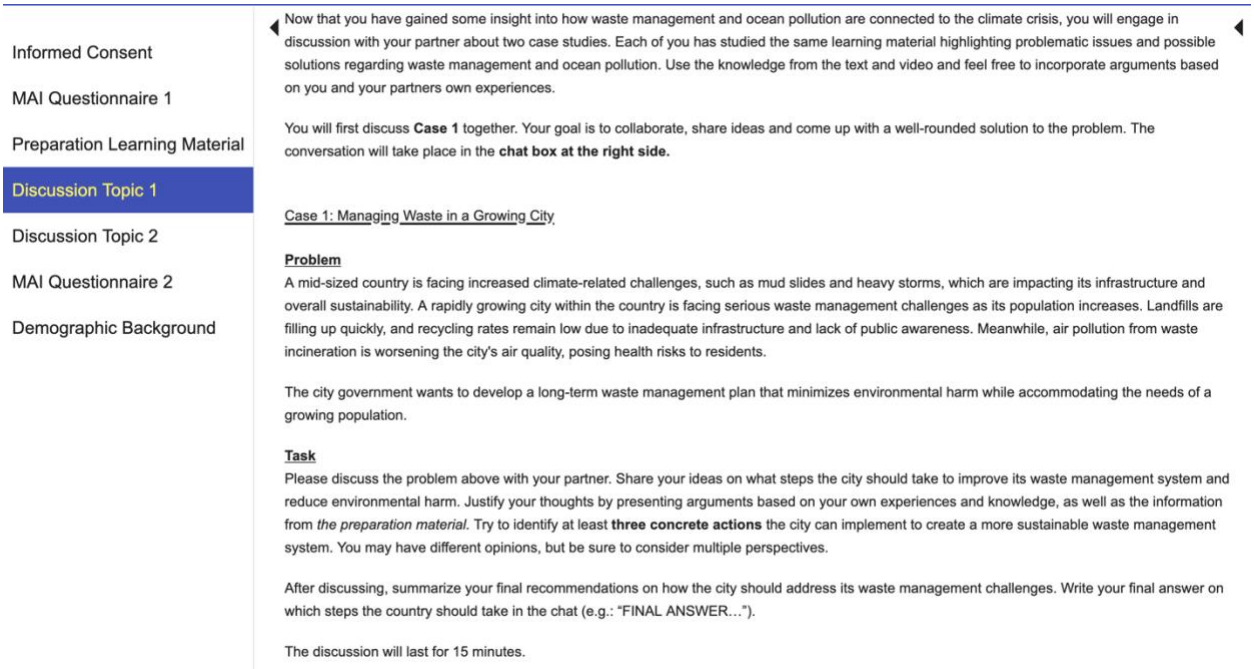
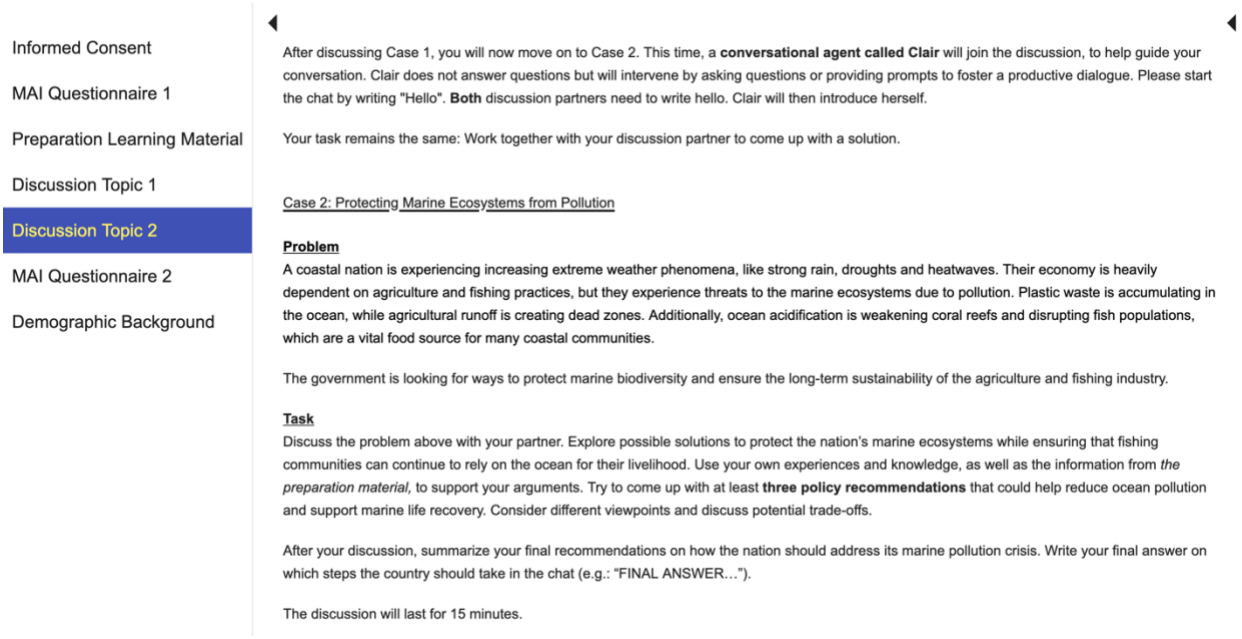


Figure 2

Case Task for Discussion Topic 2



Clair. In this study, the conversational agent Clair was used (de Araujo et al., 2024). Clair was included in Phase 2. Clair interacted with participants depending on relevant keywords (see Figure 3) or for example discussion balance. Keywords were selected based on relevant terms included in the preparation material or task formulation. Clair's prompts to facilitate discussions were based on the already mentioned APT Framework (see Table 1).

Figure 3

Relevant Keywords Used by Clair

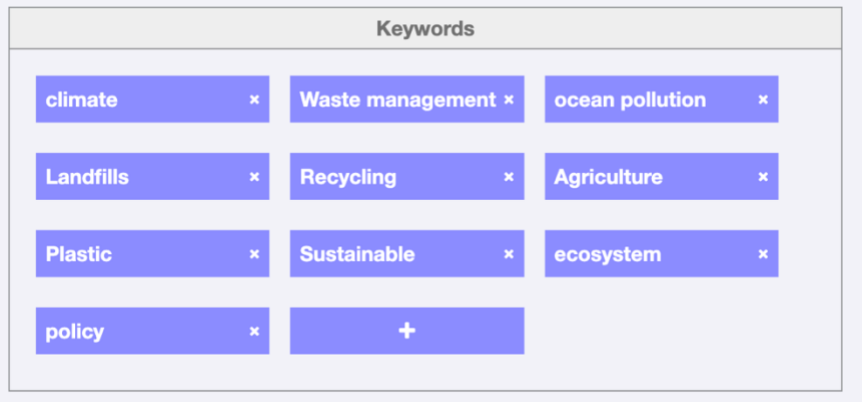


Table 1

APT Base Talk Moves of Clair

Talk Moves	Description Example
Build on prior knowledge	[<speaker>, how does this expand what <discussant> has said so far?]
Expand Reasoning	[<speaker>, could you please elaborate more on this?]
Agree / Disagree	[<discussant>, do you agree or disagree with your partner?]
Linking Contributions	[<discussant>, how do your ideas align with what <speaker> just said?]
Recapping	[This conversation is interesting. Would any of you be able to give a brief summary of what you've covered so far?]
Example	[<speaker>, could you give an example?]
Rephrasing	[<discussant>, could you put in other words what your partner just said?]
Add-on	[<discussant>, would you like to add something to what your partner just said?]

Procedure

To ensure that the dyads completed each phase of the experiment synchronously, they were asked to join a Microsoft Teams Meeting. They exclusively used the chat there to communicate technical questions and the completion of tasks. To start the experiment, participants were asked to log in with their assigned username (e.g. Participant A). Furthermore, participants read the information sheet and provided informed consent (see Appendix A for informed consent), completed the MAI questionnaire 1 (see Appendix B for MAI questionnaire), and studied the preparation material (see Appendix C for preparation material). All three sections were completed individually, within 15 to 20 minutes. Within that time, participants were grouped in dyads. The grouping was done alphabetically; thus, participant A was grouped with participant B. After completing the first individual section, Discussion Topic 1 (Phase 1) was made available to the participants (see Appendix D for Discussion Topic 1). They were asked to read the problem statement and task of Case 1 and discuss their ideas in the chat box on the right side. Discussions took place synchronously, and participants could solely communicate through the chat. They had 15 minutes for Phase 1 and were reminded shortly before the end to finish

their discussion. Simultaneously, Phase 2 was prepared by enabling Clair. After completing Phase 1, Discussion Topic 2 (Phase 2), was made available to the participants, where they had to discuss Case 2 and come to a joint answer to the task in the chat box (see Appendix E for Discussion Topic 2). This time, Clair was present in the chat box and prompted them with talk moves, to help facilitate productive discussions. They again had 15 minutes for Phase 2 and were reminded shortly before the end to finish their discussion. Lastly, they were asked to proceed with the second individual part and fill in the MAI Questionnaire 2 and the demographic questionnaire (see Appendix F for the demographic questionnaire).

Data analysis

After the data collection was completed, the data was exported from Go-Lab and prepared for analysis. For the qualitative analysis, the chats of Phase 1 and Phase 2 were imported into Atlas.ti and coded based on Schraw and Moshman's metacognitive regulation components (see Table 3 for the Codebook). Due to time constraints in the set-up of the study, coding consistency was ensured through intra-rater reliability, which can be described as inter-replicate reliability done by the same researcher coding each chat twice (Gwet, 2001).

Afterwards, the qualitative and quantitative data was imported into RStudio (Version 2024.12.1). For the quantitative analysis, MAI scores were calculated as the sum of affirmative responses per participant, after the parametric assumptions were checked. Subscale analyses were also conducted. Due to non-normality in MAI score distribution, a paired-sample Wilcoxon test assessed pre- and post-intervention differences.

Table 3

Codebook of Metacognitive Strategies

Metacognitive Strategies	Metacognitive Strategy Definition	Code	Description	Coding Indicators	Example Quotation

Planning	Students select the appropriate strategies and allocate resources that affect performance	NCP WCP	Students set goals, plan their strategy to accomplish the task, allocate time and resources *prior* to the task	- Goal Setting - Strategy planning - Allocating time *prior* to the task	"We need three concrete actions for waste management"
Monitoring	Students monitor their comprehension and task performance	NCM WCM	Student self-test their comprehen-sion during the task and self-test their performance during the task	- Statements of their current comprehension - Dis-/agreeing with statements - Questions to further their comprehension - Monitoring their resources (time) - Monitor their performance	"We are also still missing a third idea"
Evaluation	Students evaluate their learning process and results	NCE WCE	Students evaluate their performance, goals and conclusions	- Evaluating their performance - Evaluating their goals - Evaluating their conclusions	"I think that 1 and 3 are quite similar but think that that is oke"

Note. NC = No Clair; WC = With Clair. Example Quotations are taken from the collected data.

Results

Table 4 gives an overview of the frequencies of metacognitive strategies displayed by participants in all discussions of Phase 1 (without Clair). In these discussions, *Monitoring* is notably the most frequently displayed metacognitive strategy (M = 6.3, *SD = 2.98*). In total, the participants displayed 225 metacognitive strategies (M = 2.51, *SD = 3.25*). Table 5 gives an overview of the frequencies of metacognitive strategies displayed by participants in all discussions of Phase 2 (with Clair). *Monitoring* was the most frequently occurring metacognitive strategy again (M = 6.56, *SD = 2.41*). In total, the participants displayed 222 metacognitive strategies across all discussions of Phase 2. Clair contributed 62 times within the 15 Chats of Phase 2 (M = 4.13, *SD = 1.72*).

Table 4

Frequency of Metacognitive Strategies in Phase 1

	No Clair		
	M	*SD*	N
Planning	0.33	0.47	10
Monitoring	6.3	2.98	188
Evaluation	0.9	0.92	27
Total	2.51	3.25	225

Table 5

Frequency of Metacognitive Strategies and Clair Interventions in Phase 2

	With Clair		
	M	*SD*	N
Planning	0.2	0.48	6
Monitoring	6.56	2.41	196
Evaluation	0.66	0.71	20
Clair	4.13	1.72	62
Total	2.47	3.26	222

To provide further qualitative evidence, chat transcript excerpts were included. In Figure 4, example chat transcript excerpts of Planning, Monitoring and Evaluation without Clair can be seen in that respective order. Figure 5 showcases chat transcript excerpts of prompted Monitoring and Evaluation. While Planning did occur with Clair present, Clair did not seem to prompt Planning directly, as can be seen in Figure 6.

Figure 4

Chat Transcript Excerpts of Planning, Monitoring and Evaluation in Phase 1

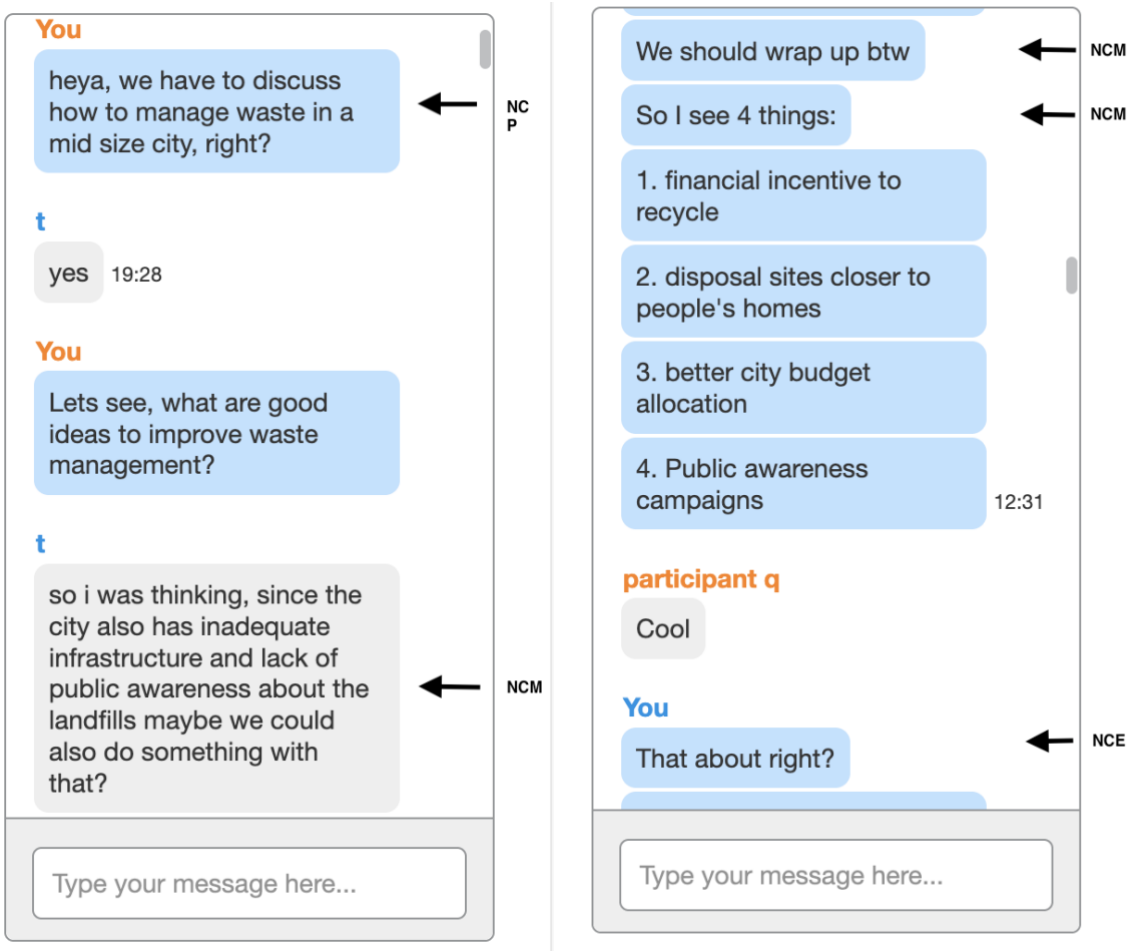


Figure 5

Chat Transcript Excerpts of prompted Monitoring and Evaluation in Phase 2

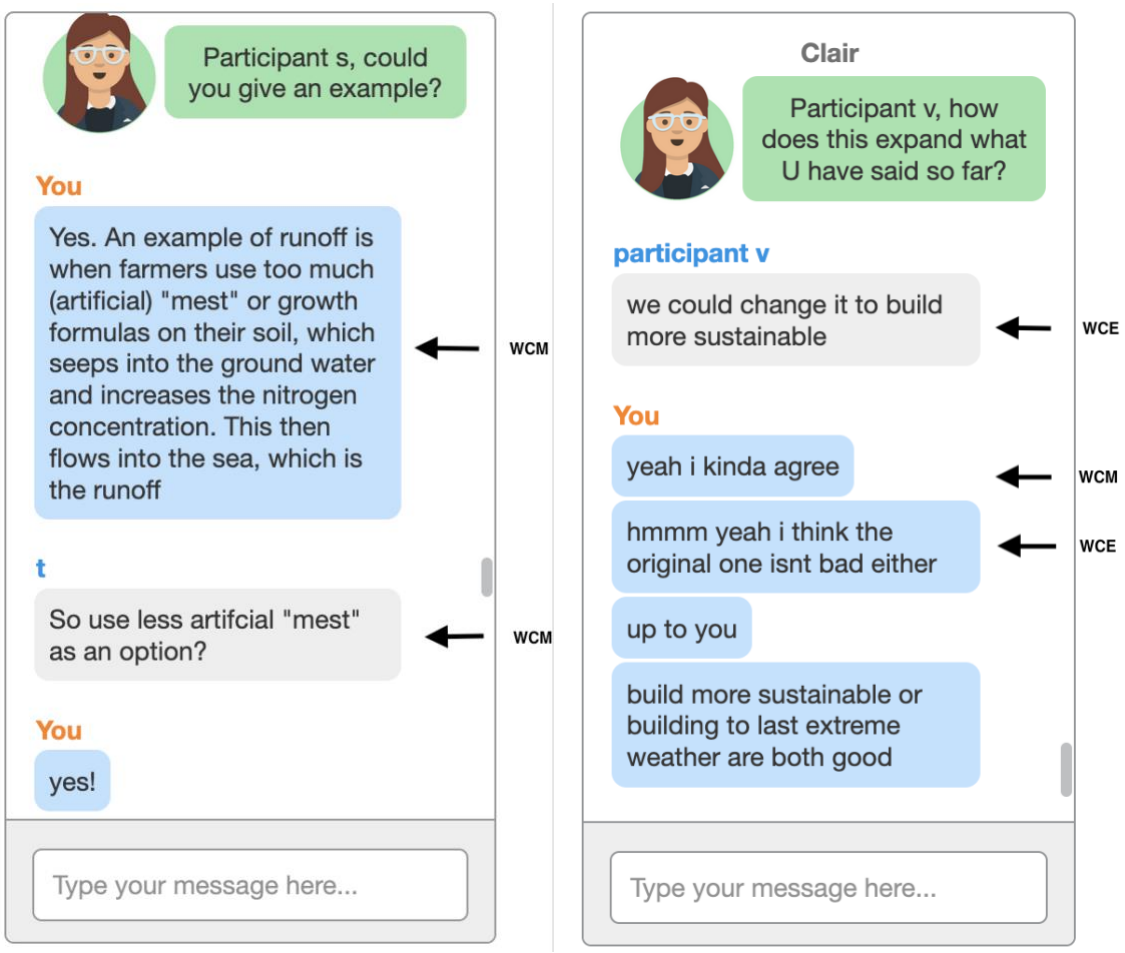


Figure 6

Chat Transcript Excerpt of Planning in Phase 2

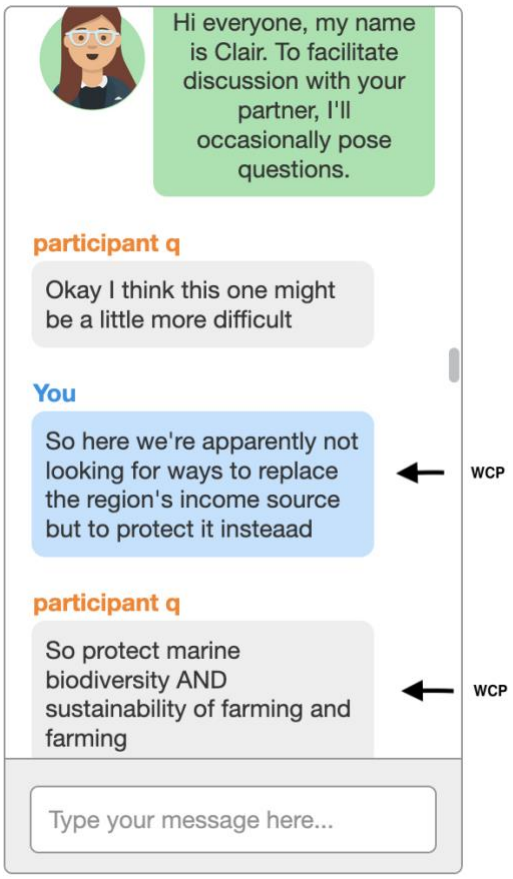


Table 6 gives an overview of the descriptive statistics of the Metacognitive Awareness Inventory (MAI) scores before the intervention, namely the discussions. Considering the difference in the number of items per subscale, participants scored highest in *Debugging Strategies* (M = 4.26). Participants scored lowest in *Evaluation* (M = 2.73). Table 7 gives an overview of the descriptive statistics of MAI after the intervention. Accounting for the difference in the number of items per subscale, participants again scored highest in *Debugging Strategies* (M = 4.43) and lowest in *Evaluation* (M = 2.93).

Table 6

Descriptive Statistics of MAI Pre-Intervention

	M	*SD*	N
Planning	3.96	1.77	30
IMS	7.93	1.46	30
CM	4.9	1.39	30
DS	4.26	0.73	30
Evaluation	2.73	1.17	30
Total	23.8	4.03	150

Note. IMS = Information Management Strategies; CM = Comprehension Monitoring; DS = Debugging Strategies.

Table 7

Descriptive Statistics of MAI Post-Intervention

	M	*SD*	N
Planning	4.43	2.01	30
IMS	8.2	1.37	30
CM	5.3	1.48	30
DS	4.43	0.89	30
Evaluation	2.93	1.46	30
Total	25.3	5.27	150

Note. IMS = Information Management Strategies; CM = Comprehension Monitoring; DS = Debugging Strategies.

As the parametric assumptions were violated, a paired-samples Wilcoxon-test was performed, to determine whether there was a significant difference pre- and post-intervention (see Table 8 for Wilcoxon-test). Of the subscales, only *Planning* showed a significant difference with a moderate effect size ($V = 15$, $p = 0.03$, $r = 0.37$). In general, a significant increase with a large effect size could be observed regarding the awareness of metacognitive strategies as a whole after using Clair ($V = 53$, $p = 0.005$, $r = 0.52$).

Table 8

Results of Paired-samples Wilcoxon-test Comparing Pre- and Post-Intervention MAI Scores

	Paired-samples Wilcoxon-test	
	V	p
Planning	15	0.03[a]
IMS	35	0.13
CM	47	0.08
DS	15	0.18
Evaluation	36	0.29
MAI total	53	0.005[b]

Note. IMS = Information Management Strategies; CM = Comprehension Monitoring, DS = Debugging Strategies.

[a] r = 0.37

[b] r = 0.52

Discussion

The overall goal of this study was to explore what metacognitive strategies students display when collaborating with and without Clair and to gain insight into designing AI to better support students' metacognitive strategies and ultimately enhance learning outcomes.

To address the first research question – exploring learners' metacognitive strategies without AI support in peer discussions – a qualitative analysis of the chats in Phase 1 was conducted. The key finding was that monitoring was the most frequently used metacognitive strategy without Clair in collaborative discussions. *Monitoring* is possibly the most intuitive strategy and thus might have been so dominant due to time pressure in a very goal-directed task, as literature suggests certain strategies such as planning and evaluation are more time-consuming (Wolters & Brady, 2020). It seems therefore possible that *Planning* and *Evaluation* remained low in occurrence because they would appear in the beginning and end of discussions and 15 minutes may not be enough time for students to not feel pressured to complete the task quickly.

Not only time pressure but also the task structure itself might be an explanation for the frequent occurrence of monitoring. The discussions were set up to include a clear problem definition and task, making them quite structured. Especially in such tasks, *Monitoring* might

have been the dominant strategy because it is reactive and context-dependent (Näykki et al., 2017). The discussions were conducted in dyads, meaning an element of shared regulation was added to the inherent self-regulation (Çini, 2024). When working in dyads, students might thus prioritise monitoring the group progress over their individual planning or evaluation (Çini, 2024). Additionally, these findings may reflect the inherent dynamics of shared regulation in dyads, which included collaborative metacognition, where the immediacy of responding to a peer's idea or reaching a consensus promotes *Monitoring* over individual *Planning* or *Evaluation* (Näykki et al., 2017).

To explore the second research question concerning learners' metacognitive strategies in interactions with conversational agents, a qualitative analysis of the chats of Phase 2, as well as a quantitative analysis to research whether awareness of metacognitive strategies changed after interacting with Clair, was conducted. There were three key findings. Firstly, metacognitive monitoring was the most frequently used strategy with Clair in collaborative discussions. This result is in line with research by Azevedo et al. (2004), showing that help-seeking alone is not enough to achieve desirable learning outcomes. In other words, solely relying on prompts does not seem to relieve students' need to actively plan, monitor and evaluate. From a metacognitive development perspective, it is plausible that conversational agents such as Clair are better equipped to scaffold 'in-the-moment' monitoring rather than strategic foresight (*Planning*) or reflective judgment (*Evaluation*), which may require more complex modelling of student learning progress (Çini, 2024).

Furthermore, it is possible that participants did not perceive Clair as a collaborative partner capable of facilitating strategic planning or evaluation. This aligns with Edwards et al. (2024), who found that the perceived social presence of an AI agent affects learner responsiveness. A possible explanation why participants might have perceived Clair's prompts as not useful might have been the lack of trust in the AI agent (Nazaretsky et al., 2025). Participants might not have trusted Clair to guide the discussion efficiently, thus leading to them behaving similarly regarding *Planning* and *Evaluation* compared to the discussions in Phase 1, without Clair.

Secondly, a slight decrease in overall strategy frequency with Clair could be found in the qualitative analysis. De Araujo et al. (2024) found that Clair boosted reasoning and elaboration, which are elements of effective discussions. Research suggests that effective discussions increase

metacognitive strategy frequency, which is contradictory to the current study's results of overall decreased metacognitive strategy frequency. This could possibly be explained by factors such as the time restriction of 15 minutes per discussion or limited keyword triggering. Another explanation might be a possible sequence effect, in that the study was set up to have interaction with Clair consistently in Phase 2 and the slight decrease in overall strategy frequency might be due to it being the second task (Yang et al., 2021). Sequence effects can occur when a previous task might affect the current task, in this case, the second discussions with Clair (Soetens et al., 2004). Tiredness or question fatigue might have been a factor, as a sequence effect could be modulated by the similarity of problem statements (Yang et al., 2021).

Despite the technically existing slight decrease in overall strategy frequency with Clair, it is important to consider that the difference between strategy frequency in Phase 1 and Phase 2 is indeed quite small and could arguably be considered no difference at all. It could just be a random variation in strategy frequency – meaning the variation could have gone in the opposite direction too. The implication is that the positive effect of Clair is not observable in the data, which could be due to the mentioned time restrictions or the possible sequence effect. It may also be that the effect of Clair in supporting metacognitive strategy use is not immediately observable and needs time to develop, i.e.: Clair is modelling these strategies rather than immediately facilitating them in participants. If Clair is indeed modelling questions learners should ask themselves, time would be a major factor in the observability of strategy frequency. Even if Clair is modelling reflective questions, modelling has been shown to promote the use of metacognitive strategies as well, thus the decisive factor still appears to be time (Volet, 1991).

Nevertheless, there was an observable effect in the quantitative data: Significant overall metacognitive strategy awareness endorsement and an increase in endorsement of planning strategies awareness. This means that participants might have been developing awareness of metacognition as a result of taking part in the study, but it is unknown whether this was due to Clair or simply through collaborative working on tasks, or possibly both.

Interestingly, while Planning was underrepresented in chat-based behaviour, the MAI indicated a significant post-intervention increase in Planning awareness. This divergence between *observed* and *self-reported* data highlights the complexity of assessing metacognition and the need for triangulated methods (Çini, 2024). Previous research suggests a difference in *awareness* and *observable* behaviour due to the method used (Çini, 2024). While off-line

methods such as the MAI questionnaire are considered a generally reliable method, learners' answers might not always align with their actual performance, as they might remember their performance differently or state intended behaviour. On-line methods, such as think-aloud protocols might capture metacognitive strategies better during a task but are currently not feasible in a classroom environment due to their disruptive nature there. It is thus possible that the post-intervention measurement of MAI captured *intended* strategy use or heightened awareness of its importance even if it could not be captured in the actual behaviour of participants.

Synthesis of Findings

Overall, the findings suggest that Monitoring dominates student regulation both with and without AI support, while Planning and Evaluation remain underutilized in real-time collaborative contexts. Clair's impact appears limited to discussion facilitation rather than metacognitive enhancement. Nevertheless, post-task self-reports suggest a shift in awareness, pointing to Clair's potential role in triggering reflective thinking that is not immediately observable.

Implications

Overall, this study contributes to the growing body of research examining the integration of AI into self-regulated learning and may inform future design and policy decisions. Regarding design implications, while Clair has not been shown to improve metacognitive strategy frequency and can in the current study's findings not be endorsed without further design improvements, Clair might still be a valuable AI-facilitated teaching tool in collaborative environments, particularly where teacher presence is limited. This is because of the findings of previous research suggesting that Clair improves the participation of learners in discussions and might thus be particularly helpful when teachers cannot give the same attention to students' discussion progress as Clair. However, Clair's prompts are open to reprogramming, thus in the context of facilitating metacognitive strategies, Clair might benefit from incorporating explicit metacognitive prompts, not only reasoning-focused prompts. This might contribute to increasing metacognitive strategy usage across all subscales.

Incorporating explicit metacognitive prompts might require the expansion of the existing framework or the use of a different one, such as the Socially Shared Regulation of Learning (SSRL) framework (Zheng et al., 2024). Compared to the APT framework, which focuses on

facilitating productive discussions, the SSRL framework's four core stages consist of understanding, planning, monitoring and evaluation (de Araujo et al., 2024; Zheng et al., 2024). While literature suggests successful enhancement of learners' collaborative learning through SSRL, the effect when integrated with a conversational agent like Clair is still underexplored.

As this study's findings suggest a difference in awareness of metacognitive strategies and observable metacognitive strategies, it should be considered to embed strategy-reflection questions before and after discussions to boost a transfer of intended strategy usage to actual behaviour. This educational implication could potentially be valuable to enhance metacognitive strategy frequency and therefore ultimately improve learning outcomes. Additionally, teachers should guide students to reflect on AI-generated prompts, which is an important factor in human-AI-trust and might potentially lead to learners' accepting the modelled prompts into their own reflective processes and thus ultimately enhance their metacognitive strategy frequency. Especially if specific metacognitive strategy prompts are included in the framework Clair will use.

All implications should be considered when further improving Clair's design in particular to make Clair more valuable as a tool in real-world classrooms.

Limitations and Strengths

One of the study's limitations was the small sample size of 30 participants, as the parametric assumption of normality was violated and the generalizability of this experiment is limited due to it. Time constraints resulted in two limitations. First, Dyslexia, as verbally noted by three participants, and the reading load could reduce the engagement with AI prompts. Secondly, time constraints limited the strategy visibility, especially for Planning and Evaluation. Due to time-constraints in the set-up of the study, only intra-rater reliability was used and no inter-rater reliability was reported in qualitative coding.

Nevertheless, the study also had some significant strengths. The preparation and learning material were constructed to fit the discussion topics, ensuring participants had a similar starting base for their discussions and enough theoretical background to make informed decisions. The topics themselves were based on realistic scenarios regarding climate change, and generated ideas of the discussions can thus be taken into consideration for overarching projects like Learning to be Green (L2BG), adding social relevance in the current time. While participants were recruited using a convenience sample, a diverse cultural background of participants was

found, adding to the possible applicability in other countries. Lastly, participants were assigned in dyads randomly and anonymously, limiting the influence of possible pre-existing relationships in the discussions.

Conclusion and Future Research

In conclusion, *Monitoring* is the most frequently used metacognitive strategy with and without Clair. This study found limited evidence of Clair's impact on metacognitive strategy frequency in learners. However, intended metacognitive strategy usage could be measured, particularly *Planning* awareness increased. Further research is required to make a decision on how Clair could be designed and implemented in classrooms as a teaching tool, and thus possibly support learning outcomes through collaborative learning.

Before Clair can be considered for implementation in classrooms, future research should focus on exploring the modification of Clair to include strategic prompts, like "What is your plan?", "How will you check your answer?". Scaffolded and un-scaffolded AI interaction should then be tested, to verify results regarding a possible sequence effect and the effectiveness of Clair's prompts once modified. As modifying Clair's prompts might require using a different framework, for example, the SSRL framework, further research into the effectiveness of this framework in facilitating metacognitive strategies through Clair is required. Additionally, longer sessions or multiple sessions should be conducted, to capture delayed strategy use and to provide enough time for both the reading load, as well as discussion time to offer space for *Planning* and *Evaluation*. To enhance observability, log analysis, think-aloud or retrospective protocols should be considered to triangulate with chat data. Due to the complexity of capturing metacognitive strategies in intended and observable behaviour, a mixed-method approach is recommended for future research.

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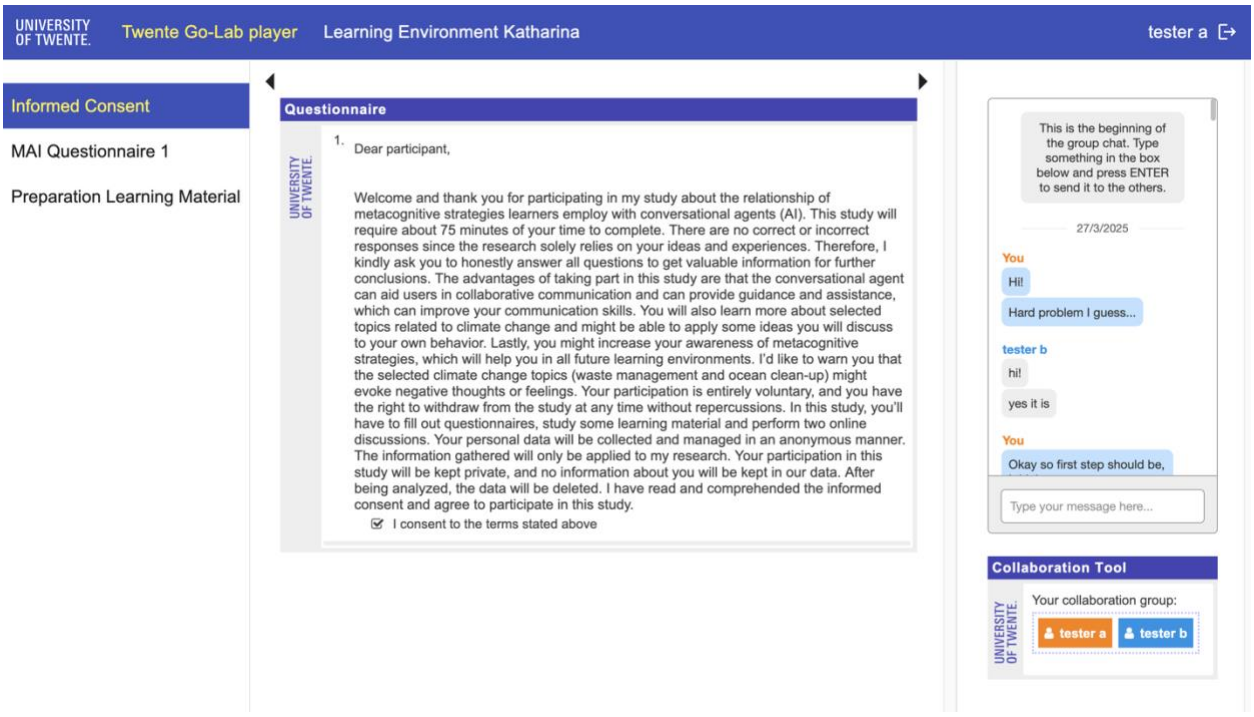
Appendices

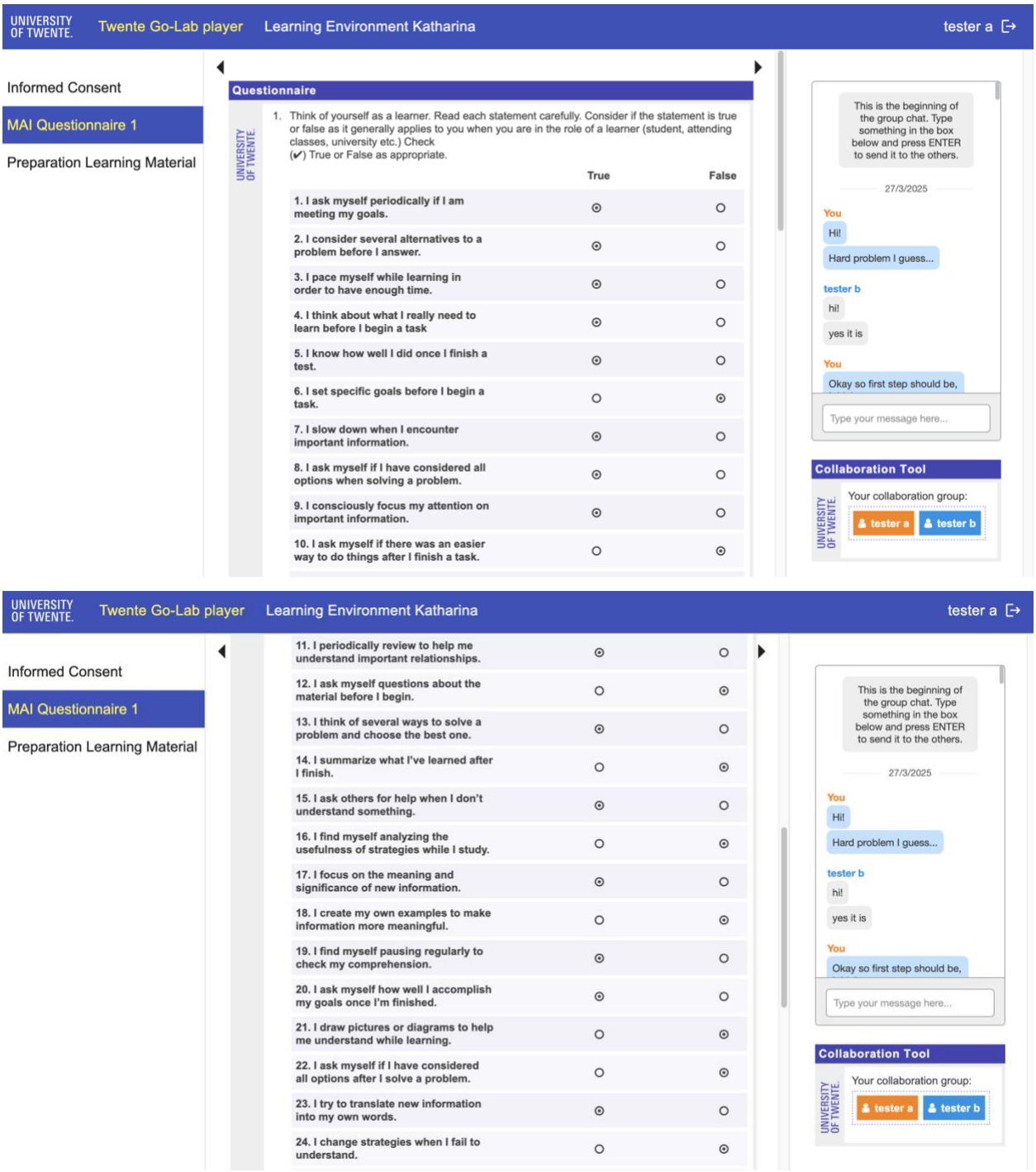
Appendix A

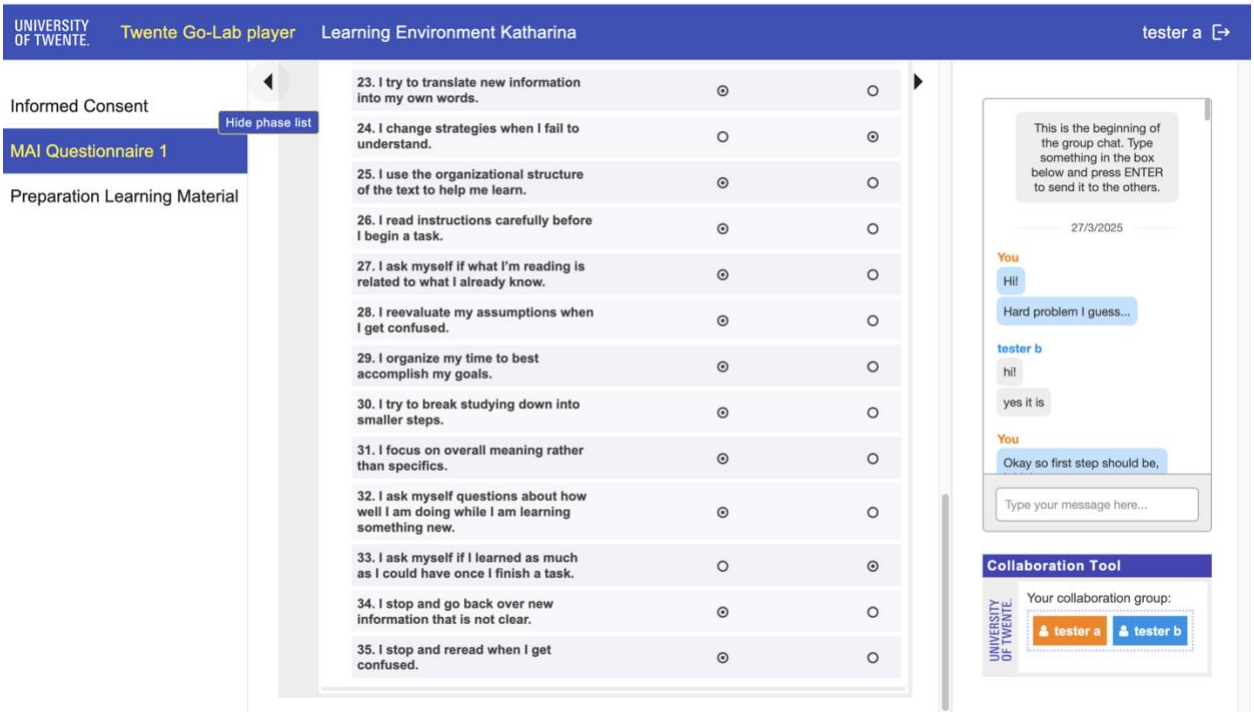
Go-Lab Environment – Informed Consent



Appendix B

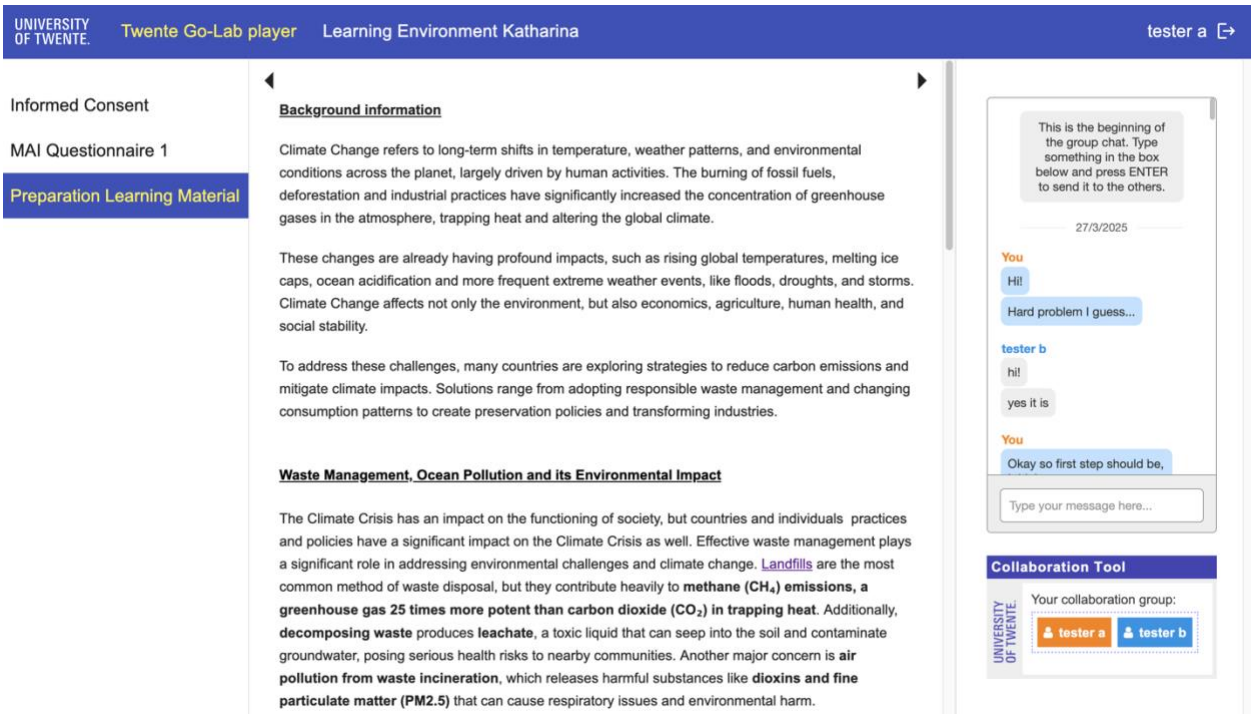
Go-Lab Environment – MAI Questionnaire 1

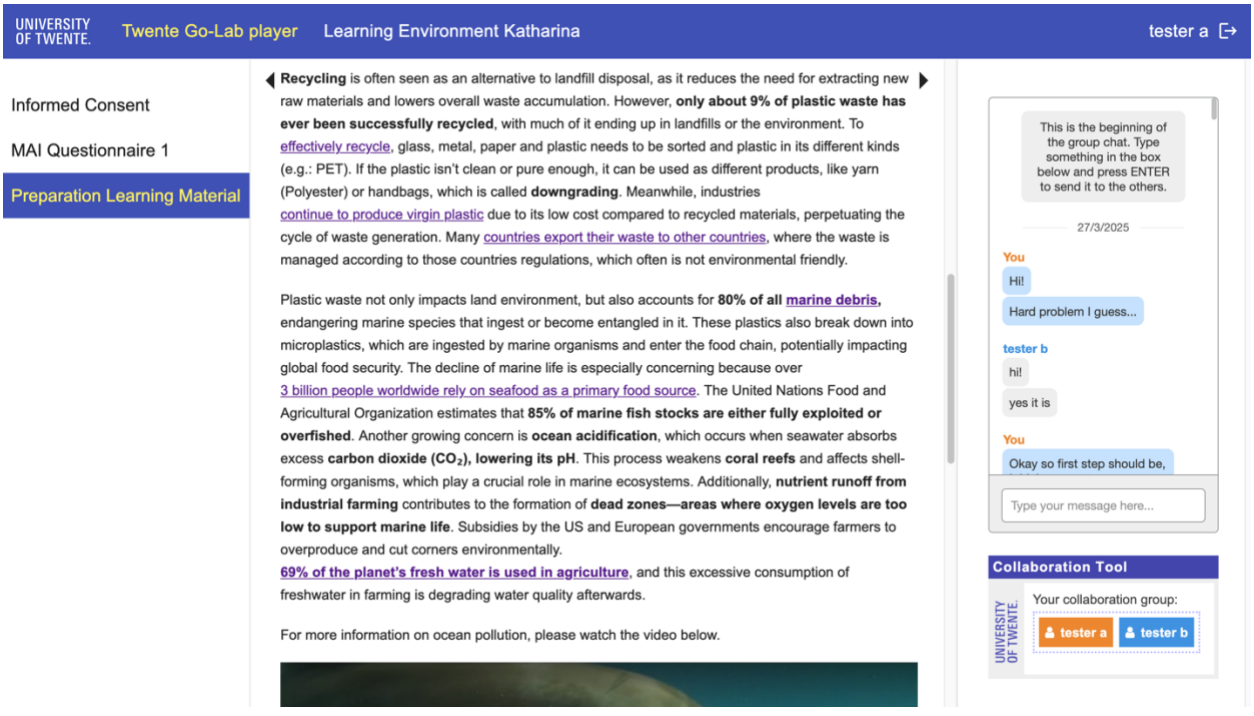


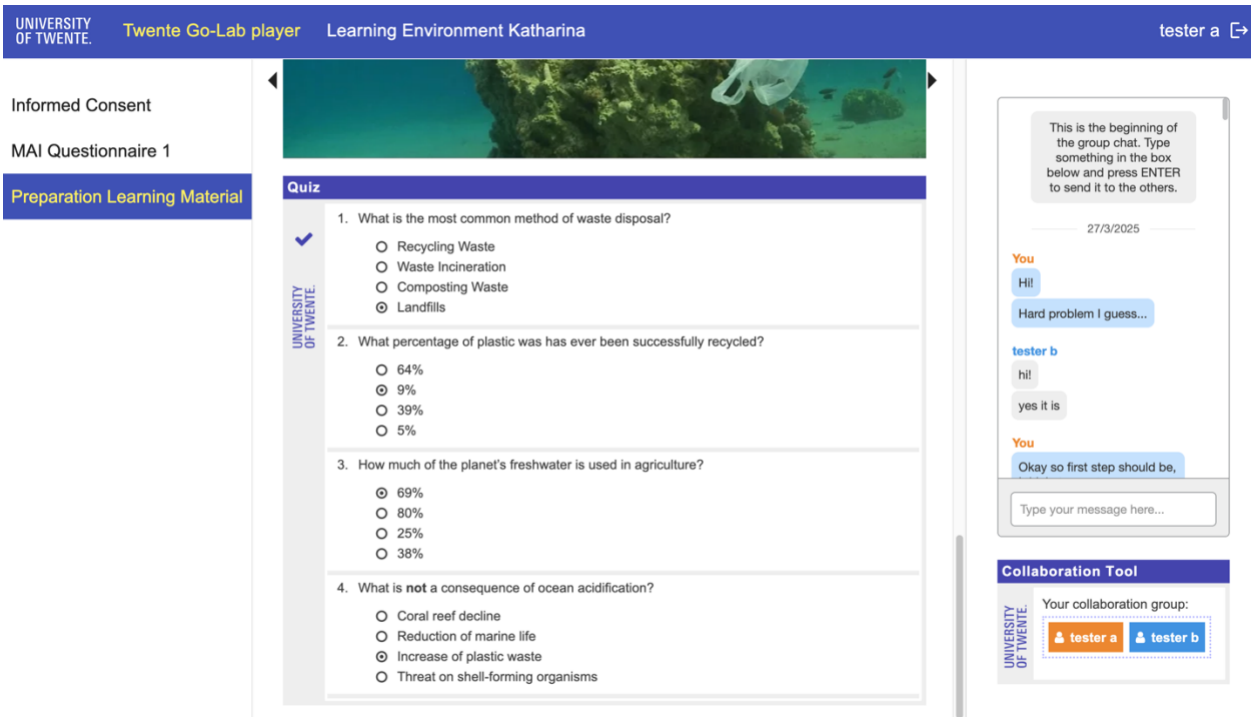

UNIVERSITY OF TWENTE.
Twente Go-Lab player
Learning Environment Katharina
tester a
Informed Consent
Hide phase list
MAI Questionnaire 1
Preparation Learning Material
23. I try to translate new information into my own words.
24. I change strategies when I fail to understand.
25. I use the organizational structure of the text to help me learn.
26. I read instructions carefully before I begin a task.
27. I ask myself if what I'm reading is related to what I already know.
28. I reevaluate my assumptions when I get confused.
29. I organize my time to best accomplish my goals.
30. I try to break studying down into smaller steps.
31. I focus on overall meaning rather than specifics.
32. I ask myself questions about how well I am doing while I am learning something new.
33. I ask myself if I learned as much as I could have once I finish a task.
34. I stop and go back over new information that is not clear.
35. I stop and reread when I get confused.
This is the beginning of the group chat. Type something in the box below and press ENTER to send it to the others.
27/3/2025
You
Hi!
Hard problem I guess...
tester b
hi!
yes it is
You
Okay so first step should be,
Type your message here...
Collaboration Tool
UNIVERSITY OF TWENTE.
Your collaboration group:
tester a
tester b

Appendix C

Preparation Material

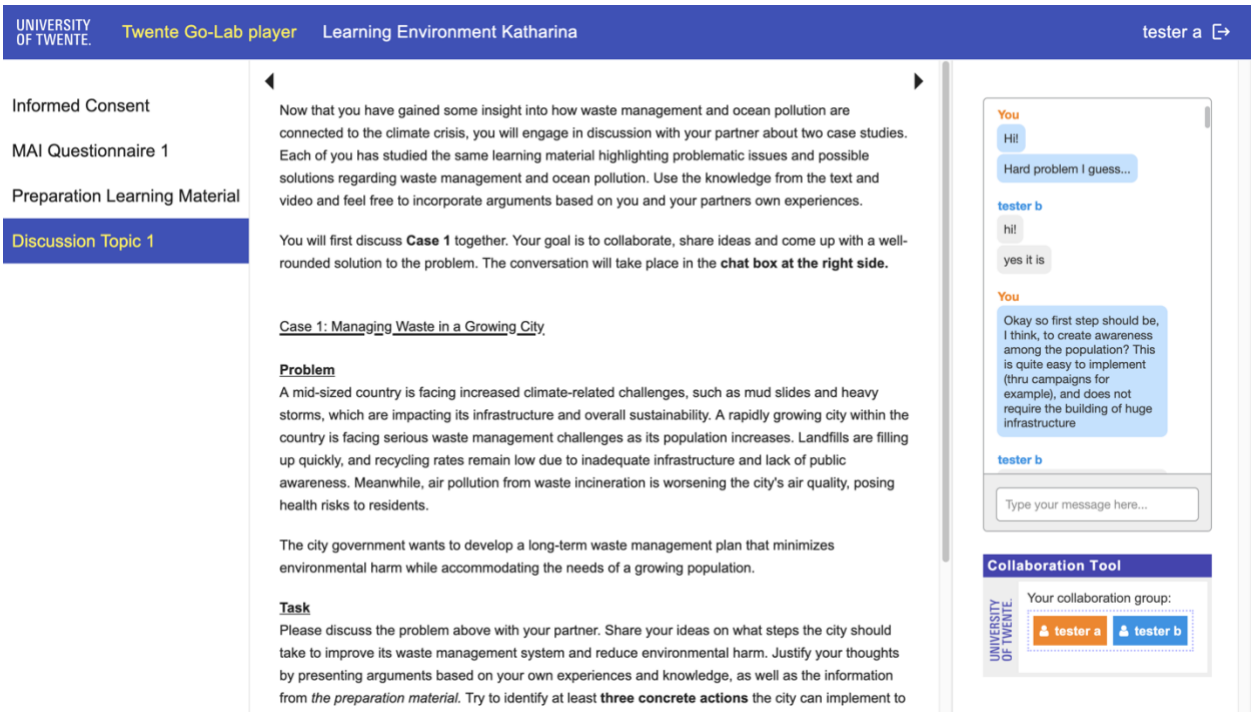


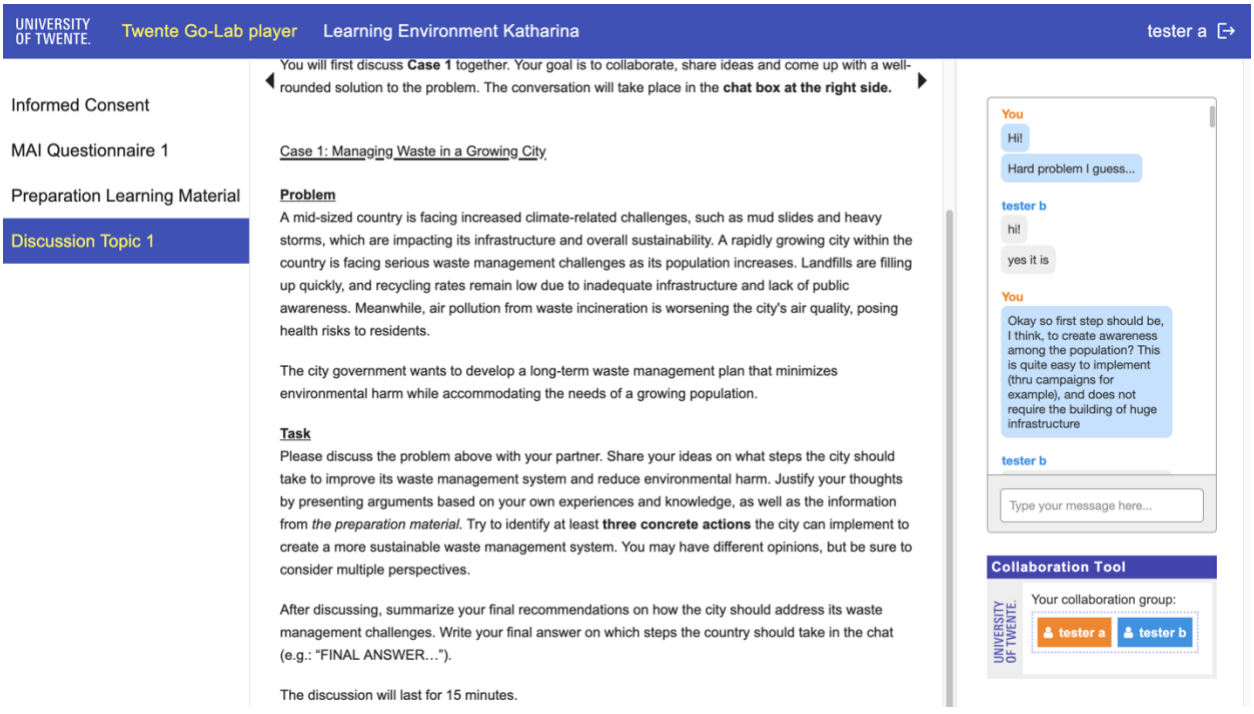



UNIVERSITY OF TWENTE.
Twente Go-Lab player
Learning Environment Katharina
tester a
Informed Consent
MAI Questionnaire 1
Preparation Learning Material
Quiz
1. What is the most common method of waste disposal?
Recycling Waste
Waste Incineration
Composting Waste
Landfills
2. What percentage of plastic was has ever been successfully recycled?
64%
9%
39%
5%
3. How much of the planet's freshwater is used in agriculture?
69%
80%
25%
38%
4. What is not a consequence of ocean acidification?
Coral reef decline
Reduction of marine life
Increase of plastic waste
Threat on shell-forming organisms
This is the beginning of the group chat. Type something in the box below and press ENTER to send it to the others.
27/3/2025
You
Hi!
Hard problem I guess...
tester b
hi!
yes it is
You
Okay so first step should be,
Type your message here...
Collaboration Tool
Your collaboration group:
tester a
tester b

Appendix D

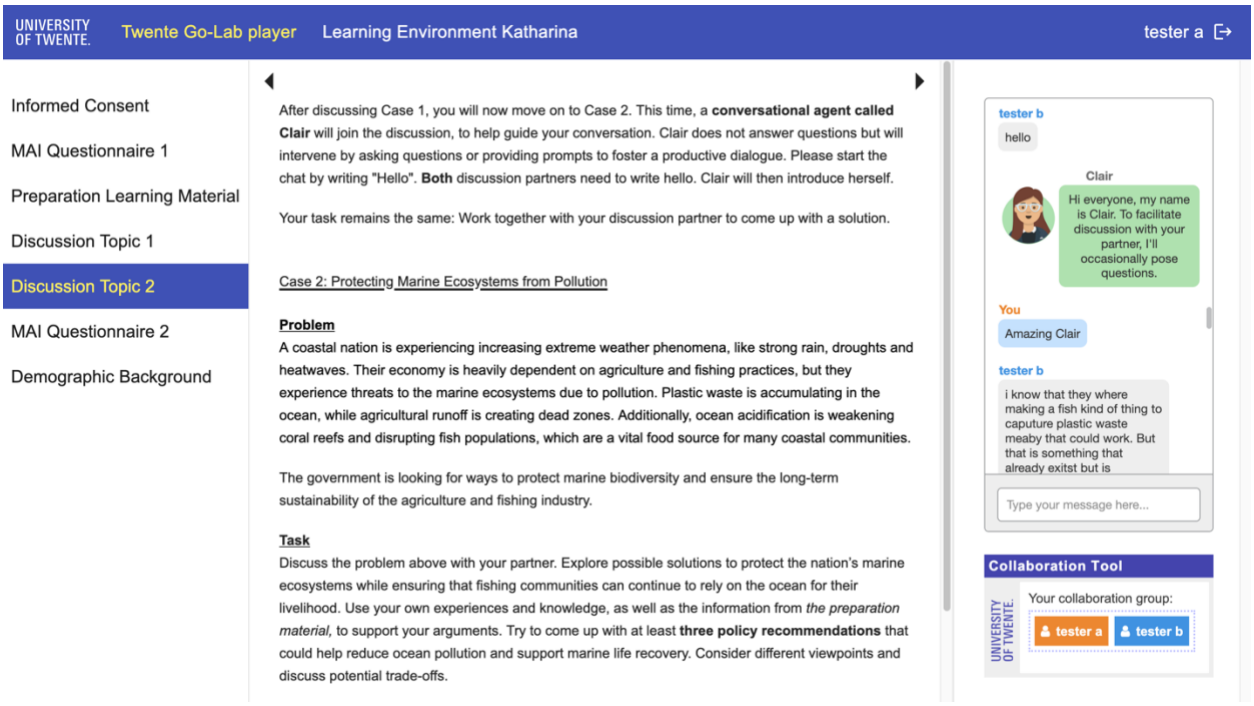
Discussion Topic 1

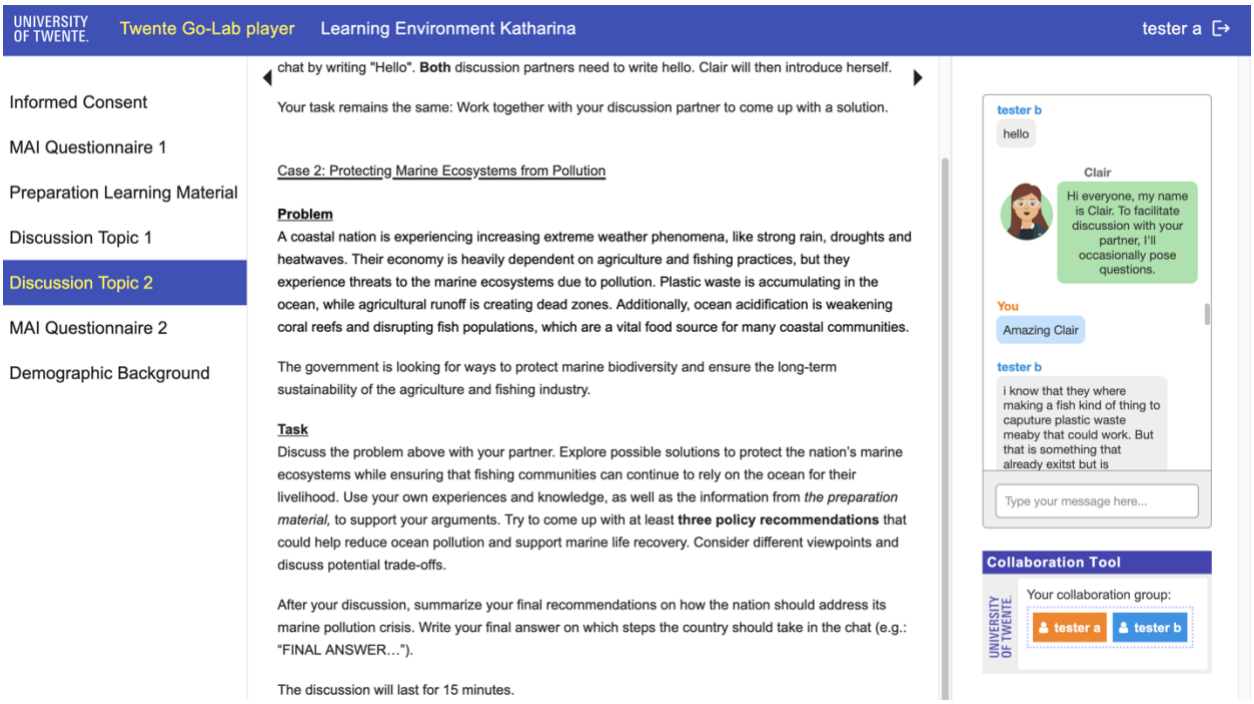




Appendix E

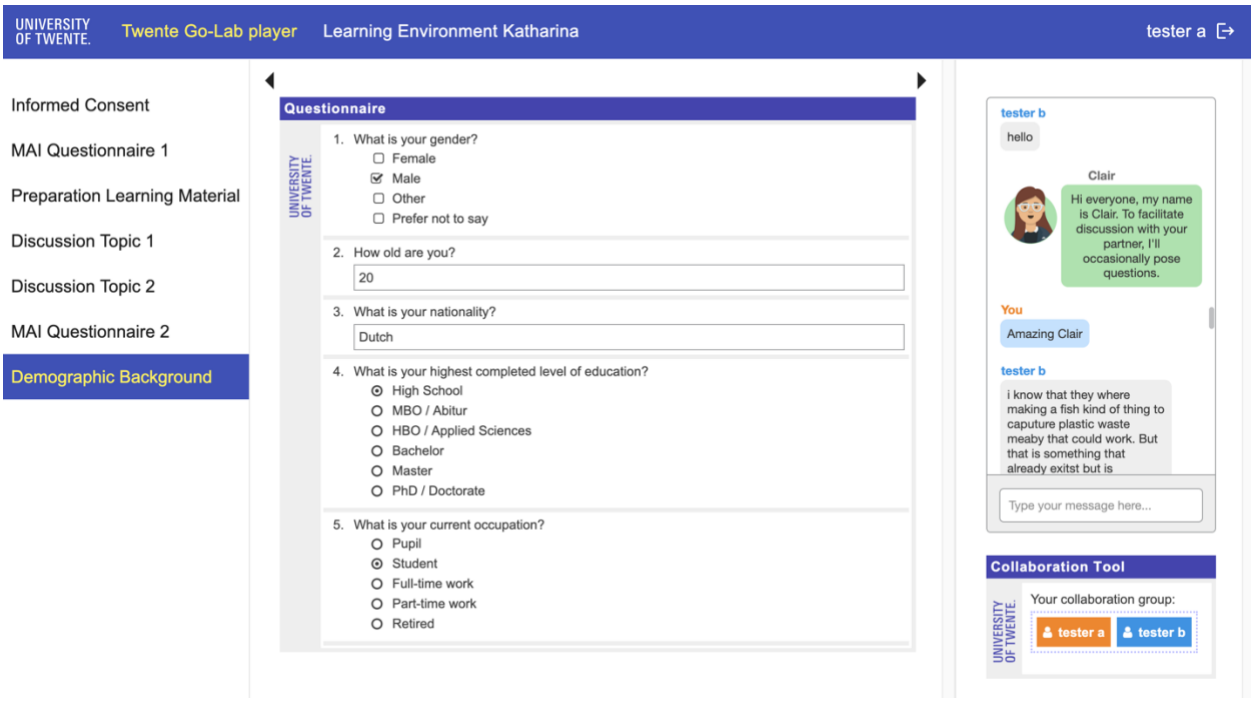
Discussion Topic 2





Appendix F

Demographic Questionnaire



Appendix G

AI Statement

During the preparation of this work, I used Grammarly to check for grammar and spelling mistakes. Additionally, I used ChatGPT to gather ideas and sentence formulations solely for the preparation material and problem statement. ChatGPT received an example and subject matters it was supposed to include and was asked to create a text and problem statement. Further software used was Word and Teams Meetings. After using those tools/services, I thoroughly reviewed and edited the content as needed, taking full responsibility for the final outcome.