Appraisal-Driven Emotional Awareness via Self-Report: A General-Purpose Toolbox and Two Studies to Support Instructional Design and Research in Affect-Aware Systems

Fritz, Mattia; Betrancourt, Mireille

Appraisal-Driven Emotional Awareness via Self-Report: A General-Purpose Toolbox and Two Studies to Support Instructional Design and Research in Affect-Aware Systems

Mattia A. Fritz & Mireille Bétrancourt

TECFA, Université de Genève

ABSTRACT: A consistent body of research has corroborated that emotion plays a pivotal role in learning processes and outcomes, for instance by reorienting cognitive, motivational, and behavioral resources; providing a sense of belonging to a group; or increasing learners' effort in having an accurate perception of colleagues. Instructional design may thus harness emotions to provide meaningful information about the learning task at hand both individually and collectively. Providing learners with emotion awareness in educational technology, though, is challenging both technically and pedagogically. Emotions can be conceptualized in many ways and collecting them can be done automatically and non-intrusively; or explicitly, for instance, by prompting learners to self-reflect on the causes and consequences of how they are feeling. This contribution presents a general-purpose toolbox that practitioners and researchers can use to equip any computer-mediated learning environment with an Emotion Awareness Tool (EAT). The toolbox implements appraisal theories of emotion in a moment-to-moment and self-reporting interface, allowing learners to rate appraisal dimensions and obtain a suggestion of theory-driven subjective feelings that may represent how they feel. To showcase its use and pedagogical assumptions, two empirical contributions are illustrated. The first examines whether a different use of and access to emotional information influences the expression and monitoring of emotions through the EAT. The second implements the EAT in ecological settings during remote learning and explores its longitudinal use and perception. The results are interpreted with respect to the pedagogical foundations of the EAT and the broader literature on affect-aware systems in educational technology.

Keywords: Emotion awareness, Affective learning, Affect-aware systems, Self-Report, Research platform

1. Introduction

Affective phenomena play a pivotal role in learning and a substantial body of research is investigating how the affective dimension may be integrated in educational technology (Brackett et al., 2019; Calvo et al., 2015; Dukes et al., 2021; Pekrun et al., 2018; Zatarain-Cabada et al., 2016). Two complementary rationales motivate this effort. On the one hand, when learning takes place in remote computer-mediated environments, especially asynchronously, socio-affective cues normally available in face-to-face interactions are reduced or absent (Derks et al., 2008; Peña et al., 2016). On the other hand, information and communication technologies can also enrich the affective experience beyond what is possible in face-to-face settings through affect-aware systems (Cernea & Kerren, 2015; Lajoie et al., 2020). For instance, a consistent line of inquiry has investigated whether intelligent tutors can be endowed with automatic emotion recognition to adapt learning processes to learners' affective states (Calvo et al., 2015; Zatarain-Cabada et al., 2016). These approaches typically assume that certain affective states should be targeted because they can facilitate or hinder learning (D'Mello, 2013; Graesser et al., 2014; Vogl et al., 2019). By contrast, other researchers argue that affect-aware tools should instead foster learners' reflection on and regulation of their emotions through voluntary rather than automatic processes (Arguedas et al., 2016; Fuentes et al., 2017; Lavoué et al., 2020). In this view, learners extract meaningful information from the whole gamut of affective experiences, and the technological artifact assists them in producing and sharing emotional awareness rather than being affect-aware itself.

Previous research has linked this voluntary use of affect-aware systems to improved learning processes and outcomes. For instance, Lavoué and colleagues (2020) found that fostering students' awareness of their own emotions and their antecedents can help them better understand how academic situations influence their feelings, evaluation of the situation, and sense of control. Such awareness offers a basis for reflection and regulation, and provides valuable guidance for designing tools that support emotional awareness. Ruiz and colleagues (2016) denote that emotional awareness at the class level can foster students' awareness and reflection, positively influence behavior, and provide teachers with actionable insights into the classroom climate. Eligio and colleagues (2012) found that partners in a computer-mediated task lacked accurate understanding of each other without emotional awareness, whereas performance and mutual understanding improved once awareness was provided, especially in remote settings. Molinari and colleagues (2013) and Avry and colleagues (2020) further corroborated these findings, showing that emotional awareness improved interaction quality and encouraged participants to spend more time modeling their partner's activities and feelings. More recently, Avry and colleagues (2021) observed that explicit sharing of emotions benefits groups with low natural tendencies for emotion regulation.

This contribution aligns with the voluntary perspective and presents two studies that further investigate the use of an Emotion Awareness Tool (EAT) in computer-mediated learning environments. In the first experiment, the interface of an EAT is manipulated to create three different conditions: one in which learners have access only to their own emotions, one in which they have access only to the emotions of their partners, and one where they have access to both. The experiment attempts at disentangling the intra-personal and inter-personal role of emotional awareness (Molinari et al., 2013; Torre & Lieberman, 2018; Van Kleef, 2018). In the second study, two cohorts of students used an EAT longitudinally in a blended course while studying remotely. The study examines how learners engaged with the tool as well as their perception of usefulness of the EAT in sustaining a sense of belonging and social presence in distance learning (Lavoué et al., 2020; Lowenthal & Snelson, 2017; Ruiz et al., 2016). Both studies employed variants of the Dynamic Emotion Wheel (DEW), a graphical interface that harnesses appraisal theories of emotion to maximize the pedagogical value of emotional awareness (Lavoué et al., 2020; Sander et al., 2018; Scherer, 2005; Shuman & Scherer, 2014). The DEW rests on the pedagogical assumption that embedding an emotion structure through a parsimonious computational model allows learners to leverage emotional awareness in two complementary ways: individually, as a means to reflect on and guide their own learning experience; and collectively, as a form of strategic signaling that channels emotion as instrumental social information (Avry et al., 2020; Dillenbourg et al., 2016; Eligio et al., 2012; Lavoué et al., 2020; Molinari et al., 2013; Scherer, 2005; Van Kleef, 2018). The article begins by introducing the Dynamic Emotion Wheel Toolbox: a web based application that allows researchers and practitioners to implement their own version of the EAT in any computer-mediated learning environment. It then presents the two studies, which adopt two different instances of the EAT. Finally, it compares and discusses empirical results with respect to the DEW's core pedagogical tenet. The aim of the article is to advance the understanding of how affect-aware systems can support learning processes and outcomes in educational technology, through both empirical investigation and methodological innovation (Buder et al., 2021; Zatarain-Cabada et al., 2016).

2. The Dynamic Emotion Wheel Toolbox

There are several approaches to emotion self-report in computer-mediated learning environments. A first relies on dimensional models, where emotions are expressed along continuous dimensions such as valence and arousal. Examples include the Self-Assessment Manikin (Bradley & Lang, 1994) and the AffectButton (Broekens & Brinkman, 2013), which allow users to indicate their affective state through visual or interactive interfaces. A second approach adopts discrete models, where learners select from predefined lexicalized emotions, either derived from basic emotion theory (Ekman, 1992; Keltner et al., 2019) or empirically based on frequently experienced states (D'Mello, 2013; Molinari et al., 2013). A third, hybrid approach integrates both perspectives by situating discrete emotions within dimensional spaces, as in the Geneva Emotion Wheel (Scherer, 2005; Scherer et al., 2013). Several tools adopted in learning contexts illustrate these strategies: *emot-control* combines icons with Russell's (1980) circumplex (Feidakis et al., 2013, 2014); the *Mood Meter app* organizes emotions into quadrants of valence and activation (Brackett et al., 2019); and Molinari et al. (2013) propose a persistent sidebar of discrete labels to support Computer-Supported Collaborative Learning. While all rely on voluntary self-report, differences in representation and sharing strongly shape how emotions are encoded, interpreted, and acted upon.

The Dynamic Emotion Wheel (DEW) extends the Geneva Emotion Wheel (Scherer, 2005; Scherer et al., 2013; Shuman & Scherer, 2014) into an EAT specifically designed to foster emotional awareness in computer-mediated learning environments. It is grounded in appraisal theories of emotion (Moors et al., 2013; Sander et al., 2018), which conceptualize emotions as adaptive responses that rapidly orient cognitive, motivational, and behavioral resources (Brosch et al., 2013; Scherer, 2019). A central tenet of these theories is that the subjective feeling of an emotion – that is, the conscious experience – can be theoretically predicted from a person's appraisal profile: the way a situation is evaluated on a set of criteria shapes whether the resulting experience can be labeled using a natural language word such as interest, frustration, or boredom (Grandjean et al., 2008; Scherer & Meuleman, 2013). Appraisal theories have been retained among the many emotion theories because the mechanism encourages learners to reflect not only on *what* they feel, but also on *why* a given feeling has emerged (Lavoué et al., 2020; Muñoz et al., 2016; Pekrun, 2006). Building on this premise, the DEW prompts learners to rate appraisal dimensions such as Valence and Control/Power, and dynamically generates, through a parsimonious computational model (see Appendix), a subset of lexicalized emotions most consistent with those ratings according to an underlying affective space (Gillioz et al., 2016; Scherer et al., 2006). The information encoded – appraisal ratings and subjective feelings – can then be visualized through graphical representations, enabling individuals and groups to monitor affective dynamics over time (Derick et al., 2017; Ez-zaouia et al., 2020). Unlike earlier tools such as *emot-control* (Feidakis et al., 2013) or the *Mood Meter* (Brackett et al., 2019), which rely on fixed circumplex or quadrant placement, the DEW explicitly operationalizes the computational link between appraisal and subjective feelings, offering a theory-driven framework to enhance the pedagogical use of emotional awareness in educational technology (Lajoie et al., 2020; Lavoué et al., 2020; Shuman & Scherer, 2014).

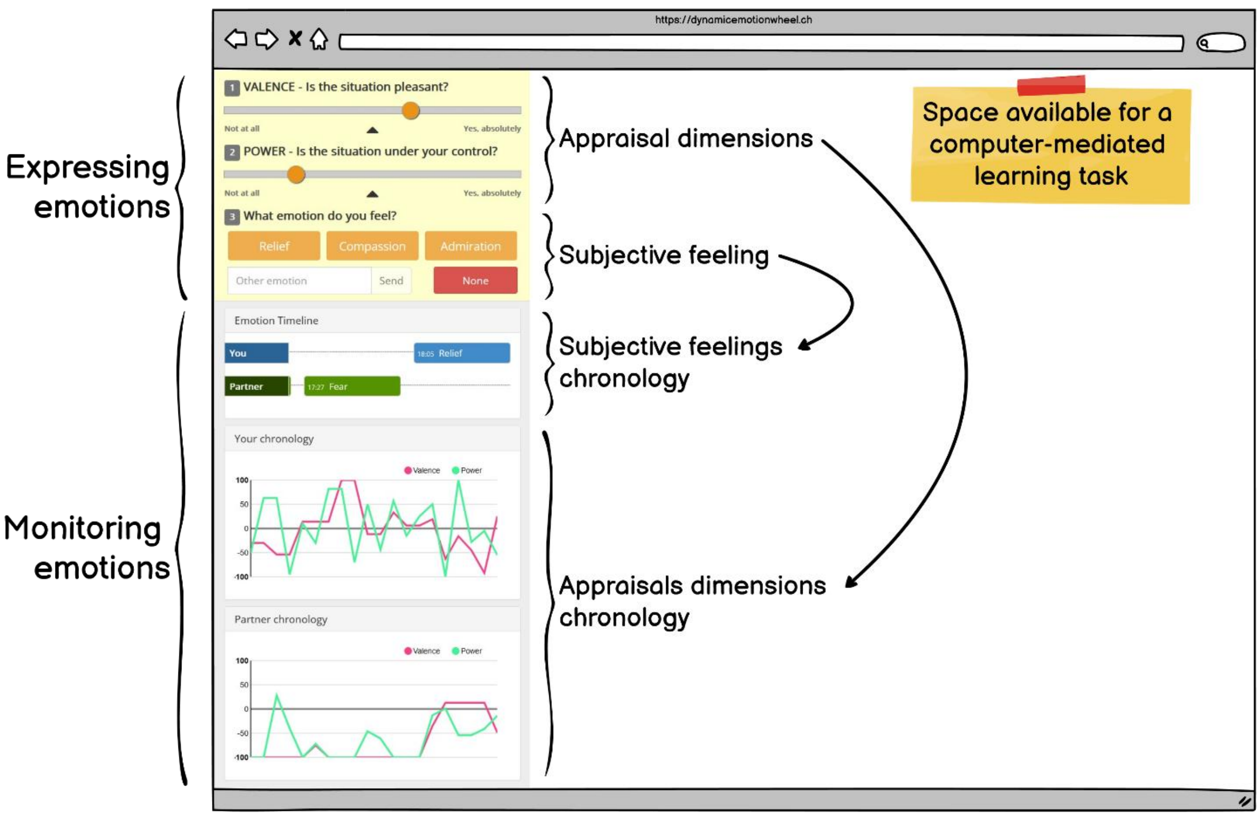

Figure 1 The interface of the DEW with cues about the role of each part of the tool. All parts of the interface can be configured with the toolbox, including the computer-mediated learning task to appear in the same window.

The computational and modular nature of the DEW provides the conceptual and technical foundation for building a broader toolbox that makes the model accessible to both practitioners and researchers (Figure

2). While the DEW itself operationalizes the link between appraisal dimensions and subjective feelings, the toolbox extends this mechanism into a configurable environment that can be adapted to different pedagogical contexts. For instance, many different underlying affective spaces can be integrated into the toolbox (Fontaine et al., 2007; Gillioz et al., 2016). As a consequence, it is possible to decide the kind and number of appraisal dimensions to be rated, as well as the number and kind of suggested subjective feelings. This gives practitioners and researchers leverage on how emotional awareness is prompted. The same principle applies to graphical representations of emotion. It is possible to choose between emotion timelines that display subjective feelings over time, line charts that show the evolution of appraisal dimensions, or word clouds highlighting the frequency by which subjective feelings have been chosen. This flexibility ensures that the tool can be tailored to support varied educational aims, from fostering self-reflection to enhancing collaboration or monitoring the socio-emotional climate of a class. Beyond classroom use, the toolbox was also designed as a research infrastructure. Every interaction is recorded as a structured set of measures, capturing both the observed appraisals and the reported subjective feelings, as well as their distance from theoretically predicted values. These data provide fine-grained insights into how learners construe and communicate emotions, and they can be exported in open formats to facilitate analysis and sharing. By making the computational logic explicit and results reproducible, the toolbox advances Open Science principles of transparency and reproducibility (Flake & Fried, 2020; Guest & Martin, 2021; Nosek et al., 2015).

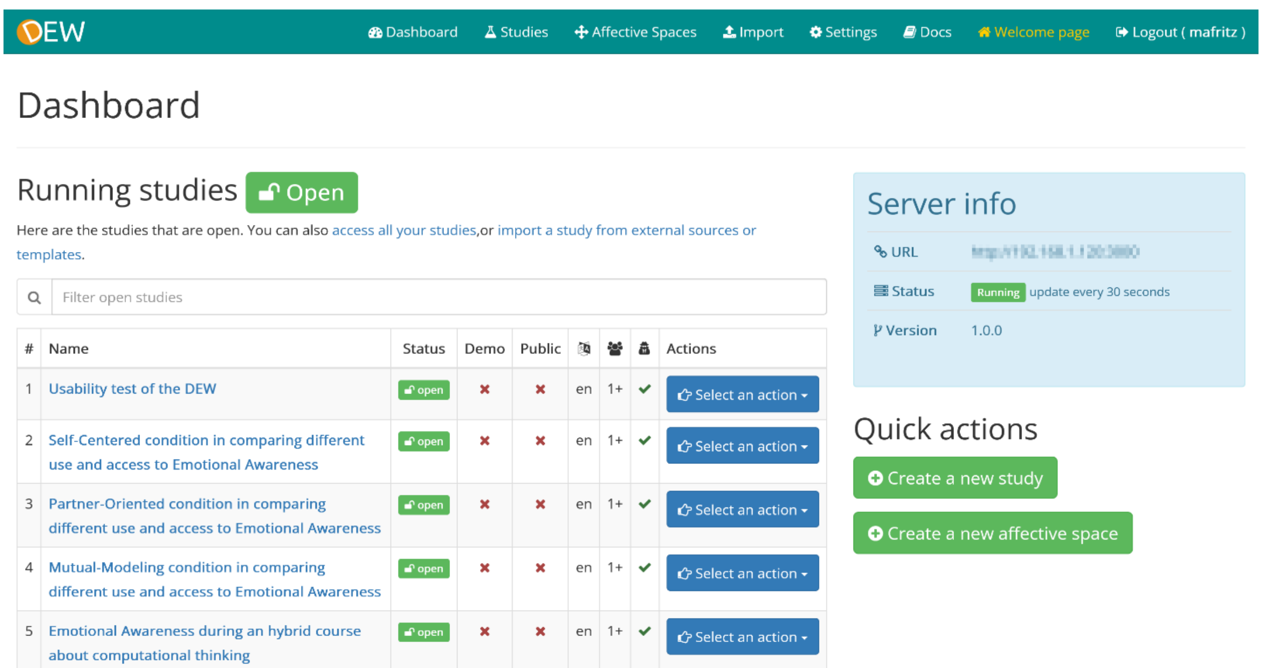

Figure 2 The dashboard page of the admin area shows a list of active instances/studies and gives access to the different features of the back-end, including affective spaces and mechanisms to import or export information to be shared with other practitioners or researchers.

2. Study 1

Previous research investigating the effect of an EAT on Computer-Supported Collaborative Learning (CSCL) has mainly adopted a treatment vs. control design, in which half of the participants had access to full emotional awareness information (about themselves and their colleagues), whereas the control group had either no awareness at all, or of a different kind (Avry et al., 2020; Eligio et al., 2012). Evidence gathered through these experimental conditions highlight an instrumental role of the EAT in learning processes and outcomes, denoting that emotional awareness supports better regulation and collaboration (Eligio et al., 2012) and fosters coordination, mutual understanding, and task performance (Avry et al., 2020). *This all-or-nothing* setting, even if coherent with the overall aim of an EAT, does not allow to disentangle the intra-personal and inter-personal instrumentality of emotional awareness (Lavoué et al., 2020; Molinari et al., 2013). Namely, learners can take advantage of their own emotional awareness as a means to enhance self-reflection and regulation; they can harness the emotions of their colleagues to infer possible causes and consequences on their behavior; or they can build upon both sources of information to enhance mutual-modeling. To investigate the matter, the toolbox has been used to build three different interfaces, depicted in Figure 3, which vary in terms of the use of and access to emotional information.

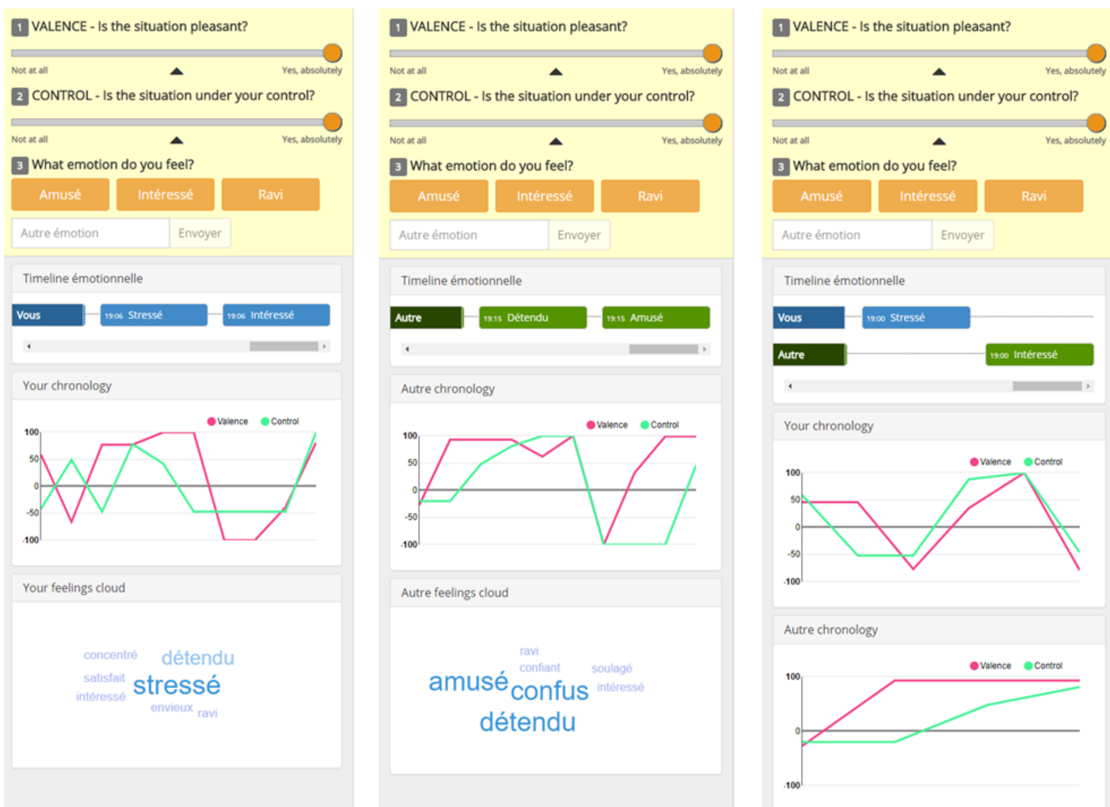

Figure 3 The three versions of the DEW side by side, each one corresponding to a different use of and access to emotional information. From left to right, the Self-Centered, the Partner-Oriented, and the Mutual-Modeling.

In the Self-Centered version, participants are the sole recipients of their expressed emotions. Here, use of the EAT primarily reflects self-reflection or self-regulation, even without an inter-subjective component.

For instance, Torre and Lieberman (2018) imply that the very fact of naming one's emotion is a form of emotion regulation. In the Partner-Oriented version, emotional information is crossed over: the emotions expressed by participant A are visible only on participant B's interface, and vice versa. In this case, use of the EAT is mainly inter-subjective, aligning with theories that emphasize the informational value of emotions at the social level (Rimé, 2009; Van Kleef, 2018). In the Mutual-Modeling version, complete emotional information is displayed to both learners, supporting the explicit externalization and comparison of their emotions in a shared representation (Dillenbourg et al., 2016; Molinari et al., 2013).

The experiment examines whether differences in both access to and use of emotional information influence how learners express or monitor emotions through the EAT. Drawing on the social perspective that views emotions as strategic interpersonal signals (Rimé, 2009; Van Kleef, 2018), we hypothesize that the Mutual-Modeling interface elicits the highest engagement with emotional information in both expression and monitoring, followed by the Partner-Oriented version, while the Self-Centered version elicits the least use of the EAT. As a complementary analysis, gaze transitions between emotion-focused and task-focused areas of the environment will be examined to assess whether emotional information is integrated differently across interfaces.

2.1 Method

2.1.1 Participants and Design

Forty-eight participants (29 women, 19 men; M = 37.3, SD = 10.01) voluntarily took part in the study. Among the participants, 23 were university students (undergraduate and graduate, various faculties) and 25 were professionals from a company adopting distance learning. No remuneration was offered. Sixteen participants were randomly assigned to each of the three interfaces (Self-Centered, Partner-Oriented, Mutual-Modeling) in a balanced inter-subject design.

2.1.2 Material

The experimental interface combined two main components: the EAT on the left and a joint problem-solving task on the right (see Figure 4). The problem-solving task consisted of four enigmas that required creative thinking. For instance, one enigma required participants to think recursively to guess the correct number of candles that could be built from the remains of used ones. Unbeknownst to participants, the partner was simulated using pre-recorded data from one of two participants who completed the task jointly and in synchronous conditions in a pilot study. The playback was identical to all participants: the simulated partner correctly solved two out of four enigmas and expressed a total of 26 emotions during the task. The emotions of the simulated partner were available only in the Partner-Oriented and Mutual-Modeling conditions. This solution was chosen to avoid the complexity of dyadic interaction, since one partner's behavior was controlled.

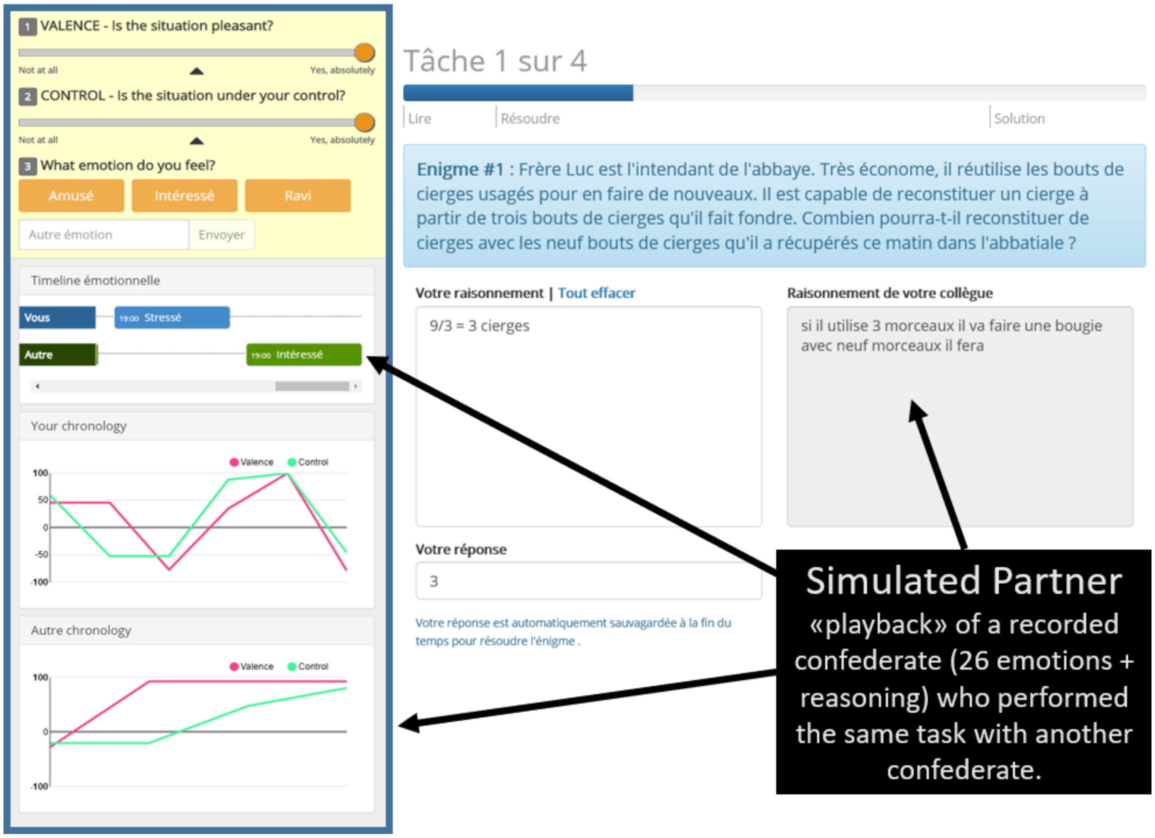

Figure 4 Example of the overall interface for the Mutual-Modeling condition with the EAT on the left side and the simulated problem-solving task on the right.

The EAT was set up as follows. For expressing emotions, participants had to rate the situation on two appraisal dimensions represented by sliders in the interface: (1) Valence, prompted by the question, “is the situation pleasant?”; and (2) Control/Power, prompted by the question, “is the situation under your control?”. Although the DEW can accommodate several emotional dimensions, valence and control were chosen because they maximize emotion discrimination when only two appraisal dimensions are adopted (Scherer, 2005). An underlying affective space theoretically placed twenty natural language words according to their position with respect to the two appraisals (Scherer et al., 2006). The words were: Amused, Annoyed, Attentive, Bored, Confident, Delighted, Disappointed, Empathetic, Envious, Frustrated, Interested, Irritated, Relieved, Satisfied, Stressed, and Surprised. These feelings were empirically determined in pilot studies and by crossing the literature as being frequently reported in computer-mediated learning tasks. Each time one of the sliders was modified, a parsimonious computational model computed the three most likely subjective feelings to occur given the appraisal profile. Participants may then click one of the buttons or choose to express another subjective feeling through a combo text-input, either by typing or by choosing from a drop-down menu reporting the complete list of 20 words.

The monitoring part of the EAT varied according to the experimental condition (see Figure 1). The Self-Centered interface comprised an emotion timeline with only the subjective feelings of the participant, a line chart with the evolution of the ratings of the participant on the two appraisal dimensions, and finally a word cloud showing the aggregated frequency of the subjective feelings. The Partner-Oriented interface was similar to the Self-Centered, except that the information displayed was that of the simulated partner. Finally, in the Mutual-Modeling interface, the timeline displayed both the participant and the simulated partner's subjective feelings over time, and two line charts displayed the evolution of the appraisal dimensions, one for the participant and one for the simulated partner.

Tobii T120 eye-tracker recorded gaze patterns on the EAT and task areas. The EAT was further divided into two Areas of Interest (AOI): the upper expressing part, and the lower monitoring part.

2.1.2 Procedure

Participants attended the study at Geneva University. Upon arrival, they were welcomed into the eye-tracking lab and briefed on the study's aims. They then received a detailed explanation about the use of the EAT, with attentive clarification about the Valence and Control/Power sliders to avoid confusion noted in a pilot experiment. The EAT's monitoring aspect was clarified based on the assigned experimental condition. Participants were informed about the emotional data they would share and the type of data they would view. The joint problem-solving task was then explained. Instructions were also given to limit communication in the text area to participants' own reasoning, without attempting to chat with the partner, which would have revealed the deception. A warm-up phase followed, allowing participants to practice with the interface. Once ready, the experimenter pretended to check in with a confederate in a similar room with another participant and then started the experimental task. Participants solved four enigmas in three phases. For 40 seconds, only the text of the enigma was revealed. Then, two text areas appeared; one for participants to share their reasoning, and the other with the playback of the reasoning of the simulated partner. The participants also had a text-input to guess the correct answer to the enigma but could not see the answer of the simulated partner. It was also instructed not to share the solution in the reasoning area, but to only specify the steps to reach the conclusion. The (simulated) partner's answer and the expected solution were revealed after three minutes in the last phase of the enigma. The experimental task lasted 20 minutes. In the end, participants were debriefed on the simulated partner.

2.1.3 Data Analysis

Omnibus one-way ANOVAs with pairwise comparisons between the three conditions (Self-Centered, Partner-Oriented, Mutual-Modeling) were planned before data collection to analyze two aspects: (1) the number of emotions expressed, and (2) the attention participants paid to the monitoring part of the EAT. For this second aspect, two eye-tracking indicators were retained as dependent variables: number of gaze visits as a measure of information seeking, and total gaze duration for information processing. These indicators were interpreted as measures of interest in the EAT (Poole & Ball, 2005). A follow-up multilevel analysis of gaze transitions between parts of the interface was conducted after seeing the data. Family-wise corrections were applied for multiple comparisons.

2.2 Results

After exclusions for technical issues, poor eye-tracking quality, and one extreme outlier (participant expressing 62 emotions against a means of around 13), only 35 participants remained (12 Self-Centered, 9 Partner-Oriented, 14 Mutual-Modeling). The small and unbalanced sample reduces statistical power, so results are interpreted in an exploratory rather than confirmatory perspective.

2.1.3 Use of the EAT for Expressing Emotions

Participants expressed a total of 483 emotions through the EAT (M = 13.80, SD = 5.68). By condition, means were M = 12.50 (SD = 5.30) for Self-Centered, M = 12.67 (SD = 6.00) for Partner-Oriented, and M = 15.64 (SD = 5.69) for Mutual-Modeling. The omnibus ANOVA did not detect an effect below the .05 conventional alpha level ($F(2,32) = 1.25$, $p = .301$, $\hat{\eta}^2_G = .072$, 90% CI [.000, .221]), and neither did the pairwise comparisons depicted in Table 1.

Table 1 Pairwise comparisons between the three conditions on the number of emotions expressed (p-values are adjusted with the Tukey method).

Comparison	***Estimation***	***SE***	***df***	***t***	***p***	***ΔM***
Self – Partner	-0.17 [-6.28, 5.95]	2.49	32	-0.07	.998	-0.03 [-0.93, 0.87]
Self – Mutual	-3.14 [-8.60, 2.31]	2.22	32	-1.42	.345	-0.56 [-1.37, 0.26]
Partner – Mutual	-2.98 [-8.90, 2.95]	2.41	32	-1.23	.442	-0.53 [-1.41, 0.35]

2.1.3 Use of the EAT for Monitoring Emotions

Information seeking was measured by the total number of visits that each participant made to the monitoring zone of the interface. Participants' gaze entered that zone on average M = 67.29 times (SD = 34.95). In the Self-Centered condition, the number of visits was M = 40.92 (SD = 16.80), whereas the count roughly doubles in the Partner-Oriented (M = 75.44, SD = 47.35) and the Mutual-Modeling (M = 84.64, SD = 23.76) conditions, for which the count was similar. An overall effect in the omnibus ANOVA could be detected ($F(2,32) = 7.42$, $p = .002$, $\hat{\eta}^2_G = .317$, 90% CI [.092,.490]). Pairwise comparisons, depicted in Table 2, suggest detectable differences between the Self-Centered vs. Partner-Oriented, and Self-Centered vs. Mutual-Modeling conditions, but not between the Partner-Oriented and Mutual-Modeling conditions. The confidence intervals around all parameters are also wide. The population effect remains thus uncertain due to inter-individual variation and small sample size.

Table 2 Pairwise comparisons between the three conditions on the number of times participants gaze entered any part of the monitoring zone of the EAT (p-values are adjusted with the Tukey method).

Comparison	***Estimation***	***SE***	***df***	***t***	***p***	***ΔM***
Self – Partner	-34.53 [-66.80, -2.26]	13.13	32	-2.63	.034	-1.16 [-2.10,-0.21]
Self – Mutual	-43.73 [-72.51, -14.94]	11.71	32	-3.73	.002	-1.47 [-2.35,-0.58]
Partner – Mutual	-9.20 [-40.46, 22.07]	12.72	32	-0.72	.752	-0.31 [-1.18, 0.56]

Information processing was measured by the accumulated time that each participant spent with the gaze inside the monitoring area of the interface. Participants spent on average M = 51.38 (SD = 32.54) seconds looking at any part of that zone, which amounts to 4.28% of the total task time. Participants in the Self-Centered condition spent M = 28.32 (SD = 17.15) seconds, whereas this time roughly doubled in the Partner-Oriented (M = 68.53, SD = 39.83) and the Mutual-Modeling (M = 60.13, SD = 27.70) conditions, for which time differed slightly. An overall effect could be detected in the omnibus ANOVA (*F*(2,32) = 6.24, p = .005, ˆη2 G = .281, 90% CI [.064,.457]). Pairwise comparisons, depicted in Table 3, suggest detectable differences between the Self-Centered vs. Partner-Oriented, and Self-Centered vs. Mutual Modeling conditions, but not between the Partner-Oriented and Mutual-Modeling conditions. As for information seeking, the confidence intervals are wide.

Table 3 Pairwise comparisons between the three conditions on the total time (in seconds) participants spent looking at any part of the monitoring zone of the EAT (p-values are adjusted with the Tukey method).

Comparison	***Estimation***	***SE***	***df***	***t***	***p***	***ΔM***
Self – Partner	-40.20 [-71.03, -9.37]	12.54	32	-3.20	.008	-1.41 [-2.38, -0.45]
Self – Mutual	-31.81 [-59.31, -4.31]	11.19	32	-2.84	.021	-1.12 [-1.97, -0.27]
Partner – Mutual	8.39 [-21.47, 38.26]	12.15	32	0.69	.771	0.30 [-0.58, 1.17]

2.1.4 Transitions Between Parts of the Computer-Mediated Environment

The exploratory analysis of eye-tracking transitions investigated how participants moved their gaze between three main Areas of Interest (AOI): the expressing zone, the monitoring zone, and the task zone. Six transitions were considered, capturing bidirectional movement between all AOI pairs. Although the method has limitations – such as potential interruptions when participants used the keyboard or mouse – it provides an initial look at dynamic, moment-to-moment engagement with emotional information. One participant with extreme transition counts was excluded, leaving 34 participants for analysis. The average total number of transitions per user was 176.41 (SD = 53.72), suggesting active engagement with the interface overall. A Type III ANOVA on a multilevel linear model with the participant as random intercept to account for repeated measures detected effects of group (*F*(2, 31) = 5.50, p = .009), transition type (*F*(5, 155) = 14.62, p < .001), and their interaction (*F*(10, 155) = 9.03, p < .001), indicating that interface type may influence the patterns of transitions, as corroborated by Figure 5.

Pairwise comparisons, depicted in Table 4, suggest that participants in the Mutual-Modeling interface generally made more transitions than the less socially oriented interfaces, except in both paths between Expressing and Task. Transitions between monitoring and task zones were also higher in this condition, suggesting that full emotional information may be instrumental to the task at hand. The Self-Centered group focused mainly on transitions between expressing and task zones, reflecting an intra-personal focus on expressing emotions, and to a lesser extent monitoring them. The Partner-Oriented condition showed intermediate patterns, sometimes resembling Self-Centered behavior and sometimes Mutual-Modeling behavior, consistent with its partial social orientation. Overall, these findings suggest that transitions provide a dynamic and sensitive measure of emotional awareness and integration, beyond static measures of information seeking or processing.

Table 4 Pairwise comparisons stratified by the path of the transitions. The Kenward-Roger approximation for the degrees of freedom is adopted, and p-values are adjusted using the Tukey method.

Transition	***Comparison***	***M Diff.***	***95% CI***	***t***	***df***	***p***
Expressing → Monitoring	Self – Mutual	–18.10	[–26.38, –9.82]	–4.31	89.68	<.001
	Partner – Mutual	–17.18	[–26.63, –7.73]	–3.63	89.68	.001
Monitoring → Expressing	Self – Mutual	–17.37	[–25.65, –9.09]	–4.14	89.68	<.001
	Partner – Mutual	–13.04	[–22.49, –3.59]	–2.76	89.68	.019
Expressing → Task	Self – Mutual	4.20	[–4.50, 12.90]	1.70	89.68	.211
	Partner – Mutual	3.16	[–5.29, 11.61]	–0.67	89.68	.783
Task → Expressing	Self – Partner	13.13	[1.89, 24.37]	2.69	89.68	.023
	Self – Mutual	7.13	[–2.42, 16.68]	1.54	89.68	.277
Monitoring → Task	Self – Mutual	–17.19	[–25.42, –8.96]	–4.09	89.68	<.001
	Partner – Mutual	–10.11	[–20.83, 0.61]	–2.14	89.68	.088
Task → Monitoring	Self – Mutual	–15.73	[–24.01, –7.45]	–3.75	89.68	<.001
	Partner – Mutual	–5.27	[–15.76, 5.22]	–1.11	89.68	.508

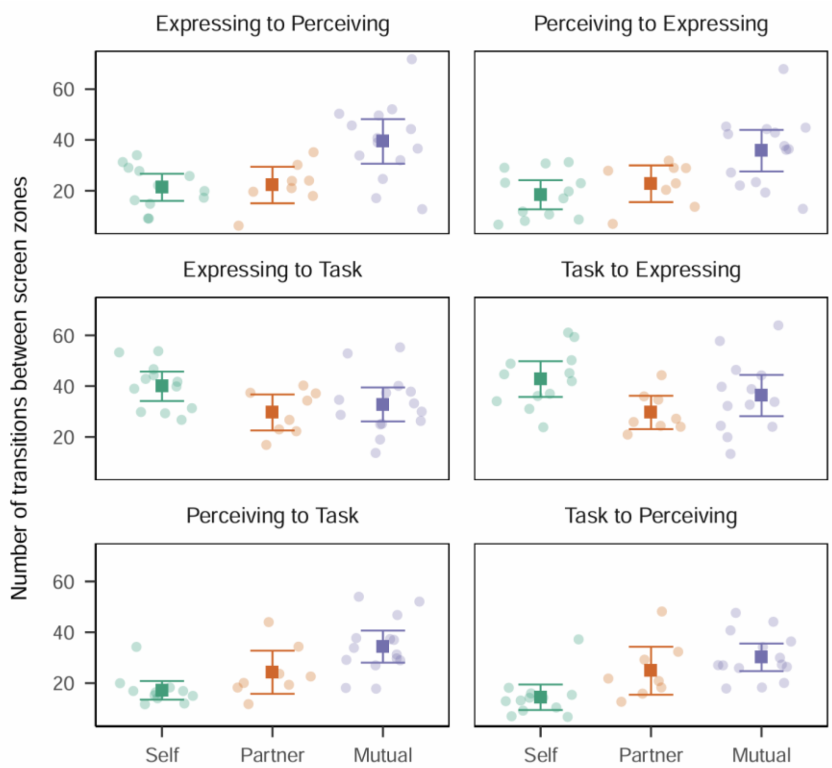

Figure 5 Marginal means of the number of transitions between Areas of Interest (AOI) on the interface in the three conditions. Bars represent 95% confidence intervals.

2.3 Discussion

The study hypothesized that more socially oriented interfaces would lead to greater use of the EAT in terms of expressing emotions and seeking and processing emotional information. This hypothesis was not supported by the number of emotions expressed and only partially supported by emotional information seeking and processing. Specifically, participants in the Partner-Oriented and Mutual-Modeling conditions engaged more in monitoring emotions compared to the Self-Centered condition, but no difference could be detected between the two socially oriented conditions, except for the exploratory analysis of transitions. This seems to suggest that information about the other is enough to enhance social comparison, questioning thus the added value provided by the possibility of direct comparison between the two emotional experiences.

From an interpersonal perspective, the results corroborates that an EAT can facilitate sharing and integrating emotional information in collaborative tasks (Avry et al., 2020; Eligio et al., 2012; Molinari et al., 2013; Rimé, 2009; Van Kleef, 2018). Participants appeared genuinely interested in their partner's emotions, and awareness that their own emotions would be visible did not inhibit expression. The presence of the partner's emotions also influenced participants' gaze patterns, promoting more dynamic transitions between task-focused and emotion-focused interface areas. This suggests that moment-to-moment emotional awareness can be instrumental to the task at hand. Although the measure of gaze transitions is not yet externally validated, it may provide a more nuanced indicator of integrated emotional information processing than static measures.

Participants in the Self-Centered condition also benefited from the EAT, highlighting its intra-personal utility (Lavoué et al., 2020; Torre & Lieberman, 2018). Even though participants were the sole sender and receiver of emotional information, they still expressed emotions and monitored their emotional data, even though to a lesser extent. This suggests that EATs can encourage self-reflection and appraisal of one's emotional state, helping learners to understand and integrate their feelings in relation to the task (Torre & Lieberman, 2018). Overall, the findings support existing evidence on the value of emotional awareness tools in Computer-Supported Collaborative Learning, while providing a more fine-grained differentiation between intra-personal and inter-personal aspects of emotional awareness (Molinari et al., 2013).

3. Study 2

Even though emotions are considered short-lived phenomena, their effects can have long-lasting consequences (Brackett et al., 2019; Pekrun et al., 2018). This has led a growing body of research to assess the development of socio-affective competences directly as part of school curricula (*ibid*.). Emotions in asynchronous digital learning are a double-edged sword: they can help students stay engaged and feel connected across distance, but also, deepen feelings of isolation and erode motivation (Henritius et al., 2019). Scholars have thus started to outline how emotional awareness may sustain learners in reflecting on their emotional experience, as well as projecting an affective social presence over long periods of time (Lavoué et al., 2020; Lowenthal & Snelson, 2017; Ruiz et al., 2016). For instance, Ruiz and colleagues (2016) asked students in a computer science class to report their emotions through a visual dashboard across the semester. They found that students' reported emotions can support self-reflection and help improve learning outcomes. Lavoué and colleagues (2020) designed an emotion-reporting grid for university students to capture their daily emotions and then conducted retrospective interviews. Their analysis, grounded in control-value theory (Muñoz et al., 2016; Pekrun, 2006), showed how students linked emotions to causes and appraisals, highlighting the role of appraisal-oriented strategies in supporting emotion regulation.

In the same vein, this study adopts a longitudinal design, providing students with the possibility to share their emotions during a semester in a blended master's course about the technical and ergonomic development of interactive learning applications. Students used the EAT during remote learning periods to express and monitor their emotions while working individually on programming assignments. Unlike traditional Experience Sampling or Ecological Moment Assessment methods (Csikszentmihalyi & Larson, 2014; Shiffman et al., 2008), the EAT solely relies on learners' spontaneous initiative rather than external prompts. Moreover, emotional information is not only collected, but also shared with peers, fostering both self-awareness and social awareness within the classroom. The primary objective of this research is to investigate whether the EAT can effectively promote emotional self-awareness and enhance affective social presence in a distant, online learning setting (Lavoué et al., 2020; Lowenthal & Snelson, 2017).

3.1 Method

3.1.1 Participants

The study involved 33 master's students (22 women, 6 men, and 5 not disclosed; age M = 33.01, SD = 7.78) in the Master of Learning and Teaching Technologies at the University of Geneva across two cohorts (17 in the first, 16 in the second). The EAT was adopted as an example of educational technology, so its use was part of the program, but students decided whether to disclose their anonymized data for research purposes. While the convenience sample limits generalizability, it offers valuable insights, since participants were technically skilled and accustomed to integrating digital tools into their learning.

3.1.2 Material

The toolbox was used to produce an EAT that had to consider the monitoring of emotions from many different learners at the same time. Whereas the expressing function remained the same as in study 1, with the same appraisal dimensions (Valence x Control/Power) and 20 subjective feelings, the monitoring part was different (see Figure 4). The configuration removed temporal references and individual attribution, providing instead learners with three word clouds displaying the expressed subjective feelings in a size proportional to their frequency. In the first Self-Centered cloud, the last 50 subjective feelings of learners themselves were displayed. In the second Partners-Oriented cloud appeared the last 100 subjective feelings of the colleagues. The third group-oriented cloud contained all the subjective feelings expressed by the cohort. The graphical representations implemented the two main social functions of emotions: distancing and affiliation (Fischer & Manstead, 2016). Through the first two clouds, learners could see the difference between their emotional experience and that of their colleagues (distancing), whereas the third cloud created a collective emotional experience of the class (affiliation). The tool was configured to appear in a standalone browser window so that learners could either place it side-by-side with another software, or prompt it as needed.

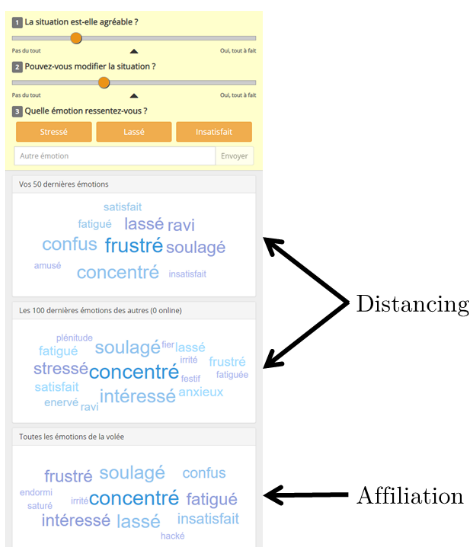

Figure 4 Interface of the EAT with three word clouds representing the distancing and affiliation social functions of emotions according to Fischer and Manstead (2016).

To evaluate the pedagogical usefulness of the EAT, the study introduced the Emotion Awareness Usefulness (EAU) scale. This seven-dimension instrument assessed the instrumentality of the EAT according to: frequency of use, affordance, social presence, self-understanding, understanding others, self-other comparison, and self-regulation. The 7 dimensions were rated on a 1-to-10 scale and were identified through a review of the literature of similar concepts or scales used in the field. While each dimension was measured by only one item – limiting reliability – the brevity was seen as beneficial for repeated measures and the technically literate sample. Usability was assessed with the widely adopted System Usability Scale (SUS), which consists in ten items rated on a Lickert scale (Brooke, 1996).

3.1.3 Procedure

The course was organized in three periods comprising an on-site course of one day followed by four-to-five weeks of remote learning. The EAT was not deployed during the first period, so that students may first experience unsupported remote learning. In the second period, they were first introduced to the concept of an EAT by a brief text. After a conceptual idea of the role of an EAT, participants filled the EAU survey for the first time in prospective tenses (e.g., I think I will use a tool of this kind frequently). After that, they could discover the actual EAT and try it for a few minutes. At the end of the demo, another EAU survey was administered again in prospective tenses. Then, the EAT was made available to students during the second and third periods of the semester, with a reminder of its existence sent out only in two forum messages. At the end of the second period, a halfway EAU survey was administered. Finally, at the beginning of the next semester, students filled in the EAU survey and the SUS scale.

3.2 Results

Results are based on 30 students, 15 per cohort, since 3 students did not complete both the halfway and final survey and were thus considered dropping out of the course or the research.

3.2.3 Use in Expressing Emotions

Overall, participants expressed 374 emotions through the EAT ($M = 12.47$, $SD = 17.18$), with 4 participants not expressing any emotion at all, and one participant expressing over 80. Whereas the means were similar in the two cohorts ($M = 11.47$ vs. $M = 13.47$), the medians highlight a more distributed use in the second cohort ($Mdn = 12$) compared to the first ($Mdn = 3$).

3.2.4 Perception of EAT Usefulness and Usability

Perceived usefulness of the EAT was measured by administering the 7 dimensions of the EAU scale in 4 surveys. To estimate marginal means and change over time, a linear mixed model was fitted to the data, with the dependent variable being the 1 to 10 rating on each EAU dimension. Fixed covariates included the longitudinal survey (Expectancy, Demo, Halfway, Final), the EAU dimension (Frequency, Affordance, Social Presence, Self-Understanding, Understanding Others, Self-Other Comparison, Self-Regulation), and cohort, with all two-way and three-way interactions included. Random effects accounted for the nested structure of repeated measures by participants, who were themselves nested within their cohort.

The Type III ANOVA on the multilevel linear model indicated that there was no detectable effect of the cohort ($F(1, 27.99) = 0.557$, $p = .462$), whereas both the longitudinal survey ($F(3, 716.75) = 63.495$, p <

.001) and the EAU dimension ($F(6, 713.99) = 29.403$, $p < .001$) showed detectable effects. Two-way interactions were detected between cohort and dimension ($F(6, 713.99) = 3.769$, $p = .001$) and between survey and dimension ($F(18, 713.99) = 2.085$, $p = .005$), but not between cohort and survey ($F(3, 716.75) = 1.173$, $p = .319$). A three-way interaction among cohort, survey, and dimension was not detectable ($F(18, 713.99) = 0.664$, $p = .848$), suggesting that the pattern of ratings over time and across dimensions was comparable for both cohorts, as suggested by Figure 5.

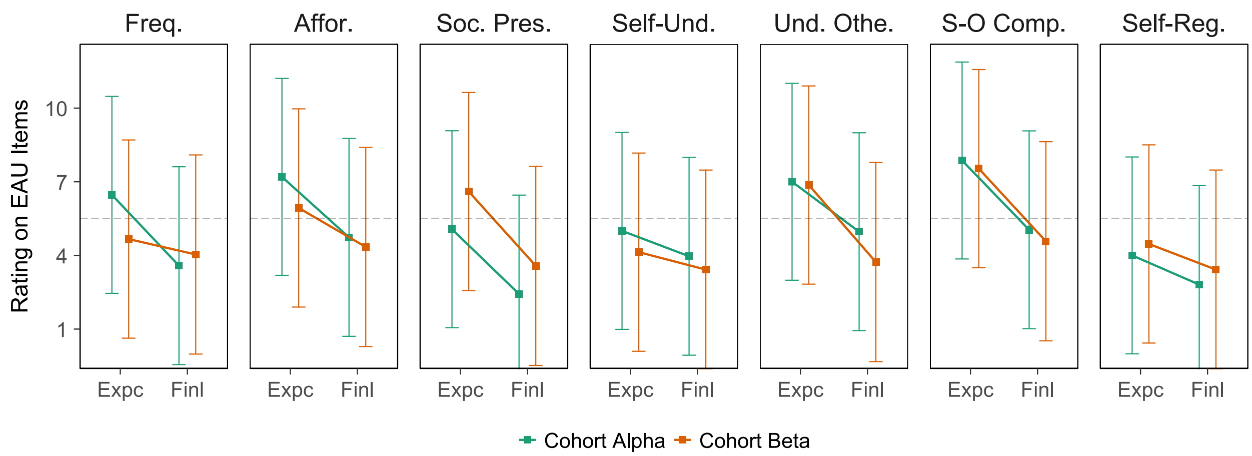

Figure 5 Rating of the EAU dimensions by two cohorts in the Expectancy and Final surveys. Marginal means and 95% CI computed through a multilevel linear model.

Table 5 shows the marginal means and contrasts only between the Expectancy and Final surveys, since the Demo survey yielded similar ratings to the Expectancy, and the Halfway to the Final. Higher expectations were rated for the more socially oriented dimensions, namely Self-Other Comparison (7.70) and Understanding Others (6.93), compared to the self-oriented dimensions such as Self-Regulation (4.23) and Self-Understanding (4.57). Contrasts between the Final and Expectancy surveys indicate decreasing ratings from Expectancy to Final across most dimensions, particularly for Self-Other Comparison (-2.89) and Social Presence (-2.83), while changes were smaller for Frequency (-1.75) and Self-Regulation (-1.11), and minimal for Self-Understanding (-0.87).

Table 5 Marginal means and estimated difference between the Expectancy and Final surveys on EAU scale computed through the linear mixed model. The Kenward-Roger approximation for the degrees of freedom is adopted, and p-values are adjusted using the Tukey method.

Dimension	***Expectancy***	***Final***	***Est.***	***SE***	***df***	***z.ratio***	***p.value***
Frequency	5.57	3.81	-1.754	0.519	Inf	-3.381	<.001
Affordance	6.57	4.54	-2.024	0.519	Inf	-3.899	<.001
Social Presence	5.83	3.00	-2.829	0.519	Inf	-5.451	<.001

Self-Understanding	4.57	3.70	-0.870	0.519	Inf	-1.676	.094
Understanding Others	6.93	4.35	-2.583	0.519	Inf	-4.976	<.001
Self-Other Comparison	7.70	4.81	-2.888	0.519	Inf	-5.564	<.001
Self-Regulation	4.23	3.12	-1.113	0.519	Inf	-2.145	.032

Reliability indicators of the EAU were generally moderate to high, with a uni-dimensionality index of 0.86 and an average correlation fit of 0.92. Exploratory factor analysis indicated a three-tiered structure: partner-oriented (Social Presence, Understanding Others, Self-Other Comparison), self-oriented (Self-Understanding, Self-Regulation), and usability-related (Frequency, Affordance). Overall reliability was good ($\alpha = 0.86$, $\omega h = 0.66$, $\omega t = 0.93$).

Additionally, 26 participants filled the SUS at the end of the semester, yielding an average score of $M = 72.82$ ($SD = 11.89$). This corresponds to Good usability according to the scale empirically determined by Bangor, Kortum and Miller (2009).

Finally, in the halfway and final survey, students could provide open-ended comments. Several participants reported forgetting to use the EAT due to a high workload. Some mentioned preferring instant messaging, for they integrated both communication and affective support. A few stated that logging emotions in real time interfered with their work. One participant reported feeling isolated during use, as they rarely saw peers online simultaneously. Another indicated that the appraisal-based questions encouraged reflection on emotional triggers and coping. Only one student expressed interest in continuing to use the tool in the future.

3.4 Discussion

The study explored the potential of an Emotion Awareness Tool (EAT) to support students in an asynchronous and individualized programming course within a blended master's program. The goal was to foster emotional self-reflection and socio-affective connection in a context known for emotional volatility (Lowenthal & Snelson, 2017). However, the results suggest that the EAT was unsuited to this particular learning environment. Usage in expressing emotions was extremely low: only one student engaged with it consistently, while the majority used it minimally or not at all. Students were already overwhelmed by technical demands, tight deadlines, and multiple digital platforms. The effort of remembering to use the EAT, to express emotions, and to interpret others' inputs outweighed the perceived benefits.

This misalignment is further confirmed by the sharp decline in perceived usefulness. While students initially expressed interest, particularly in socially-oriented functions like understanding others, ratings on the EAU scale plummeted on all dimensions. Some students explicitly stated they preferred instant messaging that offered cognitive, social, and affective support simultaneously. Moreover, word clouds provided only a shallow, static representation of emotions (Ez-zaouia et al., 2020). Contrary to other studies, the EAT failed to enhance a sense of belonging and did not broadcast an affective social presence (Lavoué et al., 2020; Lowenthal & Snelson, 2017; Ruiz et al., 2016)

The lack of pedagogical scaffolding – such as reminders, guided reflection, or group discussions – hindered the EAT's chances of success. The consistency of results across two cohorts suggests that the issue was not about group dynamics, but the inherent incompatibility between the tool and the learning environment (Dillenbourg et al., 2016). Although the EAT functioned properly and was perceived as usable, it did not achieve its intended pedagogical role. These findings corroborate that emotional awareness tools, as any awareness tool, are not universally beneficial; their success depends on careful integration into pedagogy, alignment with student priorities, and support for both intra- and inter-personal needs (Kreijns et al., 2003; Lavoué et al., 2020). Nonetheless, initial interest in emotional awareness suggests potential for further investigation in similar settings, and the EAU scale may serve as a promising instrument for assessing EAT efficacy. Future implementations may require explicit scaffolding, better visualizations, and a clear fit between the tool and the learning environment.

4. General Discussion

This article reports on two studies in which an Emotion Awareness Tool (EAT) was configured and deployed to integrate emotional awareness into computer-mediated learning environments. The first study examined a synchronous and (simulated) collaborative learning task. The second study explored a ecological remote environment, where interaction among learners was not structurally supported. Across both contexts, the core premise was that learners could benefit from an appraisal-driven EAT capable of capturing and conveying emotional states in a theoretically grounded manner. The central pedagogical assumption is that linking the expression and interpretation of emotions on the interface to a theory-driven emotion structure can enrich both intra- and inter-subjective meaning-making, thereby enhancing the reflective and strategic communication of emotional awareness.

This assumption was partially supported in the first study, where more socially oriented interfaces yielded increased monitoring of emotional information and better integration of emotional information with the task (Rimé, 2009; Van Kleef, 2018). However, this heightened engagement did not extend to the expression of emotions, suggesting that users may have an intrinsic for reporting their emotions even in the absence of social sharing (Torre & Lieberman, 2018). The study contributes to disentangling the intra-personal and inter-personal pathways of emotional awareness using the EAT as an experimental factor, which complements previous findings using an awareness vs. no-awareness paradigm (Avry et al., 2020; Eligio et al., 2012; Molinari et al., 2013). Manipulating the expressing and monitoring functions of an EAT is a way to increase understanding of which parts of emotional awareness may contribute to better learning processes and outcomes (Buder et al., 2021).

In contrast, the second study did not support the overarching assumption: despite initial interest in emotional awareness, participants showed minimal use of the tool over time, indicating a poor fit between the EAT and the learning context (Kreijns et al., 2003). The unstructured integration of the tool was too ambitious: the implementation of an emotion structure into the EAT cannot supplement accurate pedagogical scaffolding and guidance in processing information (Avry, 2021; Buder et al., 2021; Lavoué et al., 2020). This limited adoption may, at first glance, suggest that the tool's design – while potentially effective in collaborative settings – does not readily transfer to contexts lacking direct collaboration. However, given the differing designs and limited scope of the two studies, such a conclusion remains tentative and requires further empirical validation.

At the same time, by deploying the same EAT in two distinct configurations across both studies, it is possible to provide a preliminary assessment of the core assumption underpinning its design: that emotional awareness can be meaningfully structured through a computational model linking appraisal dimensions to subjective feelings (Scherer et al., 2013; Shuman & Scherer, 2014). Across both contexts, the model demonstrated moderate accuracy, with participants selecting a suitable lexicalized emotion among the three proposed options in approximately 75% of cases. This suggests that the model functions as a heuristically useful mechanism for predicting emotional experience based on appraisal inputs (Scherer & Meuleman, 2013). However, Valence and Control/Power were rated highly symmetrically (mean correlation $M\rho = 0.47$, $SD\rho = 0.43$), indicating that Control/Power may be subordinate to Valence rather than contributing independently to emotion differentiation, a finding consistent with prior work (Erbas et al., 2015; Fontaine et al., 2021). This dependency is clearly evident in Figure 6, which compares the theoretically expected positioning of lexicalized emotions in the affective space with their empirically observed placement based on average appraisal ratings (Gillioz et al., 2016; Scherer et al., 2006). In the observed data, emotion labels cluster along the main diagonal (from bottom-left to top-right). These results highlight one of the motivations behind the toolbox's design: to allow flexibility in defining the underlying affective space, including the number and type of appraisal dimensions and lexicalized emotions. For instance, the Control-Value dimensions may be better suited to certain learning contexts than the Valence-Control/Power dimensions used here (Muñoz et al., 2016; Pekrun, 2006). In some cases, more than two appraisal dimensions may be necessary to support a fine-grained assessment of emotional experience (Fontaine et al., 2007).

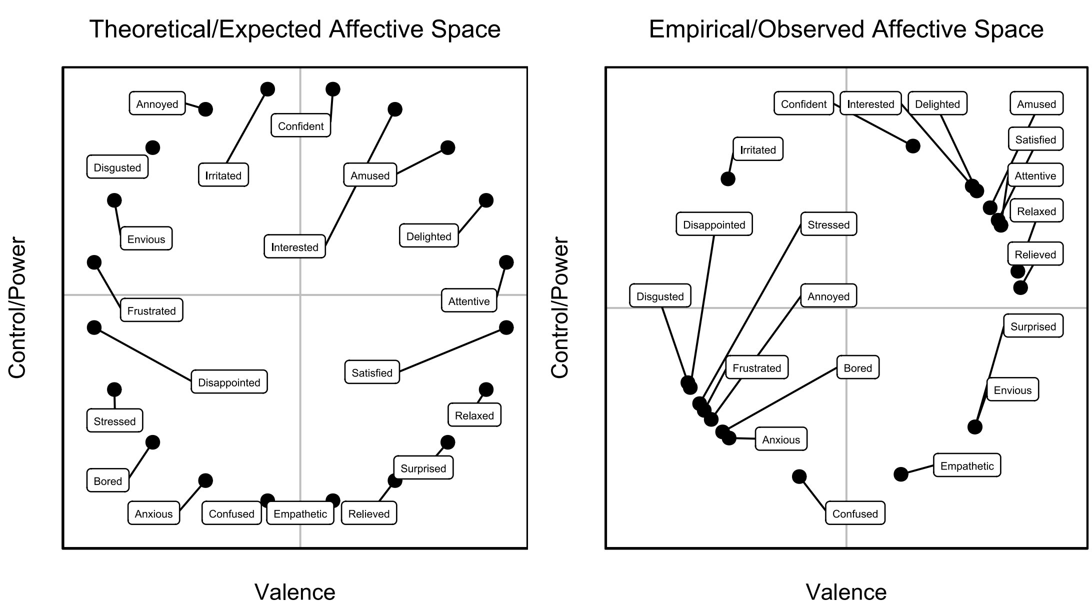

Figure 6 Comparison between the expected position of emotions and the average rating observed in the two studies.

Given these findings, it is worth reflecting on the role of the computational model. Rather than treating it as a fixed predictor, it can be understood as one of several possible approaches to linking appraisal and emotion in digital tools. Three main types can be distinguished. First, the theory-driven model – applied by the DEW – relies on a predefined affective space and the system predicts emotions based solely on theoretical mappings. Second, a data-driven model learns from users' past inputs, adapting predictions based on patterns in real usage. It could incorporate prior emotional states and use machine learning to improve suggestions over time. While potentially accurate, this approach risks becoming a *black box*, offering little transparency or pedagogical insight (Guest & Martin, 2021). Third, a scripting-driven model reverses the logic: instead of predicting emotion from appraisal, it starts with a desired emotional state (e.g., productive confusion) and guides learners to recognize the corresponding appraisal. This aligns with pedagogical strategies that intentionally evoke specific emotions to support learning (D'Mello et al., 2014; Harley et al., 2017; Vogl et al., 2019). While promising, it requires tightly controlled designs and may not generalize across contexts (Gentsch et al., 2017). Each model reflects different assumptions about how emotion should be supported in learning. The theory-driven approach prioritizes transparency and educational value over prediction accuracy (Boehner et al., 2007; Guest & Martin, 2021; Lavoué et al., 2020). Its strength lies in making affective processes explicit, inviting reflection, and allowing customization.

Finally, the experience of conducting two studies in different conditions provided useful insights for the broader implementation of an affect-aware system (Lavoué et al., 2020). Several directions emerge from these findings. First, it is important to clarify which affective phenomena the tool is intended to address: whether moods, emotions, preferences, or others (Scherer, 2005). Second, specifying whether the design draws explicitly from an affective theory can strengthen the pedagogical benefits of that choice (Lavoué et al., 2020; Muñoz et al., 2016). Third, offering competing or complementary ways of fostering affective awareness may encourage empirical comparison and critical reflection (Buder et al., 2021). Finally, facilitating the assessment of both use and perception of the tool can provide valuable feedback for further refinement (Lajoie et al., 2020).

5. Conclusion

The article contributes to the investigation of emotional awareness in computer-mediated learning environments both empirically and methodically. Two studies addressed research questions grounded in current trends regarding emotion awareness tools. To extend this line of inquiry, a flexible toolbox is introduced, enabling practitioners and researchers to customize and implement their own instance of the Dynamic Emotion Wheel within instructional or research designs. Together, these contributions aim to advance our understanding of how emotional awareness can be harnessed to support learning processes and outcomes in educational technology.

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Appendix

The computational model underpinning the Dynamic Emotion Wheel (DEW) implements a *k*-nearest neighbors (k-NN) algorithm to map real-time self-reported cognitive appraisals onto a ranked subset of discrete emotional labels. It operationalizes this link through a geometric distance function in a configurable *n*-dimensional affective space. The model is computationally lightweight, with time complexity $O(m)$ for $m = |A|$, and supports real-time interaction.

The details of the model are as follow:

- $\mathbf{E} = (E_1, E_2, ..., E_i) \in \mathbb{R}^i$ be the *appraisal evaluation vector*, where each E_j represents the user's rating on the *j*-th appraisal dimension (e.g., Valence, Control/Power), collected via continuous sliders on the DEW interface at time *t*.
- $\mathbf{P}_k = (P_{k1}, P_{k2}, ..., P_{ki}) \in \mathbb{R}^i$ be the *predicted appraisal profile* associated with a discrete (lexicalized) emotion *k*, pre-defined within an affective space *A*, such that $\mathbf{P}_k \in A$.
- $\Delta(E, \mathbf{P}_k)$ be the *distance metric* between **E** and $\mathbf{P}_k$, determining the similarity between the user's evaluation and the theoretical profile of emotion *k*.
- $k \in \mathbb{N}^+$ be the number of suggested emotions to return.

The model computes the distance $\Delta(E, \mathbf{P}_k)$ for all $\mathbf{P}_k \in A$, then selects the *k* emotions with the smallest distances. The output is an ordered list $\vec{\mathbf{P}}$ of size *k*, sorted by ascending $\Delta(E, \mathbf{P}_k)$:

$$f(E, A, k) \longrightarrow \{ \vec{\mathbf{P}} = (\mathbf{P}_{(1)}, \mathbf{P}_{(2)}, ..., \mathbf{P}_{(k)}) \mid \mathbf{P}_{(i)} \in A, \Delta(E, \mathbf{P}_{(i)}) \leq \Delta(E, \mathbf{P}_{(i+1)}) \}$$

The specific form of $\Delta(E, \mathbf{P}_k)$ depends on the structure of the affective space:

One-dimensional space:
$\Delta(E, \mathbf{P}_k) = |E_1 - P_{k1}|$

Cartesian plane (*n*-dimensional Euclidean space):
$\Delta(E, \mathbf{P}_k) = \sqrt{[(E_1 - P_{k1})^2 + (E_2 - P_{k2})^2 + \cdots + (E_n - P_{kn})^2]}$
or in summation form:
$\Delta(E, \mathbf{P}_k) = \sqrt{[\sum(E_j - P_{kj})^2]}$ for $j = 1$ to n

Circumplex model (angular distance):
Let $E_{angle} = \arctan2(E_2, E_1)$ and $P_{k,angle} = \arctan2(P_{k2}, P_{k1})$, both adjusted to the range [0°, 360°). Then:
$\Delta(E, \mathbf{P}_k) = \min(|E_{angle} - P_{k,angle}| , 360° - |E_{angle} - P_{k,angle}|)$
When E = 0 (neutral evaluation on all dimensions), $\Delta(E, P_k)$ becomes constant in the circumplex model due to angular indeterminacy (arctangent of 0/0). To avoid bias, the model assigns a small random perturbation to E, ensuring fair shuffling of suggestions.

The model has the following requirements:

- $\dim(E) \leq \dim(\mathbf{P}_k)$: the number of rated appraisals must not exceed the dimensionality of *A*.
- The domain of E_j must match that of P_{kj} (e.g., both defined on [−100, +100]).