



EMODASH: A dashboard supporting retrospective awareness of emotions in online learning

Mohamed Ez-Zaouia, Aurélien Tabard, Elise Lavoué

► To cite this version:

Mohamed Ez-Zaouia, Aurélien Tabard, Elise Lavoué. EMODASH: A dashboard supporting retrospective awareness of emotions in online learning. *International Journal of Human-Computer Studies*, 2020, 139, pp.102411. 10.1016/j.ijhcs.2020.102411 . hal-02490259

HAL Id: hal-02490259

<https://hal.science/hal-02490259>

Submitted on 25 Feb 2020

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

EMODASH: a Dashboard Supporting Retrospective Awareness of Emotions in Online Learning

Mohamed Ez-zaouia^{a,c,d,e,*}, Aurélien Tabard^{b,c}, Elise Lavoué^{a,c}

^a*University of Lyon, Université Jean Moulin Lyon 3, iaelyon school of Management*

^b*University of Lyon, Université Claude Bernard Lyon 1*

^c*CNRS, LIRIS UMR5205, F-69621 Lyon, France*

^d*SpeakPlus, Lyon, France*

^e*Woonoz, Lyon, France*

Abstract

We present EMODASH, an interactive dashboard supporting tutors' retrospective awareness of learners' emotions in a video-conferencing learning environment. Socio-affective relationships play an important role in learning processes and learning outcomes, but they are harder to develop in online-learning. This can be explained by a lack of emotion awareness due to the asynchronous interactions, technical challenges, and tutors' focus on properly conducting the learning activity and gearing towards pedagogical outcomes. We conducted an eight-week long field study with five professional tutors on how they used EMODASH while writing feedback to learners after language learning sessions. We found that EMODASH led tutors who were already sensitive to learners' emotions to incorporate more affective elements in their reports, suggesting a stronger awareness of learners' emotions. Tutors also wrote more formative and less summative feedback. Furthermore, our results suggest that glanceable visualizations of learners' emotions may be preferred and sufficient to foster tutors' awareness of learners' emotions. Finally, the dashboard led tutors to reflect on the way they conduct their lessons, using learners' positive emotions as a proxy evaluation of their teaching.

*Corresponding author

Email addresses: `mohamed.ez-zaouia@univ-lyon3.fr` (Mohamed Ez-zaouia), `aurelien.tabard@univ-lyon1.fr` (Aurélien Tabard), `elise.lavoue@univ-lyon3.fr` (Elise Lavoué)

Keywords:

Visualization, Dashboard, Awareness, Emotion, Online learning, Feedback

1. Introduction

Learners' emotions have a significant impact on learning processes and outcomes (Pekrun et al., 2011). Positive emotions, and particularly positive task-related ones like curiosity and enjoyment, can positively impact learning as they help learners focus more on the task, boost their motivation to learn, or facilitate self-regulation (Wolters, 2003). Negative emotions can have detrimental effects as they divert learners' attention away from problem-solving, consume cognitive resources and inhibit performance particularly on complex learning tasks (Pekrun, 2014). Emotions can also denote the presence of important or complex aspects of learning tasks that require attention and sustained effort (Boekaerts, 2010).

Developing an awareness of learners' emotions in online learning settings is challenging. Interactions are mediated, sometimes asynchronous, and online spaces leave few spaces for informal exchanges (Dourish and Bly, 1992) that could help tutors develop an awareness of learners' emotions (Boden and Thompson, 2015; Lavoué et al., 2015).

To improve tutors' emotion awareness, we designed EMODASH, an interactive dashboard displaying information about learners' emotions and interactions during past learning sessions. EMODASH is part of a video conferencing based learning platform for foreign language, and it integrates with the feedback reporting tool that tutors use after each learning session.

We conducted a field study of EMODASH for eight weeks with five tutor-learner pairs. We analyzed how tutors used the dashboard and the feedback reports they wrote *with* and *without* EMODASH. We sought to understand the type of emotion information tutors rely upon when writing feedback reports to learners, and investigate how an awareness of learners' emotions impacts the feedback reports tutors to share after learning sessions. We more particularly analyzed the content of the feedback reports to examine the extent to which

emotion awareness led tutors to provide learners with formative feedback on why a particular task is correct or incorrect, and ways to maintain or improve their performance (e.g. “I believe that success in interviews is attributable to practice and confidence”), compared to summative feedback that provides learners with an overall evaluation of their successes and failures (e.g. “You can make improvements”). Also, we examined the impact of emotion awareness on the incorporation of motivational (e.g. “Good job”) or affective content (e.g. “It was a pleasure to meet you”) in their feedback.

We found that EMODASH led tutors to adapt the content of their feedback reports by integrating more affective language. Tutors also wrote more formative and less summative feedback reports. The tutors who changed their feedback reports the most are those who interacted the least with the dashboard, suggesting that glanceable visualizations of learners’ emotions may be sufficient. Tutors appreciated the ability to identify learners’ emotions at a glance, and whether there were more positive or negative emotions during a session. Overall, visualizing learners’ emotions seems promising to increase tutors’ awareness of learners’ emotions, but also to develop their self-awareness. Tutors used EMODASH as a feedback mechanism on how they are when conducting their lessons, considering that learners’ positive emotions were a sign of lessons that worked well.

2. Background and Related Work

2.1. Distance Learning and Learning Dashboards

In distant computer-mediated collaboration maintaining awareness has always been a challenge (Dourish and Bellotti, 1992). When awareness cues are missing (e.g. eye gaze, gestures) it can be challenging to develop an accurate understanding of what others do, or intend to do. Awareness tools can mitigate the lack of awareness by capturing data about users’ activity and reflecting it to them (Buder, 2011). Real-time feedback systems can also improve group

dynamics during collaboration (Tausczik and Pennebaker, 2013; Calacci et al., 2016).

In the educational domain, awareness technologies have mostly been dedicated to synchronous interactions and have not been tailored to support delayed awareness of learning processes. Due to the tremendous amount of data generated by digital learning environments, learning analytics dashboards have shown great potential in providing tutors and learners with real-time or delayed behavioral, cognitive, and social information that enriches the learning and teaching experience (Siemens and Long, 2011). Such dashboards rely on an end-to-end process from collecting and mining learning data, all the way up to its visualization (Ferguson, 2012).

Schwendimann et al. (2017) systematic review of 55 learning dashboards emphasizes the over-reliance on systems logs in building dashboards, rather than developing dedicated probes capturing relevant information. In this context, Verbert et al. (2014) argue for investigating different data sources that may be relevant to increase awareness and reflection about learning. In this paper, we investigate the role of information on learners' emotion in supporting tutors' awareness, and we question the integration of emotions in dashboards. Given the circumstantial nature of emotions, we deployed our dashboard in ecological conditions over several learning sessions. While many dashboards have been evaluated in controlled settings, we argue alongside Schwendimann et al. (2017) that longitudinal research in authentic settings is most needed in the domain.

2.2. Emotion Recognition and Learning Analytics

Most systems supporting emotion awareness build on top of two theories of emotions (Izard, 2010). The first theory is known as *discrete emotions* (Ekman and Friesen, 1976). It purposes that a small set of distinct emotions (e.g. anger, disgust, fear, happiness, sadness, surprise), called universal or basic emotions, constitute the core of all human emotions. The second one is known as *dimensional emotions* (Barrett and Russell, 1998) and claims that emotions are rather continuous and structured in a dimensional space varying along with a

number of dimensions (e.g. valence, arousal). In the education field, both discrete and dimensional models of emotions are used as well as more learning-centered models (Pekrun, 2006; Kort et al., 2001).

Data collected on user emotions are generally grouped into three categories (Cernea and Kerren, 2015; Montero and Suhonen, 2014): perception-based (or behavioral) estimations, physiological estimations and subjective (or psychological) feelings. Perception-based estimations consist of recognizing emotions from facial expressions, voice, and body movements. Physiological measures of emotions are performed using devices installed on the human body and focus on the subconscious emotional responses (e.g. heartbeat, blood pressure, and sweating). Subjective feelings consist of self-reports of emotions.

In their review of data collection methods for inferring learners' emotions from a virtual learning environment, Rienties and Rivers (2014) suggest another categorization: using *existing data* (content analysis, natural language processing, behavioral indicators), or using *new data* on learners' emotions (questionnaire, interviews, self-report, ITS). Finally, D'Mello (2017) highlights the use of learning analytics (LA) and educational data mining (EDM) methods to analyze learners' emotions, based on the analysis of click-stream data (e.g. sequence of clicks labeled by students to build a classifier for emotions), interaction patterns (e.g., using/labeling observations of students' interactions with, e.g., computers, peers, to build a classifier) and bodily signals (e.g., videos from students).

In this work, we combine *existing data* collected from facial recognition algorithms (perception-based estimation) with users' interactions with the learning environment (learning analytics). In authentic online learning settings, these two measures are the easiest and less intrusive to infer learners' emotions and to capture the context in which they were felt. Facial expressions recognition algorithms infer emotions using both geometric (position of nose, eyes, mouth), and appearance (pixels values) features of the face. These emotions are used by some tools such as FaceReader (Loijens and Krips, 2019), Microsoft Emotion API (Microsoft.com, n.d.), Affdex SDK (McDuff et al., 2016) and Google Emotion API (Google.com, n.d.) to recognize emotions by providing numerical values

associated to them.

Some tools show high accuracy in detecting basic emotions, but only on specific datasets (e.g. 88% in average (Lewinski et al., 2014)). This may not be the case when classifying emotions in the wild. Based on previous work on multimodal emotion analysis combining voice and video recognition (Ez-zaouia and Lavoué, 2017), we found that the Microsoft API was reliable enough for basic emotion recognition. The API was started as a research project (MSO, 2016) before being hosted in the Microsoft Azure Platform. A paper from Microsoft Research (Barsoum et al., 2016) highlights the accuracy of emotion recognition for some emotions (happiness: 94%, surprise: 86%, anger: 82%) and neutral (90%) but also limitations in classifying emotions such as sadness (67%), fear (52%), disgust (26%), or contempt (4%). Such a method should be used very carefully when dealing with learners’ emotions. Our approach mainly relies on the aggregation of discrete emotions in two categories (negative and positive) as an insight on learners’ emotions felt during synchronous online interactions. We also put the emotion data in context with the video feed of learning sessions to mitigate inaccurate classifications.

2.3. Emotion Awareness and Learning Environments

Emotion awareness refers to the ability to perceive, identify, and understand emotions (Boden and Thompson, 2015). Emotional information can provide insights to enhance student learning (Linnenbrink-Garcia et al., 2016). D’Mello (2017) further argues that “*given the central role of emotions in learning, attempts to analyze (or data mine) learning without considering emotion will be incomplete*”.

Emotion data are generally used in Education to provide automated feedback or to adapt automatically the system to the learner. D’Mello (2013) defines such emotion-aware learning technologies as able to automatically detect and respond to student affect by providing emotional feedback or intervening in the learning process. Several Intelligent Tutoring Systems (ITS) have integrated such data, the most well-known being Affective AutoTutor (D’mello and Graesser, 2012).

A less adopted approach of emotion awareness consists of supporting learners' self-reflection on their own emotions (Lavoué et al., 2017, 2019). For instance, Ruiz et al. (2016) propose a visual dashboard that allows learners to track their emotions during the course to promote self-reflection. Montero and Suhonen (2014) also highlight the potential of analyzing learners' emotions with a text-based approach in online learning for supporting self-reflection or monitoring learners well-being during a course.

In this paper, rather than visualizing emotions to support self-reflection, we use visualization as a tool to foster tutors' awareness of learners' emotions alongside other aspects of the learning process. According to Boekaerts (2010) emotions have diagnostic value for the teacher because they reveal underlying cognitive processes, commitments and concerns. Leony et al. (2013) work is a rare example of visualizations of learners' emotions provided to tutors. The visualizations display the types of emotions felt by learners (inferred from ITS traces), the class events, and the tools used by learners.

In our work, we seek to understand more precisely what is the appropriate level of information on emotions to convey to tutors, and how visualization of emotions can help navigate through learning traces.

2.4. Emotion Awareness and Tutors' Feedback to Learners

Our study focuses on tutors' feedback after online synchronous sessions. Teachers' feedback can be effective to stimulate learners' progress, if it is explicitly related to learning goals (van den Bergh et al., 2012). Learners are more likely to improve when teachers provide specific feedback on the current performance, appropriate tasks and/or processes to improve upon, with clear goals to achieve (Hattie and Timperley, 2007). Prior work has examined learners' receptivity to feedback, highlighting the importance of the source (Nguyen et al., 2017) (e.g. anonymous source vs. from a peer or an authority), as well as the nature and the content of the feedback (Tanes et al., 2011; Sun et al., 2019). For instance, formative feedback offers ways to maintain or improve performance while the task is still being performed or completed (Tanes et al., 2011). Affective language

in feedback can also improve the receptivity of learners to this feedback (Nguyen et al., 2017).

Previous studies on the impact of emotion awareness focused on interactions between peers during collaborative activities. For instance, Molinari et al. (2013) showed that in CSCL settings, learners benefit from being aware of what their collaborative partners feel during interactions. Learners that communicated their emotions to each other are more likely to build on their partner’s ideas and to interact together in a transactive way. Lavoué et al. (2015) showed that students used emotional markers to reflect on their partner’s activity and to express their satisfaction when writing self-reports on online sessions. Another example is MoodMap (Fessl et al., 2012) that enables users to note and review their mood over time, and to obtain insights about team mood according to a given meeting and/or a date. The authors showed that mood self-tracking improves cohesion within teams, and leads managers to react proactively to changes in team members’ moods (Rivera-Pelayo et al., 2017). Samrose et al. (2017) also showed that providing teammates with post-session feedback on the group dynamics (including emotions) changes the way they participate.

Grounded in this previous research, our study focuses on the impact of retrospective emotion awareness on tutors’ feedback to learners. Emotional information may support tutors in identifying successes and failures in their interactions with learners and provide surface explanations on difficulties they encounter. Awareness of learners’ emotions could also lead tutors to adapt their feedback to learners, i.e by reassuring or motivating them (Linnenbrink-Garcia et al., 2016), or by integrating affective language. In our study, we examine the impact of emotion awareness on tutors’ feedback. Building upon the feedback content categories proposed by Tanes et al. (2011), we investigate whether emotion awareness tools lead tutors to offer formative or summative feedback or to incorporate more affective or motivational content in their feedback.

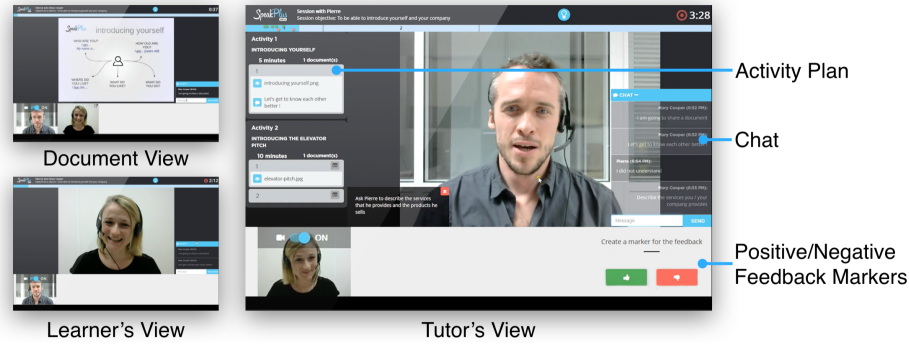


Figure 1: Example of a live learning session on SpeakPlus.

3. Context: SpeakPlus a One-To-One Language Learning Platform

SpeakPlus is a Web platform dedicated to improving oral communication skills in a foreign language (English, French, and Spanish). The platform connects professional language tutors with learners from around the world in one-to-one remote training sessions (Figure 1). While the study was conducted, there were approximately 50 active teachers (teaching at least one course per month) on the platform. Tutors can join the platform if they have previous teaching experience and a degree in teaching foreign languages, and successfully pass an evaluation interview, after which they receive training to use the platform. About 2000 users had bought at least 5 learning sessions on the platform at the time of the study. These learners had a very diverse background and skills, from novices to more advanced foreign language speakers.

The learning activities on SpeakPlus focus on goals set by learners, for instance improving oral presentation skills or preparing travel abroad. The learning process can be divided into three main stages:

1. Pre-session: before live learning sessions, tutors can create and customize learning materials (activities) for each learning session. Each learning activity has a duration and usually contains a set of documents, instructions for the learner or a set of personal notes for the tutor.
2. In-session: the tutor conducts a synchronous learning session with his/her learner. The pair (tutor and learner) communicates in real-time through video-conferencing. The tutor can to share learning materials/activities

with the learner (e.g. pdf, word, image, audio, and video), or to communicate via chat.

3. Post-session: the tutor writes a feedback report for the learner, including a summary of the session as well as a set of instructions for the next session.

During the session, tutors can add annotations (called markers), to pinpoint learners' positive and negative moments. At the end of each session, tutors use these markers to write a feedback report using a dedicated editor (Figure 4). Once the feedback report is finished, the tutor shares it with the learner, who is notified by email. Learners can read the feedback on the platform, alongside an audio recording of the session.

4. Emodash Design Process

Based on the role of emotion awareness in the learning process, we investigated various strategies to increase tutors' awareness of learners' emotions. Figure 2 presents the timeline of our design process. We went through six main iterations, for almost two years, involving different stakeholders at each stage. We started with interviews of tutors, and design explorations of live and retrospective awareness. We later explored and validated emotion recognition strategies which we tested with two tutors. We further refined the design through several iterations geared towards feedback support, and finally conducted the study discussed in this paper.

4.1. Preliminary Interviews and Early Design Explorations

Preliminary interviews with five tutors and one learner highlighted the importance (and lack) of socio-affective development on the platform. This relates to the development of trust, mentioned by several tutors, the need to engage learners remotely, and the challenges related to cultural differences. Combined, these elements have a direct influence on how learners behave, for instance, how they will ask questions, or interact with the materials.

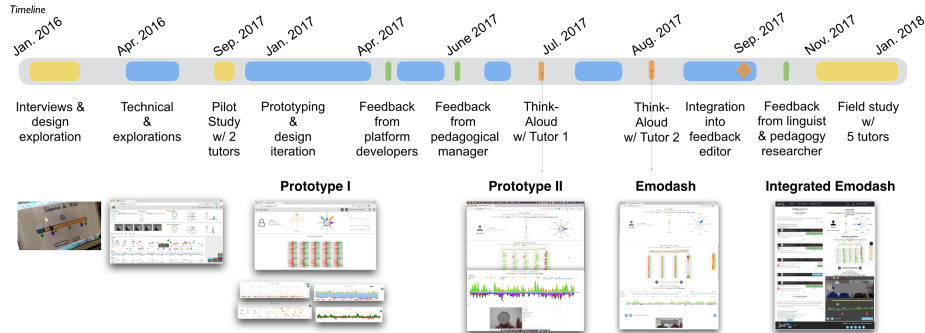


Figure 2: Key stages of EMODASH design process.

Although synchronous video conferencing enables participants to grasp facial expressions and gestures, remote learning is still poor in terms of socio-affective exchanges. Tutors' primary focus on their pedagogical goals as they conduct the learning sessions could explain the lack of emotion awareness. This problem is increased in the context of SpeakPlus, with the full-screen document sharing often hiding the video feed and further inhibiting the development of emotion awareness during exchanges.

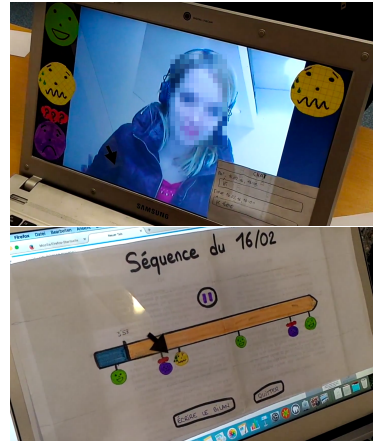


Figure 3: Early sketches of live emotional feedback (top) and dashboards (bottom).

We explored early sketches of live emotional sharing and post-session feedback (see figure 3) through various forms of emojis. The tutors reacted more favorably to dashboards offering an overview of learners' emotions over the past learning sessions.

4.2. Pilot Study: Supporting Retrospective Emotion Awareness

Our work builds upon the work of Ez-zaouia and Lavoué (2017) who focused on the technical feasibility of collecting, processing and visualizing emotions with a multimodal approach (audio + video) for higher reliability of emotion recognition. The results from in-house testing with two tutors showed that,

while relevant, representing multimodal data was too complex to explore and interpret. Given the good enough quality of the facial emotion recognition from the video feed, we decided to rely only on this source of data.

Further feedback from the two tutors emphasized three points: 1) Tutors needed a dashboard whose main take-aways were faster to grasp. 2) They needed a dashboard centered around one of their main task apart from the learning session: writing feedback reports. This task required awareness of learners' emotions over past learning sessions. 3) They needed the emotions to be contextualized with learners' activities to better understand what could have triggered them. This last point is in line with several models of emotion regulation (see, Gross, 2008; Pekrun, 2006): Tutors can better understand learners' emotions and help them reappraise the situation (i.e. positively change the perceived value or control of the learning activity) if they are aware of the antecedents of their emotions. Our goal with EMODASH has been to build upon this previous work, by reducing visual complexity, simplifying exploration for tutors and contextualizing emotions collected from video analysis with users' interaction traces.

4.3. EMODASH Iterative Design

We iteratively designed EMODASH over three months until we converged toward a dashboard that could be tested (Prototype I, see Figure 2). During this iterative process, we presented the dashboard informally to stakeholders: a pedagogical manager of the platform and developers.

After converging towards a design (see Figure 2, Prototype II), we sought to identify usability issues involving two tutors. The first author conducted two tests following the thinking aloud method (Lewis, 1982). We conducted the tests on a 13" MacBook Pro. We first read a script to explain the purpose and organization of the test. Then, we asked tutors to imagine they had conducted some learning sessions and to use the dashboard to explore the emotional state of the learner involved. We asked tutors to describe their thinking aloud as they interacted with the dashboard. Tutors gave their permission to record their

voices and the laptop screen. The first session took 30 minutes and the second one hour. After each test, we transcribed the audio, then summarized the issues highlighted by the tutor as well as those we observed during the test. We then implemented important features and fixed the issues before moving to the next usability test.

We identified the following issues: difficulties in grasping information at a glance, for instance, whether a learner expressed rather positive or negative emotions during a session; navigation across views could be improved; lack of visual clarity on the session and history views; and that more details on each session (chat content, documents viewed) would help tutors contextualize. We present the changes in each view of the dashboard as we present them in the next section. Think-Aloud observations are detailed in our supplementary material (see *Think-Aloud*).

5. Emodash: a Dashboard For Tutors

EMODASH augments Speakplus feedback report tool. It enables tutors to explore past teaching sessions through the lens of learner’s emotions alongside the interactions of tutors and learners during the sessions. Three views offer increasing levels of details: from a general overview of learners, to a detailed timeline enabling a replay of each session (Figure 4).

5.1. Data Collection and Analysis

EMODASH builds upon two types of data sources coming from the learning sessions: emotion recognition and, users’ interaction with Speakplus.

EMODASH relies on *video-based emotion recognition* to build its visualizations. We use the video stream as the main data source for analyzing learners’ emotions as it enables us to collect data in an authentic and non-intrusive manner. We used the Microsoft Emotion Recognition API, which takes an image as input, and returns normalized scores (the scores sum up to 1) for a set of emotions based on Ekman’s classification (anger, contempt, disgust, fear, happiness, neutral,

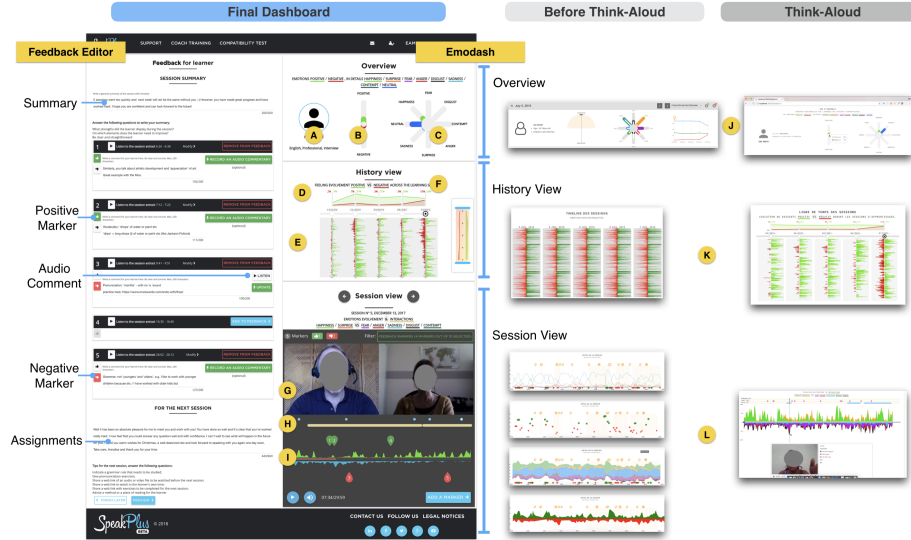


Figure 4: Left: EMODASH integrated in Speakplus feedback report editor. Right: Design Explorations.

sadness, surprise) (Ekman and Friesen, 1976). In EMODASH we refer to positive emotion as the sum of the scores of happiness and surprise, and negative emotion as the sum of the scores of the remaining emotions, without the neutral one. Details about the end to end automated process of emotions classification is provided online as supplementary material (see *Data*).

We combine learners' inferred emotions with interaction traces for tutors to contextualize and interpret them. We track the *interactions with Speakplus* performed by the tutor and the learner during the learning sessions. The data collected are: sharing files (pdf, video, audio, etc.), sending chat messages, and adding markers (positive or negative).

5.2. Overview

The first level is designed to summarize learners' emotions over all his/her learning sessions (Figure 5). It is composed of:

A. Learner's profile includes an avatar, a name, and a learning objective.

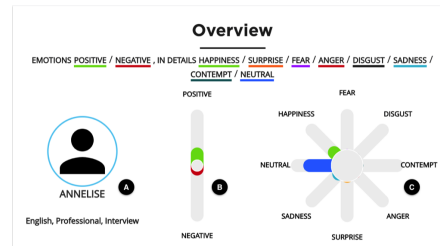


Figure 5: EMODASH Overview level.

B. Positive-negative emotions balance chart provides the distribution of positive and negative emotions of the learner.

C. Emotions radial chart gives the overall distribution of the tracked emotions (anger, contempt, disgust, fear, happiness, neutral, sadness, surprise).

We used a color encoding to distinguish the attributes both in the positive-negative balance and in the radial column charts. We integrated the legend directly in the header which participants found attractive and easily recognizable in the think-aloud evaluations. Tooltips on both charts provide additional details. They display the name of the emotion with the corresponding score.

Design exploration: The first version of the overview conveyed more information such as a timeline of positive, negative and neutral emotions, as well as a discrete count of the number of positive and negative intense emotions detected (see Figure 4.J). To simplify the reading, we simplified labels and made them larger. We also removed the timeline from the overview, and created a dedicated view (presented below), with more historical details on learners’ emotions.

Think aloud changes: Before the think-aloud, the balance of positive/negative emotions showed the “sum” of positive and negative emotions so that the chart would only go either towards the positive or the negative, our rationale was that it would make it faster to grasp the overall direction of emotions. However, Tutor 1 found it confusing that no negative emotions were visible although some were present in the other charts. We modified the chart to display both positive and negative emotions.

5.3. History View

The second level of EMODASH displays a distribution of the positive-negative emotions of the learner over time. At the top (Figure 6.A), a multi-line-area chart presents the evolution of the average positive-negative emotions across the



Figure 6: EMODASH History View.

learning sessions. The tutor can compare the distribution of positive and negative emotions in place. Underneath is a vertical timeline for each session (Figure 6.B). The positive-negative emotions are split along a central axis to make it easier to identify positive and negative peaks. The vertical timelines display a fisheye distortion on hover and, when clicked, update the session timeline view (3rd level below).

The tutor can rely on the first chart (Figure 6.A) to visualize how emotions evolve from one session to another, and on the second chart to get more details (Figure 6.B). We found it interesting to be able to see that some sessions got close averages despite having very different distributions. Similarly to the previous charts, the color encoding legend has been integrated into the view headings. On the right-hand side of this chart (Figure 6.C), a brush tool supports navigation across multiple sessions, this becomes useful when a large number of sessions are available (i.e. more than 5). The component is a miniature of the multi-line-area chart with dots representing sessions.

Iterative design: The first iteration of the History view provided dense timelines of positive/negative emotions for each session (see Figure 4.K). It was difficult to grasp the evolution of emotions across sessions. To provide a clearer overview, we simplified the timeline visually by averaging positive and negative signals over a larger time-span, so that users could more easily recognize whether a session involves more positive or negative emotions. We also added the summary timeline of positive/negative emotions (Figure 4.D).

Think aloud changes: The first think aloud revealed that navigating across sessions was not obvious, and would not scale well as the number of recorded sessions increased. We added scrubbing (Figure 4.F) for navigating across sessions. We facilitated navigation to past sessions so that clicking on one session of the history view would change the session view accordingly.

5.4. Session View

The session view is centered around a timeline of one learning session. Along with the emotions identified during the session, the interactions between users and the platform during the live learning session are visualized in this view (Figure 7). The main interactions are document sharing (pdf, image, video or audio), chat messages, positive/negative markers. Tutors can add more markers if they want. These are then used to create the feedback report for learners.

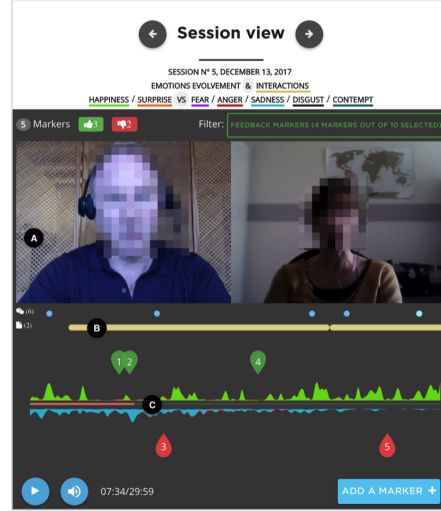


Figure 7: EMODASH Session View.

All the emotions captured are displayed in this view, except the neutral one, which corresponds to the whitespace of the chart (Figure 7.C). Splitting positive and negative emotions along the horizontal axis makes it easy to interact with peaks of emotions on both sides (positive and negative). The visualization helps the tutor recognize past sequences within the sessions, remember what happened, contextualize and reflect on the experienced emotions. The slider of the player in the middle of the chart can be used to navigate in the stream. The user can also directly click on the chart to navigate through the video, which is particularly useful to navigate to a specific pick of emotions. Two buttons support backward and forward navigation between sessions.

Iterative design: The first iterations did not incorporate a video replay of the session. They displayed the evolution of emotions alongside session interactions (e.g. chat messages, documents sharing), which overloaded the visualization (Figure 4.L). To simplify the design: (1) We removed the neutral emotion, which is the dominant emotion recognized. (2) We centered positive/negative emotions along the horizontal axis, so that positive emotions would lead to peaks going up, and negative emotions to peaks going down. (3) We moved interaction events to a separate timeline and added video playback.

Think aloud changes: Tutor 1 underlined the need for more contextual information to interpret learner’s emotions as (1) the timeline presented only the interaction events, but not the object they were on (document, chat message, etc.), and (2) the playback displayed only the learner’s video but not tutor’s one (Figure 7 – Prototype II). We added tooltips giving details on the emotions presented on the timeline, previews of shared documents, chat messages, as well as the video recording of both learner and tutor side-by-side. Tutor 1 also remarked the need to navigate the video around peaks, we added direct navigation using the streamgraph. In the second think-aloud, Tutor 2 found navigation with peaks interesting, as well as the contextual information we had added. During the test with Tutor 2, we observed that the video player was positioned too far from the emotion timeline. We decided to move the video player closer so that the timeline would be more readily used as the controller. We switched to a dark-grey background for the session view to improve the contrast with the visual elements.

5.5. User Interface and Visualizations Implementation

The user interface (UI) of EMODASH is built using JavaScript and Angular. The visualizations are implemented using D3js. The views of EMODASH work in a client/server fashion. When the UI starts loading, HTTP requests are sent to the server to pull the data. Data is pulled from the database and aggregated to produce JSON data objects for each view.

The video player is built on the top of HTML5 video specifications. It can play a video stream with play/pause/seek, volume up/down actions. We augmented it to render and visualize time series datasets with D3.js.

6. Field Study

We conducted an in-the-wild study of EMODASH over eight weeks between November and December 2017. Our goal was to investigate the impact of retrospective emotion awareness in distance learning, i.e. delayed awareness of

emotions felt by learners during synchronous interactions with a tutor. We focus more specifically on tutors’ feedback, and the impact emotion awareness can have on written feedback reports to learners. In this context, we set to answer the following questions:

1. *Do emotion awareness tools have an effect on the type of feedback given, specifically formative or summative feedback reports?*

Making tutors aware of learners’ emotions could help them interpret the way they learn and enrich their feedback with more formative than summative reports.

2. *Do emotion awareness tools lead tutors to incorporate more affective and/or motivational content in their feedback?*

We believe awareness of learners’ emotions could lead tutors to integrate more motivational or affective language.

3. *What effect do different granularities of emotion visualization, via a dashboard, have on tutor feedback?*
- Progdash conveys information at different levels, from an overview of learners’ emotions to a detailed view of emotions identified during learning sessions. We explore tutors’ use and perception of the different visualizations to provide design recommendations.

6.1. Participants

We recruited five professional tutors and five learners with English as a secondary language.

Tutors. We recruited five tutors (gender: [M=2, F=3], age: [Mean=42.8, Min=25, Max=58]) through an email to all SpeakPlus tutors. We relied on SpeakPlus pedagogical manager in selecting the final set of tutors, based on their experience and familiarity with the platform. The tutors recruited had more teaching experience on Speakplus (P1: 181h, P2: 227h, P3: 66h, P4: 20h, P5: 91h), than the average tutor on the platform ($Mean_{participants} = 103$, $Mean_{platform} = 26.45$).

Learners. We recruited 5 learners (gender: [M=0, F=5], age: [M=32.6, Min=20 Max=37]) through a post distributed via emails and social networks. The post described the study in broad terms. It was addressed to people interested in benefiting from free learning sessions on a specific learning objective. No other credit was given to learners and all of them used the platform for the first time.

All the learners were French native speakers. Their English level ranged from elementary (identified as “I know a little vocabulary but have difficulty putting words into sentences to express myself”) to proficient (“I can take part in clear and coherent, well-constructed conversations on a variety of topics”). While learning objectives were: “improving oral fluency”, “preparing a job interview”, “working with American interlocutors”, “applying for a job in an English-speaking country” and “preparing a work trip”.

Both tutors and learners were informed about the logging and the possibility to withdraw at any time. They permitted for recording and analyzing learning sessions data and signed online for consent. They also filled a pre-questionnaire that collected demographics, motivation and English level (only learners).

6.2. Procedure

The deployment lasted for eight weeks split into 4 stages: training, pair-formation, study, and wrap-up.

6.2.1. Training

The first week, as our tutors resided in different geographical places and time-zones, we shared a training video using a private link hosted on YouTube¹. In the video, we presented EMODASH (see Figure 4) along with an explanation of the different components to help them get familiar with the tool.

¹https://www.youtube.com/watch?v=QwAS_7-8JXQ

6.2.2. Pair-formation

The pedagogical manager of the platform assigned the most suitable tutor for each learner based on both his/her English level and learning objective. We then asked participants to pick preferred time slots for the first session. Once a common time-slot worked for each pair, the learner received an automated email asking to fill his/her profile and confirm the session.

Also, the pedagogical manager reached each learner by email giving them further details about how to get up and running with the platform.

6.2.3. Lessons and Feedback

During the next weeks, each tutor met his/her learner once a week for a learning session of 30 minutes (except one week where one pair met twice, at the beginning and the end of the week). Learners booked their learning sessions with their tutors at their own pace.

Tutors were automatically informed by email when the feedback report was ready to be edited after the data processing and emotion analysis was over (on average 40 minutes after the session). Tutors could then create their feedback reports using a dedicated editor (see Figure 8). Once the report finished, tutors could share it with learners, who received an email notification.

After the first session, we noticed that back-lighting issues broke the video analysis of one learner. We fixed the problem by post-processing the videos to improve contrasts and re-ran the emotion analysis. We also sent an email to all

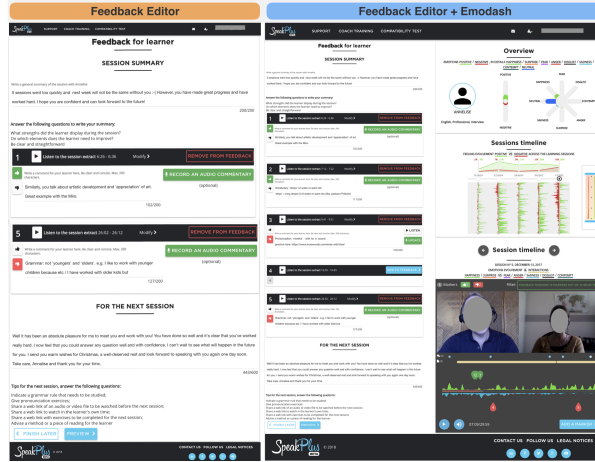


Figure 8: Left: SpeakPlus feedback report editor. Right: SpeakPlus feedback report editor with EMODASH.

learners with some tips to ensure the proper quality of the video-conferencing, mainly to avoid back-lighting, to make sure that they had the face lit up, to seat facing the camera and to make sure that the webcam and microphone work well before the session. We sent a similar email to tutors explaining the issue, and asking them to make sure to remind learners to avoid such issues.

6.2.4. *Wrap-up*

At the end of the experiment, a member of our research team set-up online semi-structured interviews with tutors. The interviews were audio recorded and lasted 20 to 30 minutes. At the end of the interview, each tutor was asked to fill a SUS questionnaire (Brooke et al., 1996) to evaluate the usability of EMODASH.

6.3. *Apparatus*

We deployed a dedicated web instance of the learning platform SpeakPlus with EMODASH. Participants used their own devices from their location of choice (mostly home or work). Participants needed to have access to the Internet, a modern web browser (Chrome or Firefox), a camera and a microphone for video conferencing. More detail about the (hard/soft)ware used by participants is provided online in the supplementary material (see *Setup*).

6.4. *Data Overview and Analysis*

6.4.1. *Logs and Screen Recordings*

We collected tutors' interactions logs (clicks, scrolls, hovers, navigations, and playbacks) when they were editing the feedback report using platform's build-in trackers coupled to the *screen recording* tool Inspectlet². We collected 20 (out of 23 sessions) screen recordings. One loss was due to an incompatibility of the recording script with the browser of one participant. The two remaining losses were due to a storage issue.

²<https://www.inspectlet.com/>

6.4.2. Log and Screen Recordings Analysis

One member of the research team analyzed interactions of tutors with EMODASH when they were editing feedback reports. Each observation has been reported with a *title*, associated *level* of EMODASH [Overview, History View, Session View], associated *visualization* if any [Balance, Radial, Multi-line, Mirror-bar, Brush, Stream, Marker, Chat, Doc, Navigation], associated *tag* [Scan (skimming), and Fixation]. A scan is a quick skim of a part of EMODASH, while a fixation lasts more than 4 seconds. We used logs to measure Interaction (clicks and hover).

6.4.3. Feedback Reports

We collected the five feedback reports written by each tutor while using EMODASH, and the five most recent feedback reports they wrote *before* using EMODASH. The average length of feedback reports was of 14.35 utterances (max=27, min=3, sd=7.56) per session with EMODASH and 13.56 utterances (max=25, min=1, sd=6.91) without EMODASH.

6.4.4. Feedback Reports Analysis

We coded and analyzed the content of each feedback report with and without EMODASH.

Content Coding. Our coding of feedback is inspired by Tanes et al. (Tanes et al., 2011) content analysis. We analyzed the focus (summative vs. formative) of the content to study the extent to which the tutors gave explanations in their feedback to learners. Summative feedback (e.g. “You can make improvements”) provides information that situates individuals with regard to a set of criteria, whereas formative feedback (“I believe that success in interviews is attributable to practice and confidence”) provides explanations on why tasks are correct or incorrect. We also focused on the motivational and affective components of the content (Tanes et al., 2011). Motivational feedback (e.g. “Good job”) provides positive or negative reinforcement regarding the learning activity. We distinguish affective feedback from motivational one as it is not directly related

to the learning activity (e.g. “It was a pleasure to meet you”).

Coding Unit. Our coding unit was the utterance, considered as the smallest piece of a sentence with a clear ending (or pause), and a full meaning considered in isolation.

Inter-Agreement. Two members of the research team coded separately a set of randomly selected feedback reports (20% of utterances), regarding the four categories: formative, summative, motivational and affective. After that, both members discussed disagreement regarding utterance units before coding again the same sample with an inter-agreement of 66% for formative/summative utterances and 81% for motivational/affective ones. Then, they both discussed disagreements regarding each utterance to reach a consensus. Finally, one member coded the rest of the feedback reports.

Statistical Analysis. We then conducted a factorial analysis on the feedback report content detailed in the results section.

6.4.5. SUS Questionnaire Analysis

We followed Brooke et al. (Brooke et al., 1996) to compute the average of each participant before computing the overall average.

6.4.6. Interviews Analysis

One member of the research team transcribed audio recordings of the interviews, then analyzed them to extract the main themes.

7. Results

7.1. Overall Use of EMODASH

The results from the usability survey indicate that there was no significant problem with EMODASH, with a SUS score of 80, 12 points above the standard average score (68) (Brooke et al., 1996)

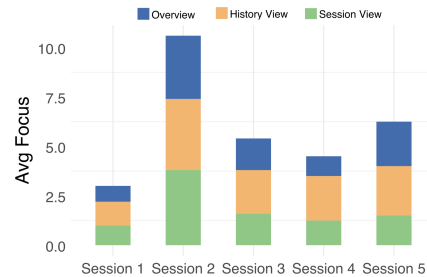


Figure 9: The average amount of focus (scans and fixations) per participant across sessions.

Tutors explored EMODASH the most during session 2 (measured in a number of scans and fixations, Figure 9). This may be because of the email we sent between sessions 1 and 2 (see section 6.2.3).

Tutors' focus was spread across the three views of the dashboard. They interacted most with the session view, especially with the streamgraph, which controls the video player (Figure 10). The overview and history view are glanceable and did not offer significant interactive features. Participants interacted more in the first two sessions than at the end than how it was at the beginning.

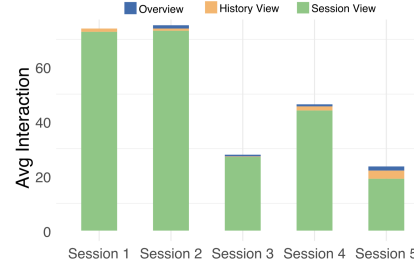


Figure 10: The average amount of interactions (hover and clicks) per participant across sessions.

7.2. From overview to session details: interaction with EMODASH views

We compared tutors' perception of the three views of EMODASH (overview, history view, session view), across the five sessions.

Overview. During the interviews, four (out of five) tutors highlighted the ease of use and usefulness of the overview to grasp learners' emotional state (positive/negative) at a glance. They focused on it on average 8.4 times (SD=6.98, P1: 7, P2: 9, P3: 3, P4: 20, P5: 3).

The one I looked at the most was the [overview] with the different emotions just because it is very easy to check. Is it more positive or negative? It's positive, great! - P1

I think the most [useful] is the overall map [meaning the Radial chart] because it's easy to understand. It shows the percentages, you know, it's color-coded, it's extremely easy to follow. I don't necessarily need the graphs of the session. - P5

History View. Participants focused on average 10.8 times on the History View, (SD=7.82, P1: 11, P2: 12, P3: 5, P4: 23, P5: 3). The history view

was appreciated for providing a glanceable view summarizing the evolution of positive/negative emotions across all sessions, rather than for its details or for navigating across sessions.

This is probably my favorite part [the History View], because, it's very clear to see the positive and negative points of the session. - P3

The history view gave you again the actual overall information of where the emotions went. Looking at it [...] shows quite clearly that there is a lot more look green on the second lesson than how it was in the first one, that said to me that I probably did better in the second lesson than in the first lesson. - P4

Participants did not interact with the history view to explore past sessions or navigate between them. Only one participant (P4) did so after editing the feedback report of her last session.

Session View. Participants focused on average 8.6 times on the Session View ($SD=5.85$, P1: 8, P2: 13, P3: 3, P4: 16, P5: 3). And, they made 281 interactions in total ($Mean=60.41$, $SD=70$) with this view. Participant 5 interacted most heavily (on average 181 interactions per session), P2 and P4 (on average 38, and 56 interactions per session respectively), and P1 and P3 only a little (on average 18, and 7 interactions per session respectively). Participants found this view interesting and relevant, even the ones who interacted little with the dashboard:

The most interesting would be the Session timeline [...] because it allows to go back to a particular point in time and look at that conversation again. - P1

Within the session view, participants clicked more on the streamgraph (compared to interactions with chats, docs, markers, and play/pause) (see Figure 11).

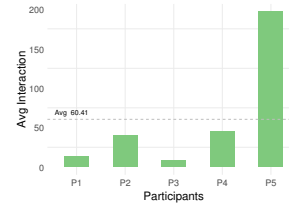


Figure 11: The average amount of interactions (hover and clicks) per participant per session on the Session View of EMODASH.

Table 1: Content analysis factors and levels.

Factor	Level
Condition (emotional dashboard)	- With (SpeakPlus + EMODASH) - Without (SpeakPlus)
Category (feedback content)	- Motivational - Affective - Summative - Formative

In most cases (202 out of 211 clicks), participants navigated to emotional peaks (computed as clicks on areas of the streamgraph over the session’s median value of the positive or negative emotions). Tutors used emotional data to navigate through the last recorded session, especially by clicking on these peaks, i.e. significant moments corresponding to high positive or negative emotions, and looked at the video for further explanations on what happened at that particular moment.

Summary. Participants appreciated the glanceable elements of the dashboard which gave them quick insights on learners’ emotions. They used the detailed session view to navigate in the video. We noticed from the interviews a difference between the useful (the overview), and the interesting (the session view). Participants did not navigate to past sessions and were mostly interested in the session they had just conducted.

7.3. Feedback Report Content

We analyzed the content of the feedback reports written by tutors after each session according to four categories of utterances: formative, summative, motivational, affective (see section 6.4.4). For each category we compared reports written with EMODASH and the most recent feedback reports tutors wrote before using EMODASH.

We conducted a factorial analysis of the feedback report content. The study was a 2x4 repeated measures design (within-subject). The factors and levels are explained in Table 1. The measured variable was the number of utterances. We identified 287 utterances with EMODASH and 276 without it (Figure 12).

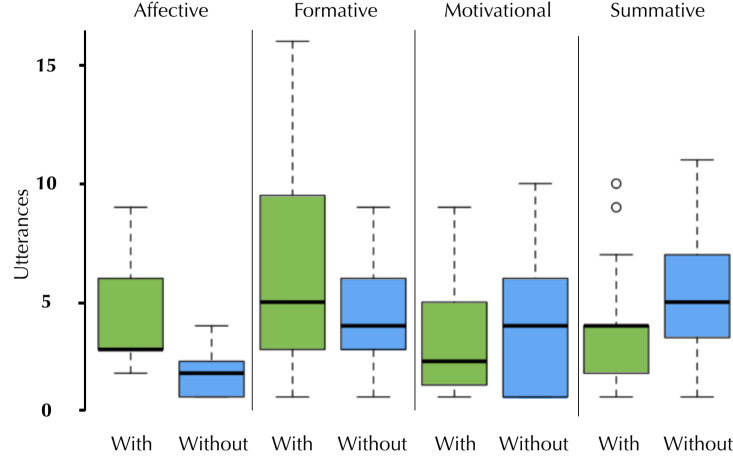


Figure 12: Boxplot comparison of feedback categories under both conditions With and Without EMODASH. With median, 1st quartile (25%) and 3rd quartile (75%). The whiskers represent the minimum and maximum.

We analyzed the number of utterances using a non-parametric generalized mixed-effects model (GLMM) analysis (Dean and Nielsen, 2007; Bates et al., 2015), with fixed effects of *Condition* (emotional dashboard) and *Category* (Feedback report) and a random effect of *participant*. GLMM does not require the assumptions normality of data (Wobbrock and Kay, 2016). We used each feedback report from each participant as a trial, which gives us enough data points to fit the model. GLMM manages the dependencies of the data within subjects. It also deals with missing data as we do not have a full balancing, for instance, a category (motivational, affective, summative or formative) may not exist for a given feedback report.

When building the models, we verified the five assumptions required to validate the good fit of GLMM model (Bolker et al., 2009) using **R**. First, we validated the goodness-of-fit of distributions of the data of each *Category* and under each *Condition* which showed a tendency towards a *Poisson* distribution which is usually the case with count data, we validated the goodness-of-fit graphically using histograms and statically using Chi-square test. Second, we graphically verified that standardized residuals of the GLMM model showed no

departure from the normal using a Q-Q plot. Third, we graphically inspected the absence of autocorrelation in the residuals of the model to ensure that the amount of information that we have on the relationship between the number of utterances and our two factors (*Condition* and *Category*) is maximal. Fourth, we verified that the variance of the residuals is equal across levels of our factors, graphically using boxplots, and statically using Levene’s test. Fifth, we verified that the model was not overdispersed using a Chi-square test, to ensure that the residual variance is not larger than the estimated mean. We provide a detailed statistical analysis as supplementary material (see *Statistical Analysis*).

We statically tested the significance of the fixed effects (*Condition* and *Category*) in the model using Wald Chi-square test (Bolker et al., 2009). We find a significant effect of *Condition* ($\chi^2(1, N=157) = 4.21, p = 0.040$) as well as a significant effect of *Category* ($\chi^2(3, N=157) = 8.87, p = 0.031$) on utterances.

We conducted post-hoc pairwise comparisons to compare the amount of feedback per *Category* before and after the introduction of EMODASH (*Condition*) (see Figure 12 for a visual summary). We used Holm-Bonferroni for adjustments (Holm, 1979). We found significantly more *formative* utterances with EMODASH than without (Estimate = 0.351, SE = 0.141, $z = 2.494, p = 0.0126$, respectively 44% vs. 38%), and less *summative* ones (Estimate = -0.341, SE = 0.159, $z = -2.139, p = 0.0324$, 28% with vs. 43% without). Regarding *affective* content, the number of utterances increased with EMODASH (Estimate = 0.935, SE = 0.294, $z = 3.176, p = 0.0015$, 19% with vs. 10% without), whereas we did not observe a significant effect on the *motivational* level (Estimate = -0.146, SE = 0.176, $z = -0.827, p = 0.4082$, 23% with vs. 31% without).

We calculated Cohen’s d , the standardized mean difference (Cohen, 2013) by dividing estimated differences by the residual standard deviation suggested as effect size (Feingold, 2013). As portrayed in Figure 13, the results show a large effect for affective ($d = 1.030$), a medium effect for formative ($d = 0.387$), (negative) medium effect for summative ($d = -0.376$), and (negative) small effect for motivational ($d = -0.160$).

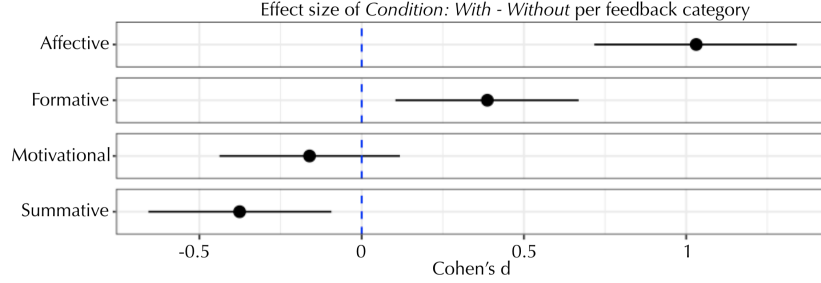


Figure 13: The effect size of *Category's* levels under *with - without* condition with the associated confidence intervals.

The differences between formative and summative, with and without EMODASH appear to be stable across sessions (see Figure 14).

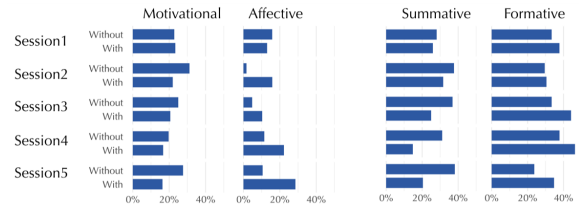


Figure 14: Percentage of Motivational, Affective, Summative and Formative Utterances per session, without and with EMODASH.

The percentage of affective utterances tend to increase with EMODASH over time, while the percentage of motivational utterances with EMODASH tends to decrease over time.

Focusing on individual tutors' feedback, we observed different ways in which EMODASH influenced (or not) their reports. P1 and P3 are the ones for whom EMODASH had the strongest impact in term of affective utterances per report (twice as many with EMODASH) (Figure 15), the amount of affective language in their reports increases.

This is associated with much less summative utterances and stable formative ones. We notice that these two tutors (P1 and P3), with P5, already

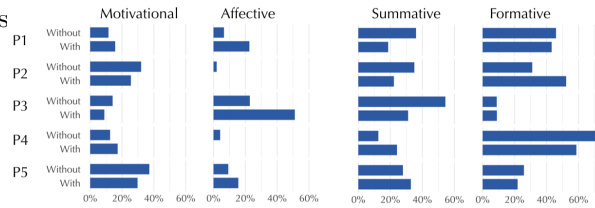


Figure 15: Percentage of Motivational, Affective, Summative and Formative utterances per Participant, Without and With EMODASH.

wrote affective utterances in their feedback reports before using EMODASH. It is also noteworthy that P1 and P3 are the tutors who interacted with the stream-

graph the least. P2 and P4 wrote few affective utterances before and even less with EMODASH. These two tutors, with P5, also interacted the most with the dashboard, but these interactions did not have the same effect. P2 wrote less summative and more formative feedback, whereas P4 wrote more summative and less formative ones. For P5, the content of the feedback is rather stable with and without EMODASH.

Summary. Tutors wrote more formative (and less summative) feedback reports with EMODASH. They also wrote more affective feedback reports. This is especially true for tutors who were already sensitive to learners' emotions, who incorporate more affective elements in their reports, suggesting a stronger awareness of learners' emotions. We did not observe changes in motivational utterances.

7.4. Impact of EMODASH on Tutors Practices

Besides feedback reports, during our interviews, tutors reported on the impact of EMODASH on their teaching practices, especially in considering their own emotions and assessing their work.

7.4.1. Self-Awareness

Although the dashboard focused on learners' emotions, tutors reported an increased emotional self-awareness after using EMODASH. Indeed, P1, P2, P4, and P5 used the dashboard while editing their feedback and reported looking back at parts of the session to focus on their behavior.

It was quite useful to see the video as I was making the feedback comments and to see myself again on the screen - P2

But more broadly, EMODASH also served as a reminder that learners' emotions have an impact on learning. Which could be forgotten, as P1 remarked:

It actually reminded me of the emotional contingency, emotional parts of the student [...] usually I'm listening to accent pronunciation, grammar, their learning skills, but I didn't really think much about

the general emotion, are they nervous, are they scared, are they worried, I just usually disregard that, but EMODASH reminded me, but wait a minute this a living, breathing, exchanging with emotion.
- P1

7.4.2. Self-Evaluation

Tutors started reflecting on their teaching practices and how they were conducting their lessons, for instance, to get feedback on how they were doing their class:

As a teacher I always want to have some kind of feedback to show that I'm doing a good job and it kind of clarifies that I'm not doing too bad [...] - P4

Similarly, two participants mentioned using EMODASH as a way to evaluate their performance or as a warning when negative reactions from learners occur:

I will definitely be concerned if I saw some, you know, a huge percentage of negativity. I do want to do better as a teacher. - P5

I wanted my students to be happy all the time and to be very satisfied with the class and when I saw negative reactions in the overview or in the [History View], it worried me. - P1

7.4.3. Perceived Limitations

Participants identified two classes of limitations. The first one is the ability to identify emotions with high intensity without the support of technology. P2 was most negative regarding EMODASH, considering it “interesting but not particularly useful”. She elaborated further:

As far as teaching is concerned, I don't think it is particularly useful. Because I think [...] if there are any extreme emotions, if someone is feeling very angry or disappointed you should get that feedback without having to see this [meaning EMODASH]. - P2

The second significant concern from other tutors was the amount of labor that EMODASH involved. They expressed shortcomings regarding the time and efforts required:

It was really extra time on the top of teaching. - P1

What you show on the dashboard, it's quite detailed information. Also I don't think you will have the time, because already you have to plan lessons, do the feedback, and that intensity of feedback takes your time, it will be very heavy workload. - P2

The increased focus on emotions and its relationship to teaching quality also led tutors to being “*worried*” about a negative emotional reaction from learners (P1). Moreover, the fact that tutors worked on a platform, probably further increased the role of emotions, with tutors wanting to please learners.

8. Discussion

8.1. *Learners' Emotion Awareness and Tutors' Formative Feedback*

Regarding the impact on summative and formative feedback (research question #1), we observed that using EMODASH led tutors to take into account learners' emotions and adjust their feedback by reflecting on the emotions identified during the learning session. EMODASH led tutors to give in proportion more formative than summative feedback, providing learners with explanations on their performance or cues on how to improve themselves. This may help learners to maintain or improve their performance during and across the learning sessions (Tanes et al., 2011), formative feedback is more effective for learning due to its corrective nature (Chen, 2001; Higgins et al., 2002). This finding raises important questions on the impact of tutors' awareness of learners' positive or negative emotions, and more studies should be conducted to identify the factors at play on larger scales.

For instance, as suggested by Montero and Suhonen (2014), there could be *human biases* in the way the tutors interpret learners' emotions and their

personal opinion on them. A learner who felt mainly negative emotions could be perceived negatively by the tutor, even if these emotions are not due to his/her interactions with the tutor but to other contextual reasons. Given that some emotions are difficult to identify based only on facial recognition (Visschedijk et al., 2013), computational emotional information should be treated carefully.

8.2. Learners' Emotion Awareness and Tutors' Affective Feedback

Concerning the influence of emotion awareness on affective and motivational feedback (research question #2), we did not observe a significant impact on the proportion of motivational feedback. This result could be explained by the fact that all tutors already incorporated motivational utterances in their reports and they may not need to be aware of learners' emotions to integrate this kind of feedback. This result could also suggest that tutors saw no difference in learners' outcomes by integrating more motivational feedback. In fact, Tanes et al. (2011) showed that students who received considerably less motivational feedback had no significant difference in their outcomes, compared to students who received more motivational feedback.

Tutors wrote significantly more affective feedback, which should improve learners' receptivity (Walz, 1982) and language acquisition. Specifically for the second language acquisition domain, Dulay and Burt (1977) first introduced the concept of "socio-affective filter" to explain that in language learning, the acquirer must not only understand the language to acquire it but must also, in a sense, be "open" to it. According to this concept, more affective language from the tutors could help learners have a lowest filter and so acquire more of the language directed at them. Our results would thus suggest that better awareness of learners' emotion would lead to better language acquisition.

Examining the impact of the type of feedback during an online writing task, Nguyen et al. (2017) also showed that positive affective language increased positive emotions and reduced participants' annoyance and frustration, which led to an increase in work quality. Previous studies also showed that positive affective language can increase positive emotions and reduce negative feelings

when receiving criticism (Neuwirth et al., 1994). This would suggest that the integration of more affective language from tutors in their feedback could lead learners to feel more positive emotions.

Finally, the proportion of affective language increased over the sessions, which suggests that the pair tutor-learner developed socio-affective relationships, which was our original motivation when developing EMODASH. More specifically, the impact was observed for tutors who already wrote affective parts in their reports without EMODASH. It would suggest that EMODASH reinforces existing practices rather than creating new ones. Further studies would be needed to explore this in more depth.

8.3. Designing Dashboards for Emotion Awareness

For tutors, paying attention to the emotion of learners comes on top of many other tasks: evaluating learners’ interventions, structuring feedback, following the lesson plan, guiding learners, sharing documents, marking moments for later feedback, etc. As mentioned by one participant one would ideally expect that emotion awareness happens “naturally”, but it is challenging in practice.

Participants showed favorable views towards EMODASH, although they used it in a variety of ways, exploring different levels of the dashboard while writing their feedback, or exploring the data out of curiosity. Regarding our third research question, we can draw some conclusions on the appropriate level of details and timescales of learners’ emotions.

First, our results suggest that an extensive historical record and visualization of emotions may not be useful in our context. Tutors seemed more interested in reflecting on the last session and used the dashboard for that purpose. This means that collecting and analyzing emotion data over the extended period of a course may not be necessary or appropriate in all contexts, although some identify it as a future theme in the domain (D’Mello, 2017).

Second, tutors tended to want their feedback to reflect the general emotions identified for the learner during the last session. General emotions meaning “positive” or “negative”, rather than more detailed discrete emotions. This leads

us to question the need to provide tutors with details on specific emotions, but rather suggests offering broader affective states as in (Noteborn et al., 2012; Mega et al., 2014).

Third, participants interacted mainly with the streamgraph to navigate in the video recording by clicking on emotional peaks, whether positive or negative ones. However, it seems that this navigation did not lead tutors to change their way of writing feedback. In fact, the tutor who navigated the most in the session view (P5) had the same kind of content in his reports with and without EMODASH, whereas tutors who interacted the least (P1 and P3) adapted the content of their feedback reports with EMODASH.

These elements suggest that tutors may need more at a glance emotional information, than detailed navigation in the past learning session. Precise and information-rich visualization of emotions may not lead to changes in the way tutors write feedback. Emotion awareness may not be directly linked to a specific kind of data or visualization but rather to the general availability of information about emotions. The visualization reminding tutors that emotions should be considered in the learning process.

Emotions in online learning environments should be studied not only as insights on cognition, commitments, and concerns (Boekaerts, 2010) but also in light of the concept of “emotional presence” introduced first by Cleveland-Innes and Campbell (2012) and defined as *the outward expression of emotion, affect, and feeling by individuals and among individuals in a community of inquiry, as they relate to and interact with the learning technology, course content, students, and the instructor*. Emotional presence should be considered as a distinct construct, apart from cognitive, social, and teaching presence, that encourages social interactions between learners and tutors (Stenbom et al., 2016). P1 illustrated the relevance of emotional presence by explaining that:

Usually, I focus on progress: Did she understand? Did she learn from that point? Which is not connected with emotion, but EMODASH made me aware of the other parts of teaching which is, is she pleased,

is she happy to learn. - P1

8.4. Self-reflection and Evaluation

We designed EMODASH to support tutors in developing a stronger awareness of learners’ emotions. We found that it also increased tutors’ awareness of their behavior, leading them to reflect on the feedback they gave in reports and other sessions.

Given the lack of direct feedback from learners to tutors, tutors also used EMODASH as a proxy to evaluate their work, to know that they are “*doing a good job and [...] not doing too bad*” (P4). We find nonetheless, that emotion awareness tools should be treated carefully. Tutors often related positive emotions to the quality of the teaching session, although the literature insists on the benefits of negative emotions such as confusion (D’Mello et al., 2014) or anxiety (Pekrun et al., 2011) on learning. Incorporating some guidance on the role of emotions in education could mitigate these problems.

9. Limitations

We conducted the study with five pairs of learners and tutors over two months. The study is limited in the number of participants, and the five learners were female. A larger-scale between-subject experiment could complement our results. While limited this is the first in the wild study to shed light on the use of learners’ emotions in learning dashboards.

Prior research focused on awareness of learners’ performances and/or behaviors, that are easier to capture and to remediate (Schwendimann et al., 2017; Verbert et al., 2014). We are opening up research on the use of emotions to enhance tutors’ reflection on learning processes. Yet further research is needed to explore how such dynamics differ and evolve over time and whether there is any correlation with the receptivity to the feedback at the learners’ end.

Our work builds upon emotion recognition algorithms. Emotion recognition is still a very active area of research, in which contextual, cultural and technical

challenges remain to be addressed. Our focus being on the impact of retrospective emotion awareness on tutors' feedback, we were less concerned by the correct identification of precise emotions at any given time, but rather in providing trends and emotional indications at different levels and timescales. This explains our use of a standard emotion recognition API for reliability purposes, over emotions more related to learning situations, such as Pekrun's achievement emotions (Pekrun, 2006; Pekrun et al., 2017).

More profoundly, Boehner et al. (2007) criticized the use of purely automated emotion recognition techniques, and emphasized the risks of disconnect between what is detected and what is actually felt by people. They argue that emotions are experienced through interactions and influenced by cultural and social factors, i.e., emotions are built and evolve through interactions between people. As such, the interpretation of emotions evolve, change and differ depending on people's context. We partly agree with such stance but argue that some strong emotional reactions can be properly interpreted with little context. Nonetheless, our work adopts an hybrid approach: while emotions are inferred from the recordings, and conveyed visually, we preserve and provide the context (e.g. video recording, the associated events, etc.) of the experienced emotions of the user to enable a better interpretation by tutors.

In the end, throughout the trial, and in our final interviews, none of the participants flagged recognition problems, although some tutors (P2, P3) discussed the recognition and expressed curiosity on how emotions were interpreted by the application. Similarly, in a previous study with an emotional dashboard using the Microsoft Azure API tutors did not raise issues related to the use of such an API (Ez-zaouia and Lavoué, 2017).

Finally, EMODASH could lead to anxiety on the learners' side, knowing that every emotion they express will be recorded and analyzed. From observing the videos, we could notice that the awareness of the recording disappeared after a few minutes. Considering larger-scale deployments, our results suggest that detailed recordings may not be necessary and that aggregate summaries may be enough to raise tutors' awareness.

10. Conclusion

The development of richer socio-affective relationships between tutors and learners is an important component of successful learning processes (and outcomes). But developing such relationships is challenging in online-learning. To tackle this challenge, we set to foster tutors' awareness of learners' emotions. We designed EMODASH, a dashboard visualizing learners' emotions alongside the activity of past learning sessions. The design process involved several iterations and the involvement of experts: professional tutors and pedagogical managers. We integrated EMODASH in the feedback editor of a video-conferencing learning platform, to support the emotional awareness of tutors as they provide feedback to learners.

We conducted a field study for 8 weeks with 5 pairs of learners and tutors to investigate the role EMODASH played on tutors' feedback. We focused on three questions: 1) Do emotion awareness tools have an effect on the type of feedback given, specifically formative or summative feedback reports?; 2) Do emotion awareness tools lead tutors to incorporate more affective and/or motivational content in their feedback? and 3) What effect do different granularities of emotion visualization, via a dashboard, have on tutor feedback?

EMODASH led tutors to write more formative and less summative feedback and to incorporate more affective language in their report. The tutors who interacted the least with the dashboard are those who changed their reports the most, suggesting that an overview of learners' emotions may be sufficient to better consider learners' emotions. Tutors seemed to favor quickly graspable visualizations, although important information might get lost. New kinds of visualizations could provide an overview and highlight important moments without overwhelming details. Indeed, tutors also relied on EMODASH richer streamgraph, pinpointing *positive* and *negative* emotional peaks, to navigate in the video recordings of past sessions. Finally, tutors also described how the visualizations led them to reflect on their practice and acted as a way to get information on the quality of their teaching. Overall, it led them to adjust the

way they shared feedback with learners.

Our study opens up questions for future research. In terms of visualization: How to design glanceable summaries that still convey nuances about learners' emotions? And how to better put emotions in context, i.e., compared to past sessions or other learners, to support tutors' interpretation of emotional data? We observed some changes in tutors' practices, but these observations need to be studied and analyzed more robustly: How much awareness tools are reinforcing existing practices rather than creating new ones? And what is the interplay between tutors' self-reflection, the awareness of their own emotions, and awareness of learners' emotions? Finally, we focused on tutors although our end goal is better learning processes and outcomes for learners. Further studies on how learners receive affective feedback fostered by emotion awareness tools would close the loop from learners to tutors and back.

Using a video-conferencing based learning platform enabled us to have good quality videos of learners' faces. Advances in emotion recognition could provide further opportunities to deploy affective computing tools in schools. For instance, to inform teachers about affective state of students, and help them provide personalized support to students in a timely fashion. In addition, affective states can also be used as a proxy to infer indicators about students, such as involvement, engagement as well as learning-related emotions such as frustration, confusion, boredom while students are engaged with learning tasks (Pekrun, 2006; Kort et al., 2001). This could have side benefits for both teachers and schools, such as monitoring students' satisfaction and well-being during courses, providing directions to improve course design and learning activities, and for teachers' own professional development (Montero and Suhonen, 2014).

Acknowledgments

The authors would like to thank all the learners and tutors who participated in this study. We also thank the Archinfo students who participated in the preliminary design explorations, and our colleagues and reviewers who

provided helpful comments and insights throughout the project. This research was funded by the French Agency of Research and Technology [ANRT, grant number 2016/884 and 2018/0093].

References

- Microsoft project oxford seconds that emotion. *Biometric Technology Today*, 2016(1):2, jan 2016. doi: 10.1016/s0969-4765(16)30004-2. URL [https://doi.org/10.1016/S0969-4765\(16\)30004-2](https://doi.org/10.1016/S0969-4765(16)30004-2).
- Lisa Feldman Barrett and James A. Russell. Independence and bipolarity in the structure of current affect. *Journal of Personality and Social Psychology*, 74(4):967–984, 1998. doi: 10.1037/0022-3514.74.4.967. URL <https://doi.org/10.1037/0022-3514.74.4.967>.
- Emad Barsoum, Cha Zhang, Cristian Canton Ferrer, and Zhengyou Zhang. Training deep networks for facial expression recognition with crowd-sourced label distribution. In *Proceedings of the 18th ACM International Conference on Multimodal Interaction, ICMI '16*, pages 279–283, New York, NY, USA, 2016. ACM. ISBN 978-1-4503-4556-9. doi: 10.1145/2993148.2993165. URL <http://doi.acm.org/10.1145/2993148.2993165>.
- Douglas Bates, Martin Mächler, Ben Bolker, and Steve Walker. Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, 67(1):1–48, 2015. doi: 10.18637/jss.v067.i01.
- Matthew Tyler Boden and Renee J. Thompson. Facets of emotional awareness and associations with emotion regulation and depression. *Emotion*, 15(3):399–410, 2015. doi: 10.1037/emo0000057. URL <https://doi.org/10.1037/emo0000057>.
- Kirsten Boehner, Rogério DePaula, Paul Dourish, and Phoebe Sengers. How emotion is made and measured. *International Journal of Human-Computer Studies*, 65(4):275–291, apr 2007. doi: 10.1016/j.ijhcs.2006.11.016. URL <https://doi.org/10.1016/j.ijhcs.2006.11.016>.

- Monique Boekaerts. The crucial role of motivation and emotion in classroom learning. In *Educational Research and Innovation*, pages 91–111. OECD Publishing, aug 2010. doi: 10.1787/9789264086487-6-en. URL <https://doi.org/10.1787/9789264086487-6-en>.
- Benjamin M Bolker, Mollie E Brooks, Connie J Clark, Shane W Geange, John R Poulsen, M Henry H Stevens, and Jada-Simone S White. Generalized linear mixed models: a practical guide for ecology and evolution. *Trends in ecology & evolution*, 24(3):127–135, 2009.
- John Brooke et al. Sus-a quick and dirty usability scale. *Usability evaluation in industry*, 189(194):4–7, 1996.
- Jurgen Buder. Group awareness tools for learning: Current and future directions. *Computers in Human Behavior*, 27(3):1114–1117, May 2011. ISSN 0747-5632. doi: 10.1016/j.chb.2010.07.012. URL <http://www.sciencedirect.com/science/article/pii/S0747563210002086>.
- Dan Calacci, Oren Lederman, David Shrier, and Alex ‘Sandy’ Pentland. Breakout: An open measurement and intervention tool fo distributed peer learning groups. *CoRR*, abs/1607.01443, 2016. URL <http://arxiv.org/abs/1607.01443>.
- Daniel Cernea and Andreas Kerren. A survey of technologies on the rise for emotion-enhanced interaction. *Journal of Visual Languages & Computing*, 31: 70–86, dec 2015. doi: 10.1016/j.jvlc.2015.10.001. URL <https://doi.org/10.1016/j.jvlc.2015.10.001>.
- David D Chen. Trends in augmented feedback research and tips for the practitioner. *Journal of Physical Education, Recreation & Dance*, 72(1):32–36, 2001.
- Marti Cleveland-Innes and Prisca Campbell. Emotional presence, learning, and the online learning environment. *The International Review of Research in Open and Distributed Learning*, 13(4):269–292, 2012.

- Jacob Cohen. *Statistical power analysis for the behavioral sciences*. Routledge, 2013.
- C. B. Dean and Jason D. Nielsen. Generalized linear mixed models: a review and some extensions. *Lifetime Data Analysis*, 13(4):497–512, nov 2007. doi: 10.1007/s10985-007-9065-x. URL <https://doi.org/10.1007/s10985-007-9065-x>.
- Sidney D’Mello. A selective meta-analysis on the relative incidence of discrete affective states during learning with technology. *Journal of Educational Psychology*, 105(4):1082–1099, 2013.
- Sidney D’mello and Art Graesser. Autotutor and affective autotutor: Learning by talking with cognitively and emotionally intelligent computers that talk back. *ACM Transactions on Interactive Intelligent Systems (TiiS)*, 2(4):23:22–23:39, 2012.
- Sidney D’Mello, Blair Lehman, Reinhard Pekrun, and Art Graesser. Confusion can be beneficial for learning. *Learning and Instruction*, 29:153–170, feb 2014. doi: 10.1016/j.learninstruc.2012.05.003. URL <https://doi.org/10.1016/j.learninstruc.2012.05.003>.
- Sidney K. D’Mello. Emotional learning analytics. In *Handbook of Learning Analytics*, pages 115–127. Society for Learning Analytics Research (SoLAR), may 2017. doi: 10.18608/hla17.010. URL <https://doi.org/10.18608/hla17.010>.
- Paul Dourish and Victoria Bellotti. Awareness and coordination in shared workspaces. In *Proceedings of the 1992 ACM conference on Computer-supported cooperative work*, pages 107–114. ACM, 1992.
- Paul Dourish and Sara Bly. Portholes: Supporting awareness in a distributed work group. In *Proceedings of the SIGCHI conference on Human factors in computing systems*, pages 541–547. ACM, 1992.

- H. Dulay and M. Burt. Remarks on creativity in language acquisition. In M. Burt, H. Dulay, and M. Finnochiaro, editors, *Viewpoints on English as a Second Language*, pages 95–126. New York: Regents, 1977.
- Paul Ekman and Wallace V Friesen. Measuring facial movement. *Environmental psychology and nonverbal behavior*, 1(1):56–75, 1976.
- Mohamed Ez-zaouia and Elise Lavoué. Emoda: A tutor oriented multimodal and contextual emotional dashboard. In *Proceedings of the Seventh International Learning Analytics & Knowledge Conference, LAK '17*, pages 429–438, New York, NY, USA, 2017. ACM. ISBN 978-1-4503-4870-6. doi: 10.1145/3027385.3027434. URL <http://doi.acm.org/10.1145/3027385.3027434>.
- Alan Feingold. A regression framework for effect size assessments in longitudinal modeling of group differences. *Review of General Psychology*, 17(1):111–121, 2013.
- Rebecca Ferguson. Learning analytics: Drivers, developments and challenges. *Int. J. Technol. Enhanc. Learn.*, 4(5/6):304–317, January 2012. ISSN 1753-5255. doi: 10.1504/IJTEL.2012.051816. URL <http://dx.doi.org/10.1504/IJTEL.2012.051816>.
- Angela Fessel, Verónica Rivera-Pelayo, Viktoria Pammer, and Simone Braun. Mood tracking in virtual meetings. In *Lecture Notes in Computer Science*, pages 377–382. Springer Berlin Heidelberg, 2012. doi: 10.1007/978-3-642-33263-0_30. URL https://doi.org/10.1007/978-3-642-33263-0_30.
- Google.com(n.d.). Google emotion api. retrieved april 2, 2019, from <https://cloud.google.com/vision>. URL https://www.noldus.com/files/file_manager/downloads/whitepaper/FaceReader_Methodology.pdf.
- James J. Gross. Emotion regulation. *Handbook of emotions*, 3:497–513, 2008.
- John Hattie and Helen Timperley. The power of feedback. *Review of educational research*, 77(1):81–112, 2007.

- Richard Higgins, Peter Hartley, and Alan Skelton. The conscientious consumer: Reconsidering the role of assessment feedback in student learning. *Studies in higher education*, 27(1):53–64, 2002.
- Sture Holm. A simple sequentially rejective multiple test procedure. *Scandinavian journal of statistics*, pages 65–70, 1979.
- Carroll E. Izard. The many meanings/aspects of emotion: Definitions, functions, activation, and regulation. *Emotion Review*, 2(4):363–370, oct 2010. doi: 10.1177/1754073910374661. URL <https://doi.org/10.1177/1754073910374661>.
- B. Kort, R. Reilly, and R.W. Picard. An affective model of interplay between emotions and learning: reengineering educational pedagogy-building a learning companion. In *Proceedings IEEE International Conference on Advanced Learning Technologies*. IEEE Comput. Soc, 2001. doi: 10.1109/icalt.2001.943850. URL <https://doi.org/10.1109/icalt.2001.943850>.
- Élise Lavoué, Gaëlle Molinari, Yannick Prié, and Safè Khezami. Reflection-in-action markers for reflection-on-action in Computer-Supported Collaborative Learning settings. *Computers & Education*, 88:129–142, oct 2015. ISSN 0360-1315. doi: 10.1016/j.compedu.2015.05.001. URL <https://doi.org/10.1016/j.compedu.2015.05.001>.
- Elise Lavoué, Gaelle Molinari, and Maxence Tranfois. Emotional data collection using self-reporting tools in distance learning courses. pages 377–378, 07 2017. doi: 10.1109/ICALT.2017.94.
- Elise Lavoué, Maedeh Assadat Kazemitabar, Tenzin Doleck, Susanne Lajoie, Rubiela Carrillo, and Gaelle Molinari. Towards emotion awareness tools to support emotion and appraisal regulation in academic contexts. *Educational Technology Research and Development*, 07 2019. doi: 10.1007/s11423-019-09688-x.
- Derick Leony, Pedro J. Muñoz-Merino, Abelardo Pardo, and Carlos Delgado Kloos. Provision of awareness of learners’ emotions through visualizations in

- a computer interaction-based environment. *Expert Systems with Applications*, 40(13):5093–5100, oct 2013. doi: 10.1016/j.eswa.2013.03.030. URL <https://doi.org/10.1016/j.eswa.2013.03.030>.
- Peter Lewinski, Tim M. den Uyl, and Crystal Butler. Automated facial coding: Validation of basic emotions and FACS AUs in FaceReader. *Journal of Neuroscience, Psychology, and Economics*, 7(4):227–236, dec 2014. doi: 10.1037/npe0000028. URL <https://doi.org/10.1037/npe0000028>.
- Clayton H. Lewis. Using the “thinking aloud” method in cognitive interface design. Technical Report RC-9265, 1982.
- Lisa Linnenbrink-Garcia, Erika A. Patall, and Reinhard Pekrun. Adaptive motivation and emotion in education. *Policy Insights from the Behavioral and Brain Sciences*, 3(2):228–236, jul 2016. doi: 10.1177/2372732216644450. URL <https://doi.org/10.1177/2372732216644450>.
- Leanne Loijens and Olga Krips. Facereader methodology note, 2019. URL https://www.noldus.com/files/file_manager/downloads/whitepaper/FaceReader_Methodology.pdf.
- Daniel McDuff, Abdelrahman Mahmoud, Mohammad Mavadati, May Amr, Jay Turcot, and Rana el Kaliouby. Affdex sdk: A cross-platform real-time multi-face expression recognition toolkit. In *Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems*, CHI EA ’16, pages 3723–3726, New York, NY, USA, 2016. ACM. ISBN 978-1-4503-4082-3. doi: 10.1145/2851581.2890247. URL <http://doi.acm.org/10.1145/2851581.2890247>.
- Carolina Mega, Lucia Ronconi, and Rossana De Beni. What makes a good student? how emotions, self-regulated learning, and motivation contribute to academic achievement. *Journal of Educational Psychology*, 106(1):121–131, 2014. doi: 10.1037/a0033546. URL <https://doi.org/10.1037/a0033546>.

Microsoft.com(n.d.). Microsoft emotion api. retrieved july 5, 22 2019, from <https://azure.microsoft.com/en-us/services/cognitive-services/>. URL <https://azure.microsoft.com/en-us/services/cognitive-services/>.

Gaelle Molinari, Guillaume Chanel, Mireille Bétrancourt, Thierry Pun, and Christelle Bozelle. Emotion feedback during computer-mediated collaboration: Effects on self-reported emotions and perceived interaction. In *Computer-Supported Collaborative Learning Conference, CSCL*, volume 1, pages 336–343, 06 2013.

Calkin Suero Montero and Jarkko Suhonen. Emotion analysis meets learning analytics. In *Proceedings of the 14th Koli Calling International Conference on Computing Education Research - Koli Calling 14*. ACM Press, 2014. doi: 10.1145/2674683.2674699. URL <https://doi.org/10.1145/2674683.2674699>.

Christine M Neuwirth, Ravinder Chandhok, David Charney, Patricia Wojahn, and Loel Kim. Distributed collaborative writing: A comparison of spoken and written modalities for reviewing and revising documents. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 51–57. Citeseer, 1994.

Thi Thao Duyen T. Nguyen, Thomas Garncarz, Felicia Ng, Laura A. Dabbish, and Steven P. Dow. Fruitful feedback: Positive affective language and source anonymity improve critique reception and work outcomes. In *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing, CSCW '17*, pages 1024–1034, New York, NY, USA, 2017. ACM. ISBN 978-1-4503-4335-0. doi: 10.1145/2998181.2998319. URL <http://doi.acm.org/10.1145/2998181.2998319>.

Gwen Noteborn, Katerina Bohle Carbonell, Amber Dailey-Hebert, and Wim Gijssels. The role of emotions and task significance in virtual education. *The Internet and Higher Education*, 15(3):176–183, 2012.

Reinhard Pekrun. The control-value theory of achievement emotions: Assumptions, corollaries, and implications for educational research and practice.

- Educational Psychology Review*, 18(4):315–341, nov 2006. doi: 10.1007/s10648-006-9029-9. URL <https://doi.org/10.1007/s10648-006-9029-9>.
- Reinhard Pekrun. Emotions and learning. *International Academy of Education/International Bureau of Education, IEA* (<http://www.iaoed.org>), *IBE* (<http://www.ibe.unesco.org/publications.htm>), 2014.
- Reinhard Pekrun, Thomas Goetz, Anne C. Frenzel, Petra Barchfeld, and Raymond P. Perry. Measuring emotions in students’ learning and performance: The achievement emotions questionnaire (AEQ). *Contemporary Educational Psychology*, 36(1):36–48, jan 2011. doi: 10.1016/j.cedpsych.2010.10.002. URL <https://doi.org/10.1016/j.cedpsych.2010.10.002>.
- Reinhard Pekrun, Stephanie Lichtenfeld, Herbert W. Marsh, Kou Murayama, and Thomas Goetz. Achievement emotions and academic performance: Longitudinal models of reciprocal effects. *Child Development*, 88(5):1653–1670, feb 2017. doi: 10.1111/cdev.12704. URL <https://doi.org/10.1111/cdev.12704>.
- Bart Rienties and Bethany Alden Rivers. Measuring and understanding learner emotions: Evidence and prospects. *Learning Analytics Review*, 1:1–28, 2014.
- Verónica Rivera-Pelayo, Angela Fessel, Lars Müller, and Viktoria Pammer. Introducing mood self-tracking at work: Empirical insights from call centers. *ACM Transactions on Computer-Human Interaction (TOCHI)*, 24(1):3, 2017.
- Samara Ruiz, Sven Charleer, Maite Urretavizcaya, Joris Klerkx, Isabel Fern’andez-Castro, and Erik Duval. Supporting learning by considering emotions: Tracking and visualization a case study. In *Proceedings of the Sixth International Conference on Learning Analytics & Knowledge, LAK ’16*, pages 254–263, New York, NY, USA, 2016. ACM. ISBN 978-1-4503-4190-5. doi: 10.1145/2883851.2883888. URL <http://doi.acm.org/10.1145/2883851.2883888>.
- Samiha Samrose, Ru Zhao, Jeffery White, Vivian Li, Luis Nova, Yichen Lu, Mohammad Rafayet Ali, and Mohammed E. Hoque. Coco: Collaboration

- coach for understanding team dynamics during video conferencing. *IMWUT*, 1(4):160:1–160:24, 2017. doi: 10.1145/3161186. URL <https://doi.org/10.1145/3161186>.
- Beat A. Schwendimann, Maria Jesus Rodriguez-Triana, Andrii Vozniuk, Luis P. Prieto, Mina Shirvani Boroujeni, Adrian Holzer, Denis Gillet, and Pierre Dillenbourg. Perceiving learning at a glance: A systematic literature review of learning dashboard research. *IEEE Transactions on Learning Technologies*, 10(1):30–41, jan 2017. doi: 10.1109/tlt.2016.2599522. URL <https://doi.org/10.1109/tlt.2016.2599522>.
- George Siemens and Phil Long. Penetrating the fog: Analytics in learning and education. 5:30–32, 01 2011.
- Stefan Stenbom, Stefan Hrastinski, and Martha Cleveland-Innes. Emotional presence in a relationship of inquiry: The case of one-to-one online math coaching. *Online Learning*, 20(1):41–56, 2016.
- Na Sun, Elise Lavoué, Chulakorn Aritajati, Aurélien Tabard, and Mary Beth Rosson. Using and perceiving emoji in design peer feedback. In *13th international conference on Computer Supported Collaborative Learning (CSCCL 2019)*, volume 1, pages 296–303, 06 2019.
- Zeynep Tanes, Kimberly E. Arnold, Abigail Selzer King, and Mary Ann Remnet. Using signals for appropriate feedback: Perceptions and practices. *Computers & Education*, 57(4):2414–2422, dec 2011. doi: 10.1016/j.compedu.2011.05.016. URL <https://doi.org/10.1016/j.compedu.2011.05.016>.
- Yla R. Tausczik and James W. Pennebaker. Improving teamwork using real-time language feedback. In *2013 ACM SIGCHI Conference on Human Factors in Computing Systems, CHI '13, Paris, France, April 27 - May 2, 2013*, pages 459–468, 2013. doi: 10.1145/2470654.2470720. URL <https://doi.org/10.1145/2470654.2470720>.

- Linda van den Bergh, Anje Ros, and Douwe Beijaard. Teacher feedback during active learning: Current practices in primary schools. *British Journal of Educational Psychology*, 83(2):341–362, may 2012. doi: 10.1111/j.2044-8279.2012.02073.x. URL <https://doi.org/10.1111/j.2044-8279.2012.02073.x>.
- Katrien Verbert, Sten Govaerts, Erik Duval, Jose Luis Santos, Frans Van Assche, Gonzalo Parra, and Joris Klerkx. Learning dashboards: an overview and future research opportunities. *Personal and Ubiquitous Computing*, 18(6): 1499–1514, 2014.
- Gillian C Visschedijk, Ard W Lazonder, Anja van der Hulst, Nathalie Vink, and Henny Leemkuil. Modelling human emotions for tactical decision-making games. *British journal of educational technology*, 44(2):197–207, 2013.
- Joel Walz. Second language acquisition and second language learning. stephen d. krashen oxford: Pergamon press, 1981. pp. 151. *Studies in Second Language Acquisition*, 5(1):134–136, 1982. doi: 10.1017/S0272263100004733.
- Jacob O. Wobbrock and Matthew Kay. Nonparametric statistics in human–computer interaction. In *Human–Computer Interaction Series*, pages 135–170. Springer International Publishing, 2016. doi: 10.1007/978-3-319-26633-6_7. URL https://doi.org/10.1007/978-3-319-26633-6_7.
- Christopher A. Wolters. Regulation of motivation: Evaluating an underemphasized aspect of self-regulated learning. *Educational Psychologist*, 38(4):189–205, dec 2003. doi: 10.1207/s15326985ep3804_1. URL https://doi.org/10.1207/s15326985ep3804_1.

Mohamed Ezzaouia (mohamed.ez-zaouia@univ-lyon3.fr)

is a Phd student at University of Lyon, LIRIS, France, with an interest in information visualization and human computer interaction. More precisely, Mohamed is interested in designing dashboards in the context of learning analytics for better online tutoring.



Aurélien Tabard (aurelien.tabard@univ-lyon1.fr) is a

Computer Scientist with an interest in personal informatics, activity based computing and information visualization; he is an Assistant Professor in the Computer Science department, LIRIS laboratory, at the University of Lyon, France.



Élise Lavoué (elise.lavoue@univ-lyon3.fr, perso.liris.cnrs.fr/elise.lavoue/)

is an Associate Professor in Computer Science at the iaelyon School of Management, University of Lyon, LIRIS laboratory. Her research interests include the design of learning environments to support self-regulated learning and learners' engagement by using interaction traces, in the fields of Technology Enhanced Learning (TEL), Computer Supported Collaborative Learning (CSCL) and Human-Computer Interactions (HCI). She has authored and co-authored more than 80 publications, including journal articles, book chapters and conference papers in these areas. She served as general co-chair (CSCL19), organizing chair (EC-TEL16), program committee co-chair (EC-TEL17) or program committee member for the EC-TEL, CSCL, LAK and ITS international conferences.

