Visualization of Sensor Data for Learners' Awareness and Reflection

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Abstract

This study emphasizes on investigating how technology is essential for today's dynamic learning environments, as learners must adapt their behavior according to their experiences and perspectives. This paper reviews specifically studies the visualization of learning state focusing on awareness and reflection, while considering both design and data visualization.

Keywords

Visualization, physiological data, emotions, awareness, reflection, self-regulated learning, metacognition

1. Introduction

Our past review "Visualization of learning process and learners' emotions: current state, limitation and future work" investigated emotional support stretching on visualization in learning, but till there was not deep survey done on the visualization of emotions to support learners by triggering awareness and reflection.

Emotions play an import role when it comes to learning and solving problems, however technology has not been deeply investigated to help learners to regulate their emotions in favor of their task, in a way to optimize their learning performance.

Data visualization can serve many purposes in the learning context like; articulating complex conceptual issues, making comparisons to understand causality, creating hypotheses to cultivate self-regulated learning, not just for the learner but also to help instructors create tools to train teacher's capacity to enhance learner's emotions, to foster more awareness and concentration.

2. State of Art

The use of visualization techniques in learning is not new, but very few experiments have been done to investigate the role of the visualization of physiological data on learner's awareness and reflection. So, this article will report the studies done in the different related fields in other to find some interconnection between them, to help draw conclusions which would help define the field been investigated. But first let's look at the state of the existing researches in the related fields and discuss possible methodologies and designs in the third section.

2.1. Visualization for learning purpose

The term visualization is said by Klerkx et al., 2014 to be the use of computer-supported, interactive, visual representations of abstract data to amplify cognition. In order words making data abstract to help the learner understanding and exploration. It relies on the design of effectiveness and efficiency --as well as sometimes playful and aesthetically pleasing-- interactive visual representations that users can manipulate for open-ended exploration or to solve specific tasks (Klerkx, 2014). In order to visualize a data set, one needs to create a visual representation or encoding of one or more of its data attributes or types, this involves mapping these attributes to visual features like shape, size, orientation, etc. (Ware, 2004).
Ware, 2004 goes on furthermore reporting learning analytics as the measurement, collection, and analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs.
Presmeg et al., 2006 describe visualization as to include processes of constructing and transforming both visual mental imagery and all the inscriptions of a spatial nature that may be implicated in doing mathematics.
For each data type, appropriate visualization techniques and tasks have been designed (Shneiderman, 1996). The following list presents them, together with original publications that describe the techniques in detail:

- for 1-dimensional data, sparklines or line charts
- for 2-dimensional data: heat maps (Pryke, Mostaghim, & Nazemi, 2007)
- for 3-dimensional data: architectural renderings or metaphoric worlds (Santos et al., 2000)
- for temporal data: timeline visualizations
- for hierarchical data: cluster dendograms
- for network data: node-link diagrams (Elmqvist & Fekete, 2010) and Balloon graphs (Herman, Melancon, & Marshall, 2000).

Data Visualization can be used in a learning context, in order to determine the emotions flexibility, observe the dynamics of monitoring and control of learning strategies, it also helps in the reasoning about the importance of metacognitive processes and interfering subsequent behaviors [1]. But the question is, how can these be achieved?

Visualization in learning processes is important because it can be used by researchers, learners, teachers, trainers, designers, administrators, and policymakers for various purposes. These purposes include: (a) articulating complex conceptual issues (e.g., emotion flexibility), (b) illustrating the dynamics of monitoring and control processes, (c) reasoning about the importance of key metacognitive processes and inferring subsequent behaviors, (d) generating hypotheses about underlying self-regulated learning mechanisms and their impact on learning, (e) developing teaching and training tools to enhance learners' emotions, self-regulation, and emotion regulation and teachers' ability to monitor and regulate learners' emotions, and (f) developing sophisticated teacher dashboards to trigger and support instructional decision-making that include interface elements (e.g., open learner models representing metacognitive accuracy) to provide learner data that may foster changes in self-regulated learning behaviors [1].

A visual representation of data cannot be possible without a database, data is either taken from logs or collected instantly from sensors. Sensors are said in Yun, 2016 to be able to report data in an extrinsic and intrinsic context, which involves external factors like position, time and environmental values for extrinsic data and personal sensing is said to be intrinsic. In this review we aim at concentrating on the intrinsic context and more precisely on physiological sensing.

2.1.1. Sensor Data in a Learning context

Sensors can be found in everyday devices such as our phones, wearables, and computers which leave a stream of digital traces of human behaviour. People leave digital traces when they make credit card purchases, send a tweet, or visit a website. This digital exhaust produced by sensors has rich information about people's behaviour, and potentially their beliefs, emotions, and ultimately mental health (Mohr et al.,2017). So, when locking at sensor data in relation to learning then we are dealing with personal sensing or physiological data which mostly involves detecting emotional levels in other to provide awareness to the user or learner.

Before looking at personal data related to learner, let's first understand what is hidden under the term "Personal sensing". Personal sensing refers to the collection and analysis of data from sensors embedded in the context of daily life with the aim of identifying human behaviour's, thoughts, feelings, and traits (Mohr et al., 2017). The use of sensors to measure physical properties for the purpose of understanding psychological states, or psychophysiology, has long been a core discipline within Psychology (Mohr et al., 2017). Advances in sensor technology have accelerated throughout the last decades, with sensors becoming smaller, lighter, and more accurate. Many sensors are embedded in devices such as smartwatches containing onboard sensors that track activity and physiological states (Mohr et al., 2017). Research on sensors provides new chances for learning environment design, since modern sensors are affordable and provide elaborate physiological data; studies on sensors are well advanced to support learning activities [19]. *This brings us to the use in the learning environment as a means of detecting and regulating emotional fluctuation during learning using technological tools, such as smartwatches which visualises these emotions or psychophysiological states in different forms and designs.*

Physiological events are involuntary activities for which our Autonomic Nervous System (ANS) is responsible and two main nervous systems are relevant for emotions like stress, the Sympathetic and Parasympathetic Nervous Systems (SNS and PNS respectively [4]. Stressful situations cause dynamic changes in the ANS whereby the activity of the SNS increases and the PNS decreases, so, in short, the SNS dominates during restless activities and the PNS during resting ones [4]. Holzinger et al., 2013 goes on saying that the different physiological signals include signals, such as heart rate variability (HRV), galvanic skin response GSR), brain activity (EEG), blood pressure (BP) etc. Note that these systems are influenced by many different factors; two of them are eustress and distress. Eustress characterizes positive states and distress negative states, therefore, not all monitored stress should be perceived as bad stress [4]. These biomarkers can also be identified in a learning context, due to the close connection between cognitive functions and learning. These does not just include stress but also metal fatigue, alertness and attention. The following take presents the different physiological biomarkers detected during learning and their efficiency to predict cognitive load, attention, meditation, mental fatigue, alertness and stress according to Durall et al., 2015.

Cognitive load is a term used to describe the amount of effort that a task requires to the person executing it (Durall et al., 2015). It can be multidimensional, meaning it takes into consideration how mental workload deals with learning, thinking and reasoning demands of the memory all at the same time. Which implies that if thinking or reasoning overloads the memory, this would limit the ability to learn efficiently at that moment. The core of the theory asserts that people have a limited cognitive capacity, which can lead to decreased interpretation, comprehension, and inferences made during visualization during learning, and problem-solving tasks (Durall et al., 2015). In addition, representations depicting processes (e.g., facial expressions of confusion, high frequencies of skin conductance responses from electrodermal activity) in real-time, call for accurate and rapid detection, discrimination, and comprehension of relevant information. As such, it is necessary to design an interface that minimizes extraneous cognitive load experienced by learners when attempting to comprehend and reason about visualizations presented in real-time during the process of emotion regulation.

Experiments showed that the increase in pupil size correlates to an increase of mental load, and as such blink rate decreases when the subject deals with cognitive demanding task [4]. The table below from Durall et al., 2015, shows Psychophysiological states and sensing analysis. As presented by the table, EEG seems to be the most effective biomarker, followed by blink rate and gaze behaviour. Due to the EEG reliability, it has been widely adopted as technique for monitoring and enhance all mental state connected to learning. Skin conductivity on the other hand is more head related sensing or emotions and less sensitive to vital states like heart rate [19].

	EEG (electroence-phalograph)	Skin Conductivity	Heart rate	Pupil Dilation/Blink rate	Body Posture/Gaze	Expression recognition
cognitive load	X	X	X	X	X	
Attention	X			X	X	
alertness	X		X	X	X	X
Meditation	X		X	X	X	
Stress	X	X	X			X
Mental fatigue	X	X		X	X	X

Table 1: Psychophysiological states and sensing analysis (Durall et al., 2015)

2.1.2. Visualization of physiological data

When looking at visualisation of physiological states, data is mostly self-reported. This means the data is usually provided by the user himself. Visualisation of emotional levels are mostly represented in form of facial symbols and the different emotions are shown with different grimace or colours. Emotions can also be visualised on a map geographically depending on the purpose of the visualisation. An example of this is illustrated in Guthier et al., 2014 where the emotions of the citizens are represented on a map as coloured circles. Other ways of visualising physiological states include radial and block chart, and time-based graphical representation, with x and y-coordinates.

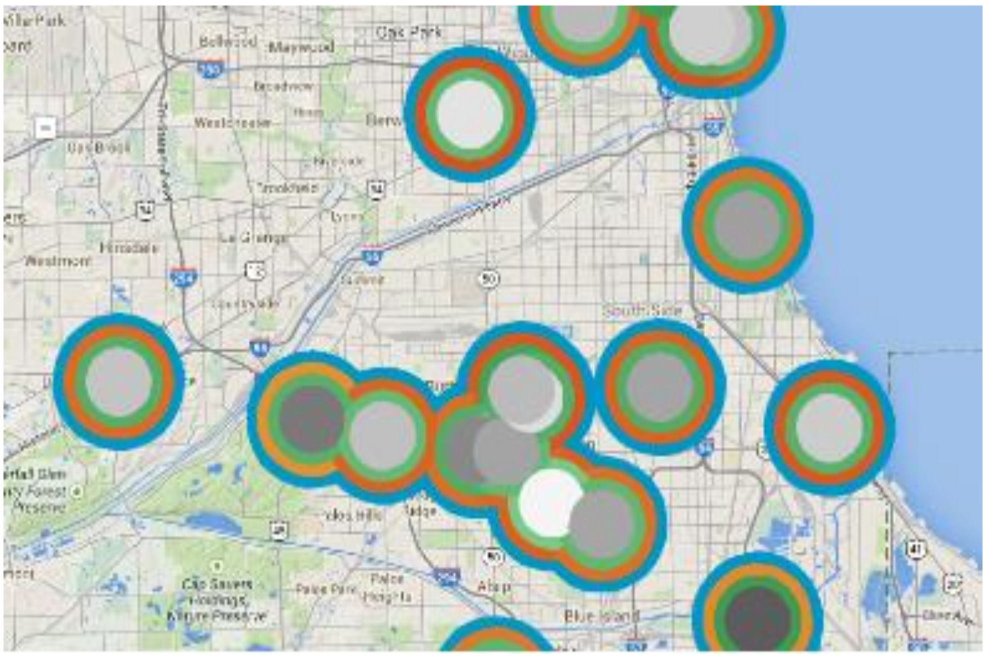

Figure 1:Visualization of geo-tagged emotional Twitter messages originating from Chicago (Guthier et al., 2014)

Smart cities use various deployed sensors and aggregate their data to create a big picture of the live state of the city (Guthier et al., 2014). This live state can be enhanced by incorporating the affective states of the citizens, such affective states include, physiological emotions. On the figure above (figure 1) are Pleasantness, which is associated with the grey colour, arousal is shown in green, dominance is red, and unpredictability is displayed in blue. In some places the red colour seems to look like orange or yellow (less intensity implying less dominance), this is because the rate of dominance in these places is weak, so the red becomes lighter till it looks yellow. The blue and the grey also vary depending on their intensity (deep grey or light blue for lower Pleasantness and unpredictability respectively). In some places the blue becomes lighter meaning unpredictability is less abundant in the area and the grey becomes white, meaning in the same way as the others, that Pleasantness is weak in these areas or inexistent. On the other hand, arousal seems to be less variable meaning the recorded rate is almost constant although the region.

The next figure shows a 3D representation of the physiological data of a biker on the hills of San Diego USA. He tracked his blood pressure, heart pulse and respiration rate during the ride, which was then visualised in Real-time by his tracker. Each point of the data is represented by a 3-dimensional vector and is distinguished by their colours. The heart rate is represented by the red colour, while the respiration by the light blue and the blood pressure by the deep blue. The intensity of the dots seems to differ as he goes down and up the hills (as shown in the figure 2), and the exact values of the data can be read when clicking on the corresponding dots.

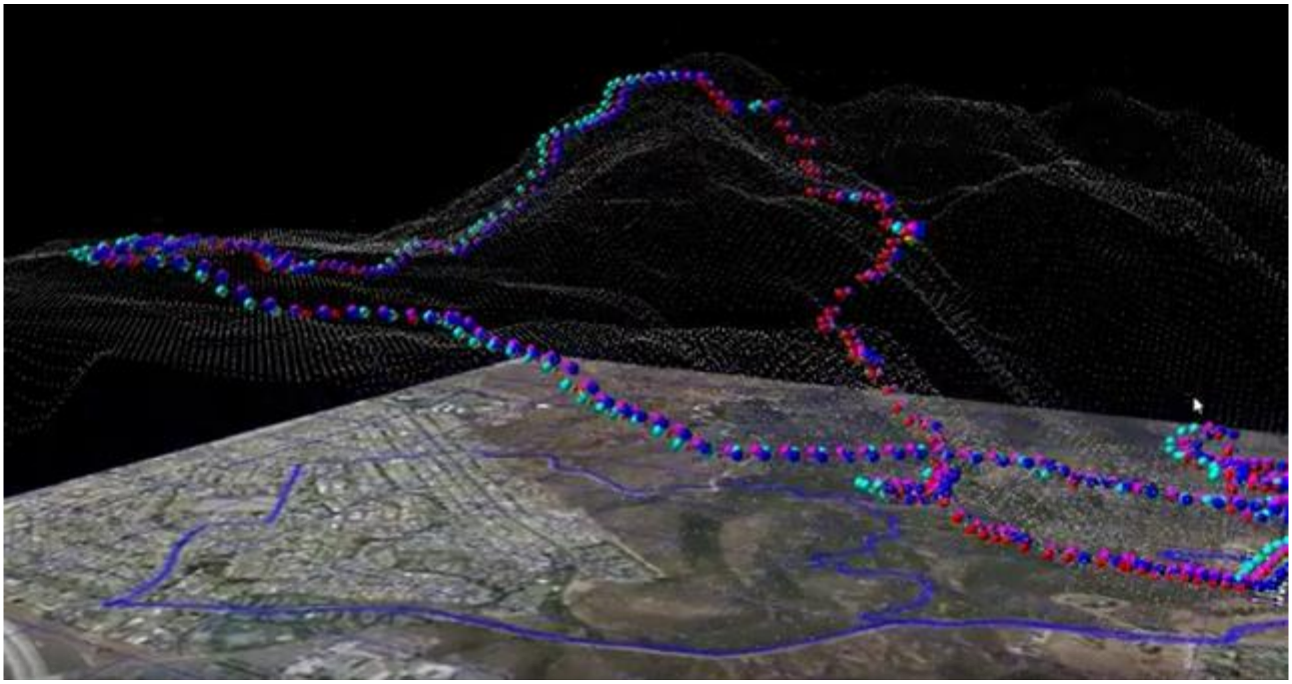

Figure 2: Interactive data visualization of a cyclist
Source: https://www.youtube.com/watch?v=CI5iwYVCz_U

Both figures above (1 and 2) both use map system and colours to visualize physiological states but the difference here is that figure 2 is represented in 3D and is interactive, meaning the user can select different angles to observe the data and can select different points to read to exact values visualized. This give a more detailed representation of the data and shows openness.

Another visualization method also used in the visualization of physiological states, includes Star Plots or radar charts, also called spider web diagram, polygon plot, polar chart, and Kiviat diagrams [3], these are graphical methods of displaying multivariate physiological data in the form of a 2D chart of three or more quantitative variables represented on axes starting from the same point. An example of this is represented in the next figure from [3], which reports on an experience of a project named EMOMES, where the goal was to design and develop an end-user centred mobile software for interactive visualization of physiological data. Their solution was a star-plot visualization, which results from tests with data from N=50 managers (aged 25-55) taken during a burn-out prevention seminar. The results demonstrate that the leading psychologist could obtain insight into the data appropriately, thereby providing support in the prevention of stress and burnout syndromes. Skin conductivity data over time is illustrated alongside with start plots showing details related to the stress levels [3]. The three smaller Star Plot diagrams show the feature values of the corresponding phases (first is a relaxing phase, second a stressful and finally a recovering phase), the bigger spider diagrams with the darker areas on the right show the overall feature values. The values of each feature are only displayed if a user hovers a feature caption. As example, is the mean skin conductance.

If a user hovers one caption, the corresponding value is shown in all four diagrams. If a user makes a right-click on a caption, they receive a short textual introduction to the meaning of this feature regarding stress.

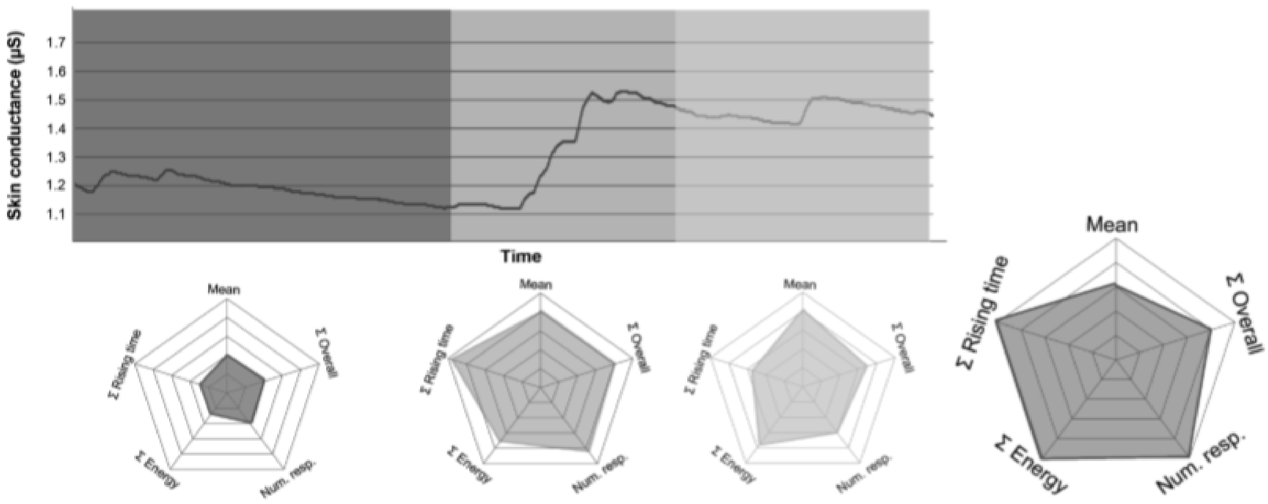

Figure 3: Star plot representation to support skin conductance visualization [3]

Now let's present cases, where the visualization of the data was been made for the purpose of learning. Clegg, et al. 2017 made some experiment of live physiological sensing in a school of Washington D.C on 75 Pupils in 3 Days. The first case shows a "magic mirror metaphor", which uses augmented reality to visualize human body functionalities in real time. This magic mirror was presented in a classroom where the respiration and heart rate of the students was visualized to them. The data was transmitted using wearables to the tool and then projected for the students to observe. The pupils were able to see each other's respiratory organs and compare their results.

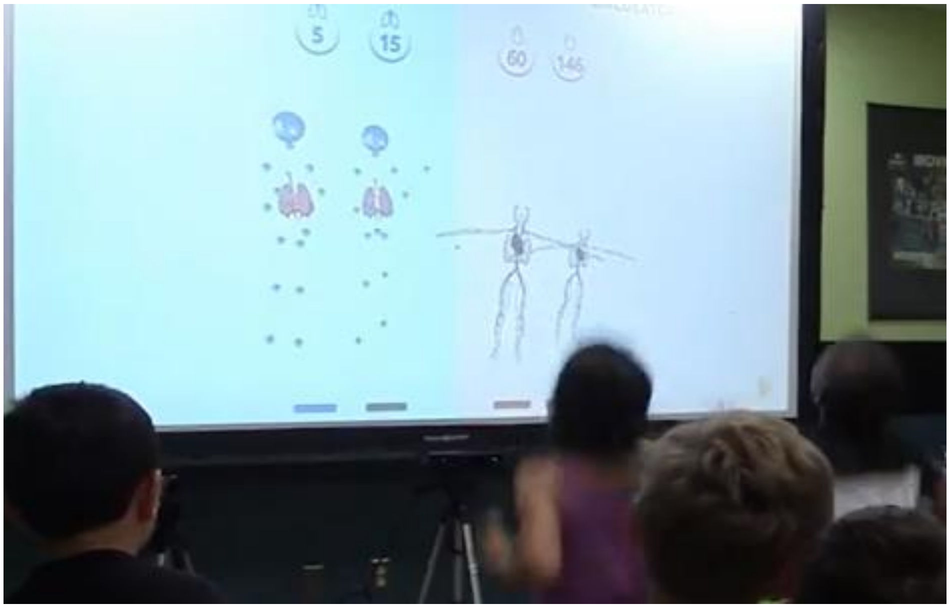

Figure 4: magic mirror metaphor

Source: https://www.youtube.com/watch?v=eRIO4AzPd8s

The experiment was carried out to probe two main tools called BodyVis and SharedPhys, with the aid of an electronic textile (e-textile) shirt and a large-screen display respectively (see figure 5 and 6 below) the Children could experience a live visualization of their states. “BodyVis shows internal layers of the human body along with physiological phenomena of the wearer on the e-shirt. Shown below on the e-shirt is: (a) the heart vibrates and lights up according to the wearer’s heart rate, (b) the lungs visualize the breathing rate with lights, (c) the stomach shows how food is processed, (d) the intestines illuminate the digestion pathway”. Designers of BodyVis, emphasize on dynamics, interactivity, and reactivity to the human form and function, and for SharedPhys physical movement, live physiological data, and social/temporal comparisons.

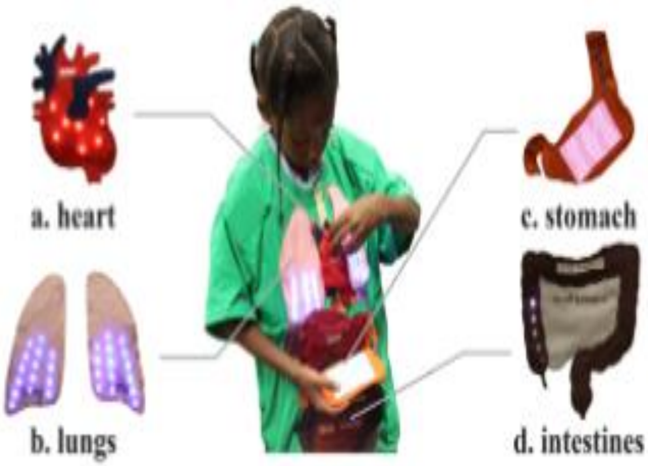

Figure 5: E-shirt live sensing visualization [18]

On BodyVis, users can dynamically detach and reattach organs to view the multiple layers of the human body. If organs are returned to the proper place, they immediately function again. Digestion is simulated via animated LEDs and an animated video of stomach activity, which is displayed on an embedded, modified smartphone screen. SharedPhys is the analytical representative tool (see figure 6), which uses mixed reality in which multiple learners' physiological data can be represented as previously shown above in the figure 4. A real-time visualization is done on a large display in a classroom, SharedPhys uses moving Graphs for representing the students, and the data is shown in form of line graphs visualization per student. Up to six learners can use the system simultaneously (lines are color-coded and labeled per user). This analytic representation enables learners to investigate how their physiology changes with physical activity and supports the development of STEM skills including graph literacy, quantitative comparison, and basic statistics.

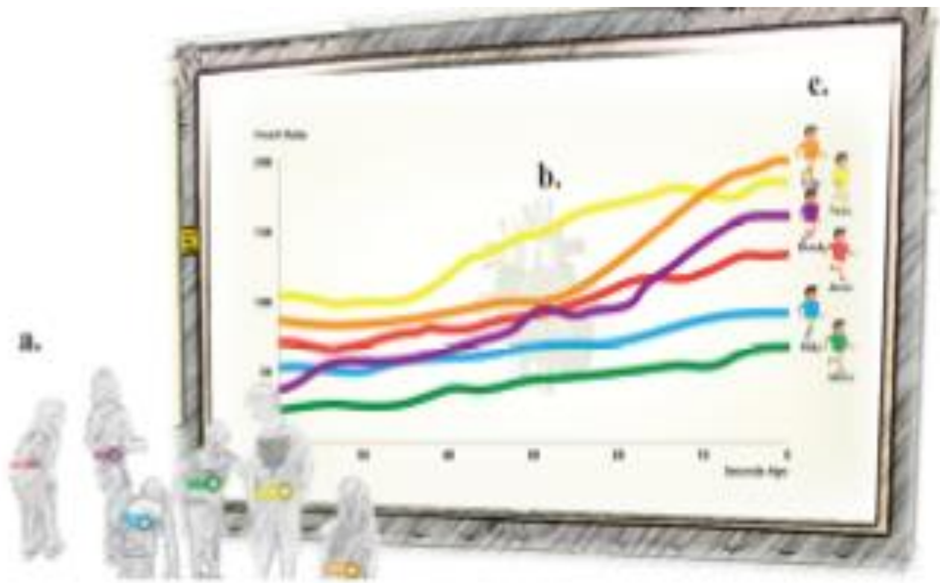

Figure 6: six wearers sensed physiological data into a graph in real-time. Personalized avatars run fast or slow according to the user's heart rate [18]

These experiences (BodyVis and SharedPhys) were quite interesting for the children and were found to give different results according to the learners age. Younger ones were found to be more interested in interacting with the e-shirt, or making competition of who had the fastest rates, while elder ones were observed to ask more complex questions regarding the tools and their aims. Their research focused on the analysis of video observations of users' experience, interview data, and post/daily assessment responses, and it was found that Teachers and facilitators played important roles in scaffolding learners' scientific inquiry, especially as learners planned their investigations and asked questions. As learners carried out their tests, they continuously needed to be reminded **to slow down between activities** so that they could start the next experiment with their resting heart rates, furthermore analytic representations in SharedPhys inspired and scaffolded scientific inquiry skills and processes, but they observed **a need for simpler visualizations** (e.g., showing just one learner at a time) especially for younger learners (Clegg et al., 2015). These findings offer particularly useful insights for supporting learners across age ranges.

Durall et al., 2015 discusses of a reflective tool based on EEG, which helps develop awareness in other to impact learning. This tool is built around a script that structures a study activity in three stages, including;

Meditation: Users receive guidance to perform deep breathing and relaxation exercise before studying.
Study: User study behavior is monitored, and the collected metadata is stored and visualized once the learning session is finished.
Self -assessment: Once time for learning is over, the user is encouraged to answer some reflective questions about their activity. The set-up of this tool called Feeler can be observed in the next figure.

Figure 7: Feelers prototype equipment and (on the right) visualization design [4]

The boxes and the headset represent the equipment of Feeler, while the visualized data observed by the user is represented on the left. The Prototype was tested on 22 highly educated student, with ages from 22-45 years old. The information recorded includes attention levels, meditation, brain waves (delta, theta, alpha, beta, gamma) and blink rate (Durall et al., 2015). EEG activities are monitored by the headset. Students receive a set of physical and computational blocks that guide their actions and so when interacting with the blocks, they receive task through visual and haptic feedback. Design methodology is reported as follows "for supporting reflection that was taken into consideration during Feeler research, slow technology and inquisitive design were used. Slow technology is a design philosophy in which time is considered as a prerequisite for reflection", more is not said.
Students feedback in their experience, reported that, the time they were willing to allocate to reflect on their own activity, no matter what benefits it may bring in the future, was quite short. They then introduced a slow down of academic activity with the aim of encouraging students to take time to think about their study performance, through self-assessment. *Meaning inquisitive design emphasizes on the role of experience and how people make sense of the use, when designing tools to support reflection.*

Other design methodologies mentioned included, 4 phases identified as follows: Contextual inquiry, Participatory Design, Product Design and Prototype Design. The design here is characterized as being highly iterative and should not be understood as a linear process. Contextual inquiry was aimed at defining the design space and identifying the main possibilities and design challenges. And for this reason, the candidates chosen for the experiment were then interviewed on concepts like health, mindfulness and wellbeing. Participants showed interest in having access to raw data and the need of some initial analysis. They also highlighted the necessity to distinguish between learning and academic activities, since learning is not limited to studies. Participatory Design made use of feedback obtained from Contextual inquiry and help to extend understanding on how to monitor learning and visualize information. Ambient visualization and data privacy were also desired.

2.2. Awareness and Reflection

For learners, awareness refers to the metacognitive process of being conscious of one's own state, of understanding and progress (self-awareness), as well as teachers' awareness of the state of their students and classes, which is also called 'state awareness' (Rodriguez et al., 2017).

Reflection builds on awareness. Reflection is a metacognitive strategy to help learners as individuals or organizations reflect upon experiences, actions and decisions taken. There are various definitions for reflection, but it is generally agreed that reflection requires retrospective thinking of one's experiences and critical examination of presented information, ponder experiences, question their validity, and draw critical conclusions (Hoyrup & Elkjær, 2006). Reflection can be self-reflection (by the learner) or 'state reflection' about the learner's state of understanding by others (such as teachers or administrators). And because learning is tightly related to experiences, we can then assume that reflection may have a strong influence on learning. There is a widely documented argument that self-reflection enhances learning and practice, since the learner is involved in processes that explore experiences as means of deepening understanding (Rodriguez et al., 2017). Self-reflection enables learners to gain insights from their experiences, which can foster further learning.

Looking at awareness in refers to learning, Schmidt et al., 1995 says "A low level of awareness, called "noticing", is nearly isomorphic with attention, and seems to be associated with all learning. A higher level of awareness "understanding" is involved in contrasts between explicit learning (learning on the basis of conscious knowledge, insights, and hypotheses) and implicit learning (learning based on unconscious processes of generalization and abstraction)". N., Pam M.S., 2013 defines awareness as consciousness of internal or external events or experiences, that is thought by some to separate humans from non-humans or animals. Evidences of self-awareness is most often determined by whether an individual can use a mirror to groom an otherwise unseen dirty spot on its own forehead. Taking us to conclude that a person with awareness would likely be able to report his or her internal or external state. Reports on internal states is seen here as reporting physiological state. We can then understand that awareness provided by physiological state reporting in a learning context refers to conscious learning. Since we know understand the link between awareness, reflection and learning, let's briefly see how these both terms can improve learning.

2.2.1. The importance of awareness and reflection in learning

Reflection as already mentioned is discussed by many studies as an act of retrospective thinking on experiences or events and this may help the learner make more sense out of the process of acquiring new information and knowledge but not just that;

- Reflection and self- awareness allow us to consciously develop our own **repertoire of strategies** and techniques to draw upon by synthesizing and evaluating the data. In the end, it also means applying what we've learned to context beyond the original situation in which we learned something (Kolb et al., 1984).
- In this way to be able to evaluate the visualized data and draw conclusions helps the learner to be able to take informed actions that can be **justified and explained** to others.
- Reflection is therefore not passive but leads to **active experimentation, creativity and progression**. Kolb et al., 1984 suggest that reflective **observation transforms concrete experiences into learning experiences**.
- By awaking the awareness of the learner through data visualization, it allows him to **adjust and respond** to issues and problems faced during the learning. This involves mostly the control of emotional state. And the listed points above promote a **positive learning environment**.

2.2.2. The relation of emotions to awareness and reflection

Reflection and awareness as defined are seen to be closely related, because they both include a metacognitive process in other words critical thinking. So, in other to trigger the learner's awareness and reflection, a self-critical analysis of his own state should be done during or after the learning process. This state refers to the emotional state and goals, because emotions trigger reflection. Reflection as mentioned before is the retrospective thinking of experiences which in turn foster emotions. Reflection involves linking a current experience to previous learnings (a process called *scaffolding*) (Costa et al., 2008). In other words, one is the result of the other. This brings us to **self-regulated learning**; this is the art of regulating emotional state during learning. Self-regulated learners are actively constructing knowledge and use various cognitive and metacognitive strategies to control and regulate their learning. This means such learners are aware of their task, needs and objectives. They set standards or goals to strive for in their learning, monitor their progress toward these goals, and then adapt and regulate their cognition, motivation, and behavior in order to reach their goals [1]. This is then an adaptive form of learning in which the learner controls his state or emotions in other to meet his goals. Using different technics and strategies this brings us to reflection, metacognition or thinking. "Applying a self-regulated learning perspective to multimedia learning suggests that learners need to be supported in assessing what they (do not) know (monitoring support) and in regulating their learning behavior in a way that matches their current understanding. So far, support measures have focused on verbal or visual instructions that convey strategy knowledge and make its use in a given learning situation and for instance, a number of studies have used prompts or prompt-like instructions that tell students to apply certain cognitive processes such as information integration, and visual instructions have been used where learners were shown eye movements that illustrated helpful visual behavior in advance to learning from multimedia materials" (Azevedo et al., 2017).
Understanding this statement means that learners need support to achieve self-regulated learning, this review goes on proposing different emotional strategies aimed at supporting the learners through this process. These strategies would then be discussed in the next following of this article.

2.2.2.1. The role of emotional stability in Learning

Emotions are known to play an important role in learning (Kort et al.,2001; Trigwell et al., 2012). Emotions drive attention, which, in turn, drives learning and memory (Värlander, 2008). Furthermore, emotions play an essential role in studies on attitudes and motivation (Pintrich, 2003; Meyer and Turner, 2002). Prior

research has highlighted the importance of supporting learner awareness of his emotions (Ashkanasy and Dasborough, 2003). Information on affective states can, for instance, help students (or stimulate interest) to reflect on the type of emotions they felt, the activities that generated certain emotions or their evolution over time. By analyzing such information, students can take a pro-active role in regulating their learning as well as taking decisions on their improvement needs during learning processes, based for instance on information from studies that relate learning outcomes with affective states (Baker et al., 2010).
A learner can increase his receptivity when placed in a positive emotional condition or emotional state. Amongst these emotional conditions, we find characteristics such as relaxation, concentration and the ability to visualize tasks or motivation [28]. Also, recent studies confirm that certain emotions reduce our capacity to learn while others improve it. Positive and negative emotions can go as far as affecting the way the brain processes and retrieves information [28]. Liu, et al., 2010 defines eight basic emotion states: anger, fear, sadness, disgust, surprise, anticipation, acceptance and joy. All other emotions can be formed by these basic ones, for example, disappointment is composed of surprise and sadness An "emotional high" will provoke the release of endorphins in the brain, which in turn, trigger the flow of acetylcholine, the vital neurotransmitter that orders new memories to be imprinted in various parts of the brain (Liu, et al., 2010). Pulitzer Prize-winning science writer Ronald Kotulak describes acetylcholine as "the oil that makes the memory machine function. When it dries up, the machine freezes", often resulting in Alzheimer (Benchetrit et al.,2004). It is said in Azevedo et al., 2017 that *self-regulated learning impacts on emotional stability, which can be achieved through data visualization of physiological data sensor*. Here are several **theoretically based self-regulated emotional strategies** that are described in Azevedo et al., 2017 aimed to support learning. As emotion is said to be closely related to reflective thinking and self- awareness the following strategies are discussed:

a) **Selection of a situation:** Selecting or avoiding situations which may trigger related emotions. For example, to avoid looking the scores of passed evaluations just before a new evaluation to avoid frustration which may lead to lack of concentration in the next evaluation.
b) **Development of attention**: This involves the redirection of attention within a situation in other to influence emotional reaction. Concretely it is the shifting of concentration to another task. Learning with video presentation catches more attention than learning just with text, same as with image visualization.
c) **Modification of situation:** This refers to the instant change of situation in other to impact emotions.
d) **Modulation of responses**: This is the direct experimental, behavioral and physiological influence of emotional response, when the emotion is already well evolved. An example of this is to smile even when feeling frustrated.
e) **Cognitive change:** Cognitive change is explained to be the modification or change of appraisal of a situation in order to influence emotion. An example will be the ability to think that an increase in the heart rate is not a sign of anxiety and instead think of a positive emotion related to that heart rate in order to gain back stability.

These strategies can be achieved through the visualization of physiological data which are used to reflect the emotional state of an individual for example eye-movement behavior or facial expressions but need to be supported through either verbal or visual instructions. Let's look at *the emotional strategies mentioned before and how they can be applied by visualizing physiological sensor data. The illustration in the table below proposes ways of introducing these strategies to data or sensor data visualization.* (Azevedo et al., 2017)

Self-regulated emotional strategies through reflection and awareness	Scaffolding techniques	Data Source	Visualization methods
Modification of situation	Multiple representation of the same information	Galvanic skin response and electro dermal activity	Use of different modelling forms to represent information (eg icons, graphs, maps**)**
Development of attention	Show diagrams to ensure understanding of state and provide audio instruction to draw attention	Eye tracking	Visualizing gaze behavior in relation to relevancy of content as a graph
Modulation of response	Smile or laugh after receiving negative score and focus on feedbacks, not on score (positive feedback and future progress visualization)	Heat rate, Galvanic skin response and electro dermal activity	Highlight specific time points of low/high arousal and how they are related to other expressions of emotions like facial expression (visualize negative effect of anxiety on scores)
Cognitive change	Spend more time reading content, than rushing over it (anxiety)	eye tracking, screen recording, heat rate	Comparison of Frequencies like duration of eye focus or heat rates

Table 2: emotional strategies for sensor data visualization (Azevedo et al., 2017)

As describe in the table above we can understand that **modifying a situation** would mean for example using different forms or designs for representing the same emotions. This would give a better understanding of the visualized data and hence foster reflection and awareness. **Developing attention** of the learner by introducing metacognitive questioning in between the reading. This can be achieved by visualizing gaze behavior to let the learner be aware of his point of focus on relevant or non-relevant material and through some audio instructions to draw back attention, or if the learner is distracted from the learning by some other activity on the internet this probes the degree of concentration and in this way catching up one's awareness. To achieve **modulation of response** the application or tool can notify the learner to smile when high level of anxiety before exams, detected by high levels of arousal. Visualizing past experiences of emotional state and obtained scores and module future progress in relation to emotional regulation and stabile arousal in the way promoting emotional stability and supporting learning. And then **cognitive change** calls up the learner's consciousness and reflection, by making a time visualization of point of focus or fixation, in relation to the goal to be achieved. Like a goal may be to read a book in 2hr and a real-time visualization of the time spent on each page can be done simultaneously, and if the learner spends more than 10 min fixing the same spot, the tool can make some instruction pop-ups to notify the reader on the time left for a particular page and at the end of the reading presenting a graph of average time spent on each page or phrase in relation to the goal to be achieved. Now let's look at the different ways by which emotions in relation to learning are been visualized.

When talking of learning the frequently involved emotions include boredom, frustration, confusion and happiness or let's call it enjoyment of task. The following diagrams demonstrate how these emotions can affect the performances or grade of students reported by Leony et al., 2013. This is because learners who are bored would likely less employ adaptive learning (self-regulated learning) strategies, such as elaboration and metacognition, and due to their reluctance, they would also be less aware of their state, hence resulting to no mental effort for this understanding. Moreover, a negative emotion such as frustration, would predict elaboration but positively predict metacognition.
The first representation below shows the time-based visualization of a student over a period of 4 months (from September to December). The emotions mentioned are rated from 0.1 up to 0.7. The learner is observed to be very emotional between 22. September till middle October, and less emotional between middle October and middle November. The high emotional period may be because of examinations or personal issues, but although the probe period, happiness is seen to be predominant over other emotions, then comes boredom and frustration (with 0.18 around October 17), is on other side the least predominant emotional state.

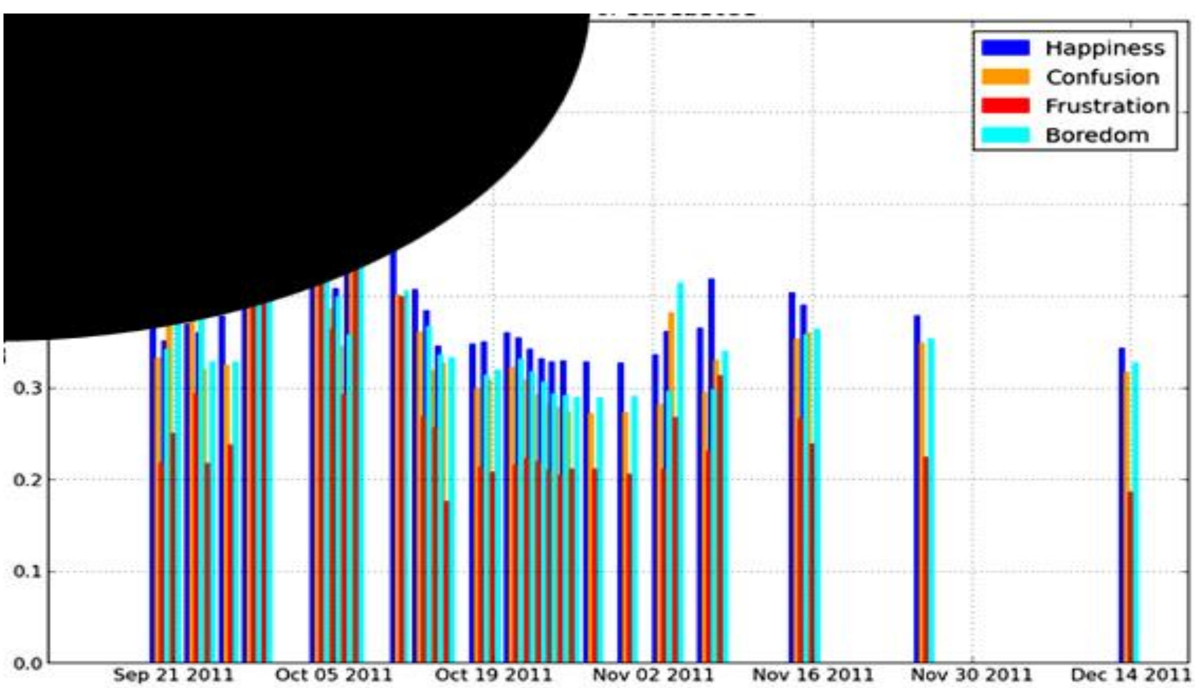

Figure 8: Data visualization over Time [5]

The next visualization diagram presents unlike the previous visualizations, the emotion visualizations of a whole class group in relation to the learning tool within a period of 4 months. Results represent emotion of students when learning with different tools (moodle, gdb, firefox, kdevelop, and valgrind). Results (figure 9) show that when using moodle the students were less frustrated as compared to gdb or valgrind. Valgrind and kdevelop brought up less confusion, but also developed less happiness or enjoyment. Meaning the Students understood the task but didn't like the learning process. The learning tools are allocated around the circumference having four angular bars, each of which represents the emotions in reference to a tool. The average level of each emotion is rated from 0.1 up to 0.5.

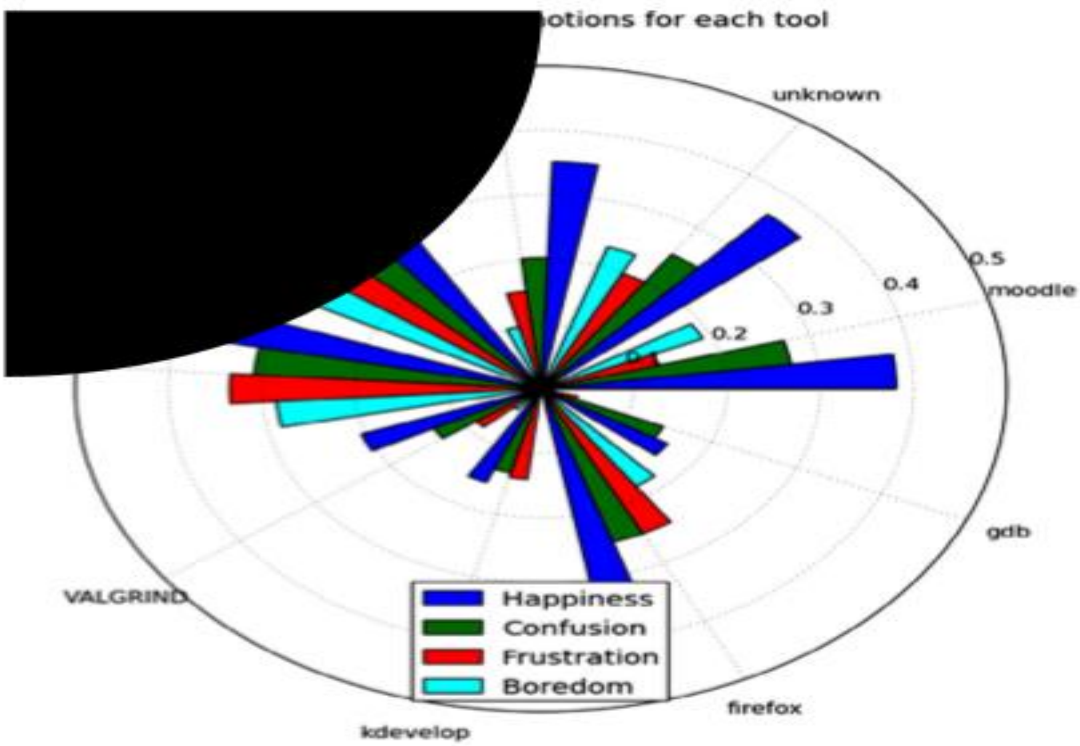

Figure 9: Visualization of emotion in relation to learning tool (meta-data perspective) [5]

The next figure also represents the emotions of a classroom group. This diagram points out the relationship between the student's grades and their emotions. This help the student to directly identify the role of his emotions on his performance, hence fostering more *motivation* for emotion regulation in other to achieve better grades. The X-axis is associated to the final score of the learners in a course, and the size of the globes is ruled by the average level for the given emotion and the given learner. There are two significant changes in this version. First, a learner is represented by a set of circles aligned vertically. The second difference is that his position at the Y-axis is fixed according the reflected emotion. From this visualization passed is with 50 and failed from 40 downward. It can observe that the learner with 40 had a high rate of boredom and confusion, represented by larger circles. In general, it is also interesting, for most learners had the feeling of happiness, regardless of whether they passed the class at the end or not. In addition, happiness and boredom are the predominant emotions for students with high scores and few events.

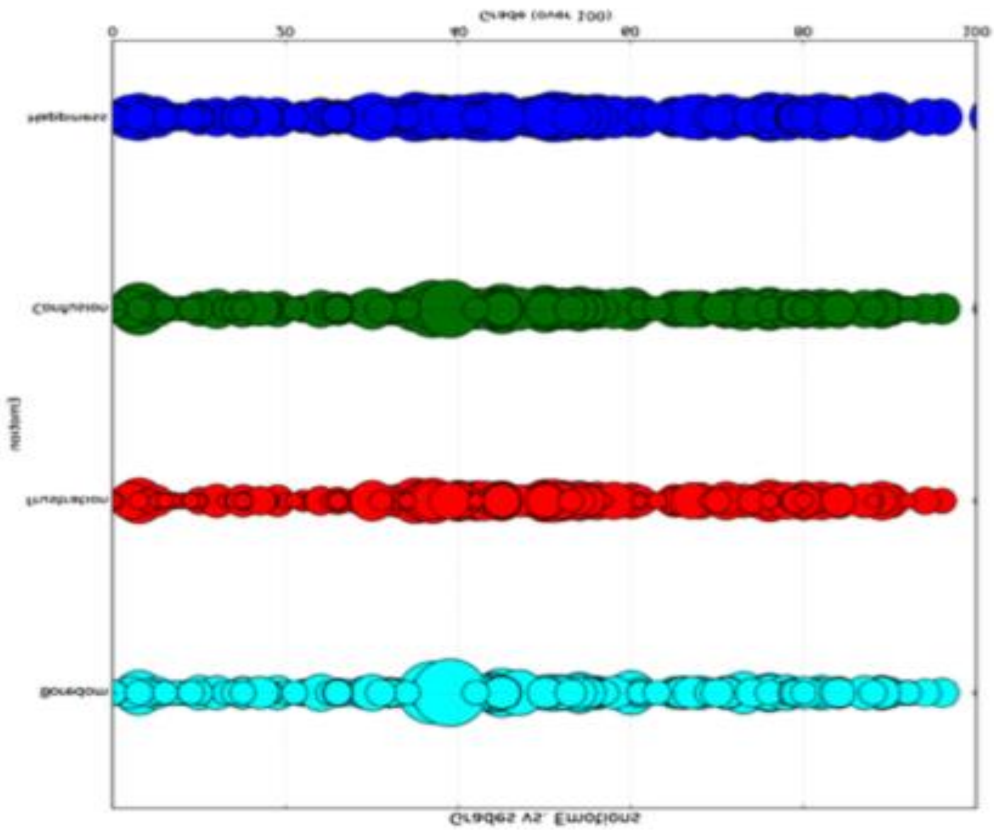

Figure 10: Visualization of emotions and grades of the learned subject (external perspective) [5]

These visualizations seem to be of good relevance to support learning, but how can emotions be probed? To answer this question, we explicitly discuss at the beginning of the second section of this review, what physiological sensing is. For the aim of making it understandable, of how emotions like happiness or confusion are being distinguished. Deep explanations related to this matter is not the focus of our investigation, we already know physiological sensing involves low-level data, and as reported in Leony et al.,2013, low-level data is analyzed and processed in a second stage, with the goal of visualizing emotions during learning experience, to support both instructors and learners. As mentioned, eustress characterizes positive states and distress negative states, therefore, all positive and negative emotions around from these [4].

3. Design Considerations and Visualization perspectives to support learning

There are some other factors to consider like the design, methodology, and the appropriate perspective when visualizing emotions to support learning. But how can these be achieved. Let’s get to know some basic features deducted from the reported experiments above, that a visualization tool for learners should fulfill:

- Data should be portable i.e. can be accessed from all digital devices. This is the elementary feature of any digital tool dealing with data.

- Approximation, to visualize uncertainty in other to conserve the credibility of the data.
- For the visualization of physiological data several software packages exist, most of which include Matlab and Microsoft Excel. These software packages enable designers to format data and create charts, but the memory limitations of these programs limit efforts to small data slices that can then be printed and collated into large notebooks for visual data mining
- Other challenges involve data privacy and ethical issues. In other words, recording and usage of sensor data must be completely transparent to the user and under his control
- Private data with no relevance must be ignored
- Should follow data privacy legislation
- Data should be easily understandable (too much information may compete learner's attention)

Regarding design consideration, it is preconized that the data needs to be carefully sorted based on the **immediate needs of the learner**. The visualization of the physiological data must be **clear and easily understandable**, to avoid compete of attention with the learning stuff. The data should also be **self-recordable and online traceable** on different timelines i.e. prior to learning, during learning and following learning and across time spans (days, months or semester). Data can be represented as histogram of frequency of use for learning strategies vs facial expression of emotions with the corresponding effectiveness of the use of specific emotion regulation strategies. However, there may be individual factors that may restrict the success of emotion regulation.

Designers aiming at selecting a visualization that makes sense to the user and their work practices must consider users' preferences, the nature of the work, and the intended learning goal in terms of expected outcomes of the reflection session as already mentioned. The most common visualization perspectives are analyzed and summarized as follows: Social perspective (comparing own performance/measures with others or aggregating data over multiple users), spatial perspective (the location of the user, allowing to understand the relation between place and behavior (see figure 1)), historical perspective (comparison of current values to historic values), meta-level perspective (using item metadata that supports the understanding and interpretation of the data) and external perspective driven by other data sets (visualization according to data provided by other standard sources of information like e.g. the weather). (Müller et al., 2015) In some cases, there are already established visualizations, which have proven to be intuitive and accepted, e.g. timelines for the historical perspective or social networks for the social perspective. However, other types of context can result in more complex visualizations, which must be adapted to the type of captured data as well as to the learner's background.

Providing different ways to visualize data can be useful for users. This allows users to select the visualization they feel comfortable with. Of course, there is a trade-off: users will require more time to understand multiple visualizations versus only one.

Time-based visualization (historical perspective) where the physiological data are being represented over time, here months (See Figure 8), the following visualization involves **context based visualization**, whereby the learner's emotional state is visualized alongside with a particular learning tool, is been represented as a bubble or radial graph (See Figures 9). Figure 10 shows a meta-level perspective where the relation of between emotional state and grades are being represented, which means the emotions generated by the learner during exams preparation and these are then visualized with the final score of the corresponding subject.

But before drawing any conclusion let's discuss how the experiences above can contribute to develop a visualization tool which would be able to trigger learner's awareness and enhance reflection.

A good visualization tool as mentioned before, should be able to project different visualization design to the learner, using the same data. For example, figure 1(illustrating a heat map of citizens' emotions in a city) can inspire a design of a heat map of emotions alongside with time. As shown in the example below, are many students represented at a time. But the learner should be able to decide of an individual visualization or a group visualization. This brings us to the importance of privacy, control and ethical issues. The example below (figure11) from Derick et al., 2017 is a heatmap visualization, in which columns represent time units, such as days, weeks, and months, and rows represent students. Each affective dimension is represented by a cell, while the frequency level of each emotion is represented through the intensity of the cell color (a more intense color represents a higher level of the emotion). And again still about figure 1, this can also inspire the geographical visualization of emotions in relation to a tool like in figure 10, but this would be of more relevance for the instructors and hence help them improve the learning processes, regarding how learners feel about the tools, or learning activities like brainstorming, interface design, documentation etc.

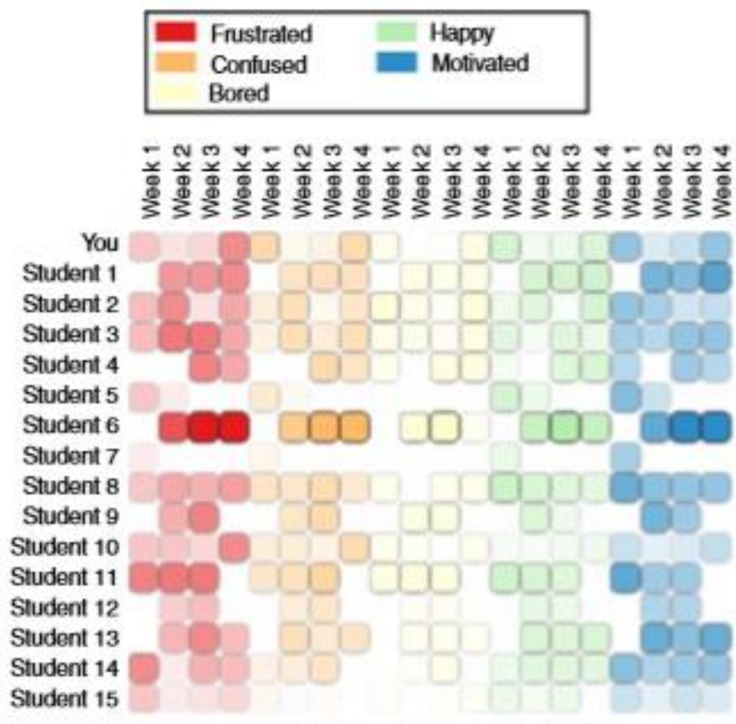

Figure 11: heatmap visualization [28]

We can deduct from all the visualization figures that colors play an important role in the design for representing emotions. So, every emotion is identified by a specific color, figure 1, 8, 9, and 10 all represent happiness or pleasantness in blue tones let it be lighter or deeper, and dominance and frustration as red. But is this enough to conclude that negative emotions are to be red and positive emotions blue? Till here there were no studies found or experience made to conclude such assumptions.

An important design technique is the relation of emotions to grades, because this can directly trigger more

motivation and consciousness, hence awareness.
Azevedo et al., 2017 presents a complex visualization framework (see next figure) based on the integration of self-regulated physiological data visualization, that can be used to provide elaborate adaptive scaffolding to a learner by illustrating how cognitive and metacognitive processes are the basis for this emotion regulation. This adaptive emotion regulation scaffolding technique explicitly illustrates critical variables such as time spent on different (relevant and irrelevant) areas of interest as well as the time spent on and accuracy of use of specific cognitive strategies. The visualization of the relevancy is draw from comparing the answers in the text with the blink rate or pupil dilatation of the learner. So, this is not a direct visualization of the blink rate, because visualizing just the blink rate to the learner would be of no relevance to his learning, or he may not understand the relevance of this visualization directly.

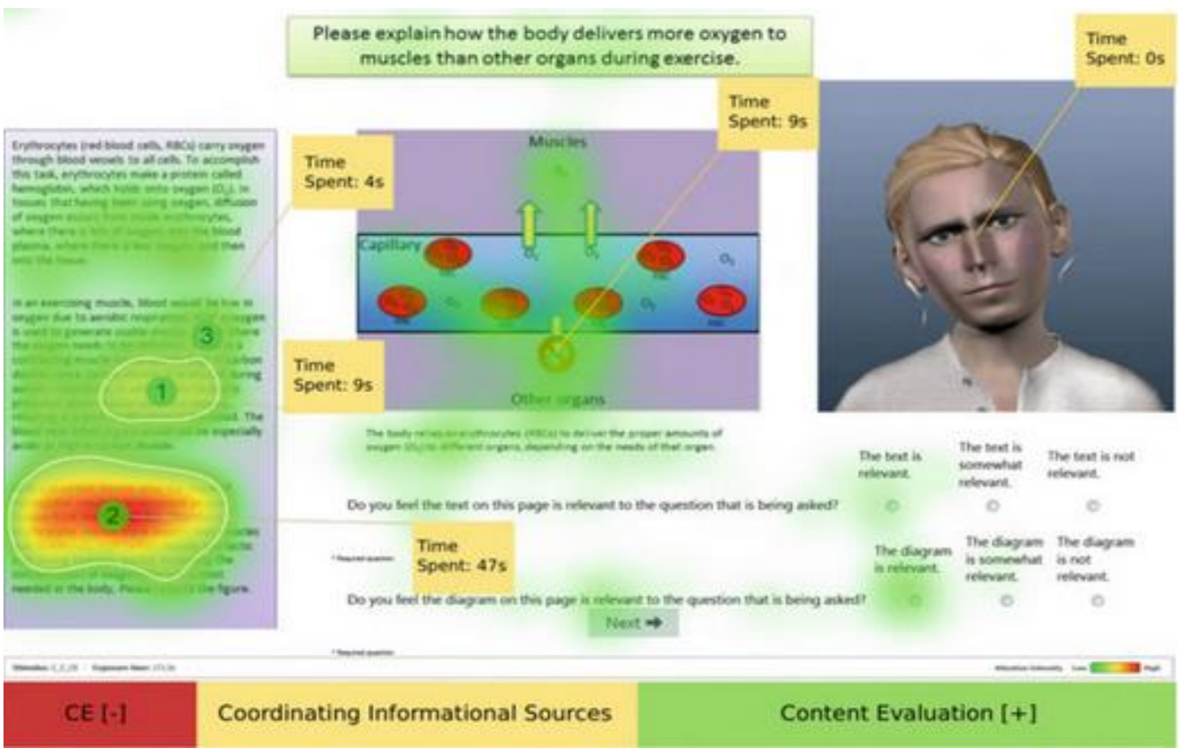

Figure 12: Visualization of physiological sensor data to support learning process to impact awareness [1]

The illustration above shows 2 different visualization methods; time visualization of point of focus or fixation, and content evaluation in relation to the goal. The content evaluation is shown as a heat map, where red shows the irrelevant content and the green represents, relevant content. The figure above aims at showing a design representation of how a physiological visualization tool can look like.

4. Discussions and Conclusion

In this section we would not just discuss how the different techniques mentioned above affect learners but also instructors, because impacting instructors would help them give the appropriate guide the students need, and as mentioned in the emotional strategies, students need assistance to implement such techniques and make sense out of the data visualized at some point (as seen in the study of Clegg et al., 2017). All the experiences reported underlined the importance of assisting the learner, this means in the journey of using visualization tools to support learning, teachers and instructors may play an important role, and most of the time these tools are been designed by them. To skip the presence of instructors in this process the tools need to assist the learners by giving visual instructions.

In a pedagogical context, looking at all the visualization and emotional regulation strategies mentioned, these may be very useful to detect students with problems. For example, students with punctual problems in the time, or periods where the emotion of most students are weak. In this way these analyses would help instructors in reviewing the learning activities during this period, as well as learners by improving their learning strategies by regulating their emotions. Monitoring learners' emotions in order to give reliable feedback to instructors, hence help in personalizing students learning experiences and in creating awareness with the aim of enhancing self- regulation skill.

Little is known about the effectiveness of different visualization techniques to give students insight into their learning-related data. Different visualizations have been proposed above, but to which extent these visualizations can be interpreted in correctly by students, and which techniques work better than others, both need further research. Interpretation of data may vary from an individual to another, so in providing the user with variable visualization would be the best solution to achieve global comprehension. Figure 12 shows an image of a finished tool, but this proposes very little visualization of physiological data. Figures 8-11 represent emotions within different aspects but presents no interaction with the user, on the other side, figures 2 and 3 show visualizations of tools which are said to be interactive with the user, showing hence more insight into the data (the possibility to select points on the visual representation to see detailed information). Interactivity is a very important feature of data visualization tools because it provides control and openness. So, the design of the user interface should be made simple, detailed and comprehensive.

In the BodyVis and Feeler experiences it is reported that after learning and sensing the user were asked to response to an assessment, which included reflective questions, meaning reflection should be enhanced after the learning and visualization processes, and a slowdown of vital organs was requested through activities like meditation.

In summary, the results indicate that visualizations of emotions can support awareness and reflection of student data, but they need to be designed with care to address the needs of students, and aspects like interaction with the tool and user interface are important, but during the research, not enough articles about concrete tool were found apart of Feeler's prototype which seemed to still be in experience, implying, no specific conclusions were drawn.

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