Title: "Mouse tracking and user experience in game-based learning environment."

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Abstract

This dissertation was written as a part of the MSc in E-Business and Digital Marketing at the International Hellenic University.

Peoples' behavior is of significant interest in the field of Human-Computer Interaction because it could reveal information about how human behave when they interact with computers. Mouse tracking, according to previous HCI research, can offer a full overview of human behavior under advanced intellectual loads such as a decision or the development of an activity. However, there is a scarcity of learning research. In this paper we look at the possible correlations among mouse movement metrics and users' emotions when they are interacting remotely with a game-based learning (GBL) task. Towards this goal, we conducted an experiment on 33 participants who completed a GBL quiz task after watched a video course about physics. A JavaScript mouse monitoring mechanism was embedded in the game to track the mouse movements events in real time and store them in JSON files. A set of behavioral and dynamic mouse features was extracted to measure i) average mouse speed, ii) average acceleration, iii) average time between movements, iv) total count of movements, v) total count of time between movements short pauses, vi) total count of time between movements long pauses, vii) count speed number of pauses, viii) task completion, ix) time count movements/task completion time, x) count speed=0/task completion, xi) count pauses>2/task completion, xii) count pauses>5/task completion time. A self-reported questionnaire was used to measure the participants' perceived emotions of i) self-efficacy, ii) engagement, iii) immersion, iv) enjoyment, v) confusion, vi) frustration, vii) stress, vii) dissatisfaction during playing the GBL task. The results of the experiment revealed the existence of some significant relationships between users' emotions and mouse features. In particular, the following significant correlations was found: i) the variance of time between movements is significantly correlated with frustration, ii) engagement of users during the game-based learning task significantly associated with mean acceleration, iii) age has a significant correlation with total count of movements v) age has a significant correlation with the count speed=0 (number of pauses), vi) age has a significant correlation with total count of time between movements (short pauses), vii) a significant correlation was founded between level of familiarity and self-efficacy, vii) a negative significant correlation was

founded between level of familiarity and the count speed=0(number of pauses). The findings of this paper can reveal an interesting new research direction and may motivate the HCI and GBL fields of study to search further the user's cursor movement behaviors when interacting with a game-based learning environment, since this method has recently been widely adopted in the education filed, due to the COVID-19 situation.

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Contents

Keywords: Mouse tracking, game-based learning (GBL), user’s emotions, mouse cursor, game-based learning quiz, mouse movements metrics.

1.Introduction

Human-computer interaction studies the development, the integration, and analysis of interactive systems (Cepeda et al., 2021). People today spending an increasing amount of time online due to the rapid advancement of digital technology and due to COVID-19 more and more tasks it becomes online, for example in education field the distance learning is emerged. Users leave digital traces as they explore through various web applications, mouse movements are one of these (Meidenbauer et al., 2021). So, understanding user behavior attributes while interacting with the web environment is important for assessing emotions and user experience. The method of eye tracking has been the most common one for tracking user patterns, but it necessitates the use of a distinctive tracking device and the user's physical presence to acquire eye movements. On the other hand, the mouse tracking is a not expensive, highly scalable alternative way for obtaining insights on user behavior patterns during the use of a graphical user interface. For analyzing the dynamics of pointer movements, many metrics, or features, can be extracted from pointer data. Some of them is the total count of clicks, distance traveled, angle direction, hovering patterns, long pauses, short pauses and directional changes which will be discussed later in the literature review part, and we will analyze some metrics that we will contribute to our research (Cepeda et al., 2021).

The goal of this paper is to investigate the relationship between users’ emotions and mouse movements in GBL tasks. Earlier studies have used mouse trajectories to track attention in computer interactions (Rodden et al., 2008) and measure website engagement (Arapakis & Leiva, 2016; Rodden et al., 2008). It's also been discovered that mouse movements are strongly linked to people's attitudes. Studies have analyzed the time and trajectory from one location on screen to another to evaluate hesitancy or "corrections" to initial decisions in the context of assessing unconscious bias. Mouse hover time and movement patterns can be used to estimate a user's self-efficacy and risk perception, according to movements (Tzafilkou and Protogeros ,2018). The researchers also discovered that a person's feelings about a web-based tool, such as its perceived usefulness or ease of use, can be implied from their mouse movements (Tzafilkou and Protogeros ; Meidenbauer et al., 2021).

Our main objective is to find out if there any significant correlation between mouse movements and user's emotions during a game-based learning task. Therefore, it is important to detect in an accurate way the users' learning situations because it may offer useful data to researchers or teachers to recognize users' having positive or negative feeling during the online learning procedure. When it comes to distance learning, the tracking of learners' progress is not as natural as it with the physical presence of the students. On the contrary, the "traces" of user interaction with the learning system reflect this. The emotion of engagement, for instance, relates to an individual's great level of involvement in online activities and can be measured using students' logs (Zhang et al., 2020)

Motivated by the above, this study aims to examine, as we mention above, the correlation among mouse movements metrics and users' emotions during their interaction with a game-based learning task. In this paper we will analyze all the significant mouse metrics and some of the significant emotions that could be felt by a user when completing a game-based learning activity. The aim of this work is also to investigate if there any significant correlation between users' emotions and mouse movements metrics. Besides that, this paper studies the effects of demographic factors such as gender, age, level of education, education field on users' emotions as well as potential differentiations in mouse movements and expressed emotions cross users of different mouse device for example mousepad or mouse input device.

The structure of this paper is arranged as follows: At the first part presented the theoretical background of mouse tracking, mouse behavioral patterns and dynamics being studied in the underlined literature. In the second part demonstrated the research objectives and described the research methodology. In the third part presented the data analysis and experimental results. Then it follows the discussion section in which we display the findings and current limitations. Finally, we summarize the conclusions and expresses thoughts for future work.

2.Theoretical Background

2.1 Mouse Tracking

Human Computer Interaction (HCI) studies and investigates the design of computer technology and more specifically the interaction that users have with the computer systems. In this broad research field have been an effort by the researchers to measure human movement when users performing pointing tasks on computers and other devices. This topic has been introduced in many studies and the movement that the mouse cursor does is the most critical part in the whole field. The goal of the mouse tracking, like most online tracking systems, is to offer a better understanding of how people behave in many different situations and show the intentions or emotions of each user.

The technology that tracks peoples' computer mouse movements while they choose between answer options is called "Mouse-tracking technology" and is a relatively recent. This technology has the potential to provide novel insights into a wide range of psychological phenomena by providing a widely available, data-rich, and true perspective of how people define and make decisions. Researchers have obtained useful insights into the evolution of cognitive processes through an increasing variety of psychological domains thanks to the use of mouse-tracking. Firstly because, mouse-tracking can measure more correctly the relative quantity of conflict existing during a particular decision, enabling researchers to test hypotheses about conflict's causes and effects. Secondly, researchers receive a real-time window into how this conflict is handled by mouse-tracking and allow them to examine theories about how personal assumptions and decisions are made (Stillman et al., 2018). By monitoring mouse movements en route to replies on a screen, researchers receive ongoing information regarding preliminary commitments to distinct response possibilities across time. More specifically, in mouse-tracking experiments, participants choose from a variety of response possibilities represented on a screen, and the point that the mouse pointer is, is continually monitored as individuals move towards and eventually select one of the options. According to the theoretical concept, mouse movements are perceived as factors of commitment to or conflict between alternative choices throughout the decision-making procedure (Freeman & Ambady, 2011).

In recent times, both mouse and hand tracking have become well-known techniques for investigating intellectual processes in many research domains, as well as speech perception, memory functional areas, social cognition, and preferential and ethical decision making (Freeman & Ambady, 2011; Xiao & Yamauchi, 2014). Mouse and hand tracking became popular due to its promise of providing an unprecedented temporal resolution window into the progression of cognitive processes. This promise is based on a proposed connection between movement features, such as trajectory form, and the attributes of the underlying cognitive process (Wulff et al., 2018).

Spivey et al., (2005) were the first to introduce the method of mouse-tracking as a paradigm in cognitive science. They introduced a language processing study in which participants received audio guidelines to click on one of two items, they heard a phrase, for example "click a specific object". A photograph of the target object was displayed alongside a photograph of a distractor that was either phonologically related to the target object, for example "chair" or unrelated, for example "ice-cream". The mouse movements of the participants were proved more curled towards the distractor if it was phonologically related than if it was different, indicating that auditory data was processed in parallel, activating competing representations. According to some researchers, mouse-tracking technique is often used to obtain insight into the temporal assessment of mental procedures in a variety of mental health events such as social cognition, decision-making, and learning. A very first concept has recently been expanded by incorporating mouse-tracking. For instance, mouse-tracking in combination with eye-tracking has been employed to investigate the dynamic interactions of data retrieval and preference development in risky decision making. Also, in an experimental study where participants interacted in real-time, mouse-tracking revealed various levels of cognitive conflict linked with collaborating against defecting in social dilemmas. As these examples demonstrate, a rising amount of academics from various backgrounds and with varying needs are utilizing mouse-tracking to examine cognitive processes. As a technique, mouse-tracking is increasingly being integrated with other ways to construct complicated paradigms and integrate data from several sources, resulting in a more complete understanding of cognition (Kieslich & Henninger, 2017).

Based on observed cursor activity, certain mouse-tracking theories suggest the creation of a user categorization. One of them is Fitts's law for movement time and it was one of the first and most important measures employed in that research. This emerged from the willingness to measure human pointing behavior, and it is now most famous theory which is used to assess the layout effectiveness of an interface. The efficiency is measured by the amount of time it takes to use the interface, such as clicking buttons or navigating through it. To understand users' behavior, cognition, perception, phycological aspects level of difficulty and many other factors researchers utilized this mouse movement method since the existence of Fitts's law. Mouse behavior monitoring is an important part of web-user interaction because it could offer implicitly and dynamically helpful insights about the user's mental workload, their perceived user experience, and the usability of a system. Besides that, mouse dynamics were investigated for user authentication and revealed a significant correlation between user identity and mouse movements (Fitts, 1954).

According to researchers, mouse features can represent user affective and cognitive states regardless of task or environment, as well as eye behavior. Zavadskas et al., (2008) , for example, define emotion state measurements as the pressure on the mouse, the speed that has the mouse when it moves, the acceleration of mouse pointer movement, the scroll of the mouse, and right- and left-clicks. Some researchers consider that 'If a system knows how its users feel, it can properly respond to these moods and give a better insight,'. In this context, Reeder and Maxion (2006) created a method for detecting user difficulty in web interfaces through hesitation analysis. Mouse events and keystrokes were used as input for their prediction method (Reeder & Maxion, 2006).

As a result, mouse-tracking has expanded the cognitive horizons established by classic response time analyses and newer innovative solutions such as eye-tracking. Despite being a modern technology, mouse-tracking has spread rapidly into a wide range of psychological domains, as evidenced by recent studies, as we mentioned above.

2.2 Mouse cursor movements

Mouse pointer tracking is a low-cost high-scalability option to collecting data on user behavior patterns while using a graphical user interface, as we mentioned before (Chen et al., 2001). The process of collecting traces of cursor positions as directed by the user's mouse movements is known as pointer tracking. Pointer tracking metrics is usually used to enhance user experience and check the functionality of web pages as far as concern the development of websites (Cepeda et al., 2021). For analyzing the dynamics of pointer movements, many metrics, or attributes, can be derived from pointer data. Velocity and acceleration are the most popular temporal features. The travel distance, direction, curvature, and straightness are some of the spatial features. Some researchers find out some more complex feature that necessitate more in-depth analysis such as hovering patterns, long pauses, and directional changes. It is also noteworthy that many studies of user interaction have used pointer data, particularly low-granularity features like mouse clicks and the number of pointer movements. These features have been used as indicators of many user emotions like interest, engagement etc. to check the functionality of a web page. Later research focused on using cursor movements for user authentication while more recent developments have used pointer analytics as a behavioral research method to link user experience to underlying psychological processes. In this field of research, machine learning was used to assess user engagement based on temporal and spatial mouse movement features (Arapakis & Leiva, 2016). Another discovery which concerns this field was the link between mouse patterns (e.g., movements patterns or hovers) and usability, usefulness, self-efficacy, learning behavior, and risk perception (Tzafilkou, Protogeros, 2018). Another article stated that random mouse movement occurs because of either slow UI elements or increased learning loads. It expresses itself in the same way in both cases: quick back-and-forth or circular motions with no usable purpose or relation to objectives on the page. It can be taken as a sign of anxiousness; users may do it to pass the time while waiting for a video to load. When confronted with a frustrating or confusing task, it can also be a source for stress and tension, with users demonstrating random patterns (Tim Rotolo, 2008). According to Pimenta et al. (2013), a reduction in mouse acceleration and velocity resulted in a decrease in cognitive performance. Only mouse movement variables were used by (Seelye et al., 2015) to make a distinction between older users with and without mild memory problems. Some researchers discovered a link between cursor motions and emotional responses (University of Duisburg-Essen et al., 2017; Zimmermann et al., 2003). Finally, based on long distance covered by and decreasing speed of the mouse cursor across an interface, researchers founded that not positive emotions can be implied (Cepeda et al., 2021).

2.3 Mouse movements features

The movement of the mouse is a constant physical process in which the cursor starts in a certain location with no movement, then is speeded up by the computer user in some position, moves at non-zero speed for some time, and at the end slowed right down by the user and ended at some target place. As a result, the movements is a physical process with a distinct starting point and ending point (Hagler et al., 2011).

Some tasks that oriented as goal-directed, cursor movements are characterized by organized, effective, sequential patterns. For example a user moves the cursor from a starting point to a specific target in an effort to accomplish a goal as efficiently as possible (University of Duisburg-Essen et al., 2017).

More specific we can consider mouse features the following ones, according to some research. For instance, based on Katerina & Nikolaos, time-related features refer to pauses and fixations, a long pause is described as cursor inactivity lasting more than 4 seconds, while a fixation is described as micro-movements within 25 pixels lasting more than 250 milliseconds (Katerina & Nicolaos, 2018).

Following we demonstrate some fundamental mouse features in order understand how we can measure them and explain them in our analysis.

Time: The duration of a mouse cursor movement is measured in ms (milliseconds) (Arapakis et al., 2014).

Distance: The overall distance covered by the cursor, as well as the maximum, minimum, average, and standard deviation of the distances of all consecutive sets in a gesture, are among these characteristics. Since we do not know whether this relationship is positive or negative, the distance traveled by the mouse cursor shows us how engaged is the user with the task and, if he finds it interesting (Arapakis et al., 2014).

Speed: According to previous research the speed of mouse cursor movements has discriminative attributes and can aid in determining intent of the user. Slow movements may demonstrate that the mouse pointer is stops for a while, while the user is engrossed in a cognitively demanding activity, such as careful reading, whereas ballistic movements may demonstrate that the user is performing a quick scan to locate relevant information in the text. (Arapakis et al., 2014).

Acceleration: Similar to speed, acceleration refers to the total distance traveled by the mouse pointer, including the highest, lowest, mean, and standard deviation of all sequential sets of accelerations in a movement (Arapakis & Leiva, 2016).

Clicks: By recording mouse clicks, data on the depression and release of mouse buttons, and the coordinates of the incidence in pixels, can be obtained. All the click events are all possible (left, right). Mouse click recordings were practiced before recording mouse trajectories. Now, capturing mouse clicks is more common than capturing mouse trajectories (Purnama et al., 2020).

The movements of the mouse: Mouse trajectories are the same as mouse movements. The capture of mouse movements collects data in pixels on the mouse cursor's coordinates (horizontal and vertical axes). Mouse movement and mouse press can be combined to create mouse drag. Mouse movement consumes the most resources among other event loggings (Purnama et al., 2020).

Following we demonstrate the use of mouse tracking in relation to different fields and the interesting results of some studies that had been conducted via mouse tracking in recent years.

2.4 Emotions in relation to HCI

Emotion is an essential aspect to consider when interacting with computer and information systems. A user interacts with a computer while feeling negative or positive emotions, even when performing the specific activity. Darwin and Rachman (1979) was first investigated the association among facial gestures, physical reactions, and emotional responses, concluding that emotions are integrally linked to human behavioral habits (Yi et al., 2020). According to more recent research, there are some fundamental emotional states that must analyze in relation to human computer interaction field, some of them are attention, enjoyment, frustration, anxiety etc. Some researchers have recognized the importance of user emotions in the study of HCI. Researchers claimed that investigation about feelings in HCI is large-scaled, because include studies that has to do with user experience, sensorial design, and user activity.. All in all, analyzing human-computer interaction behavior allows for the identification of a user's emotions (Cowie et al., 2001). Only a few studies have looked at emotions based on mouse behavior, and almost no HCI emotional research has been applied to trusted interactions (Yi et al., 2020). In this point it is noteworthy the fact that a researcher compared the differences in movement characteristics between participants with higher and lower levels of emotional arousal and discovered that there were important differences in movement speed and precision. To sum up, we have to say that establishing human-computer trusted interaction becomes more difficult due to the unpredictability of different emotions' influences on web users' behaviors but with the right research methods we can end up into concrete conclusions (Yi et al., 2020).

In recent years, recognizing the emotions of computer users has become a heavily debated study topic as we can ascertain with the above research. To determine how a user feels, a variety of methods have been created and tested. These methods rely on a variety of data sources, including visual (facial expressions, movements), auditory (speaking, voice), text-based (word choice), physiological (heartbeat, temperatures, skin conductance, and so on), input devices (keyboard, mouse, touchpad), and a combination of these are all possibilities. Affect-sensitive systems are capable of not only recognizing but also reacting to users' emotions. The ability to apply affective computing methodologies in real-world areas, such as (ITS), adaptive interfaces, gaming, software engineering, web page design, and others, has boosted the popularity of affective computing research (Kolakowska, 2013).

Researchers have been studying the behaviors of the computer cursor for emotion recognition for the past 15 years. Some of them recommended implying the user's emotional state from computer device usage and mentioned the benefits of this approach over current emotional state detection methods. This approach started with a theoretical paper by Zimmerman et al. They started their research because they had the desire to enhance the user experience in human-computer interaction field by allowing the computer device to understand about the user's emotional state and adapt accordingly. After 5 years, Zimmermann performed empirical research in which participants were required to complete an online purchasing task following emotional manipulation via movie clips. According to the findings, there was a significant relationship between mouse movement parameters such as cursor movement and participants' self-rated excitement (Zimmermann, 2008).

Since then, other studies have taken this concept and tested it using a variety of mouse tasks, mouse usage parameters, and emotional states. For example, other studies looked at the relationship between mouse use and the two dimensions of emotional states, the emotion of valence, and the emotion of arousal. More specifically, Grimes et al., (2013) made use of images to manipulate emotions and recorded different mouse movements patterns like the distance, speed, and a shift in direction while participants expressed emotions like their valence and arousal. The results indicated that after viewing arousing images, people that participated in the research made by far lots of directional changes in their cursor movements and relocate their mouse in a significantly larger distance. Also, it was observed that a negative image made the participants moved their mouse a greater distance after viewing it. (Grimes et al., 2013)

Other authors, more specifically Hibbeln et al. (2017) conducted three studies in which they examined the association between valence and mouse traveled distance and speed. At their first survey, they used a mouse-dragging task and a biased versus an unbiased intelligence test to manipulate bad feelings versus neutral valence. At their second study, participants bought something from a fictitious online store and during their navigation on the website no errors or delays occurred. Participants at the third study, a correlational one, scored their valence after each task. The results showed that in all experiments, mouse traveled distance increased while mouse speed decreased when the valence was negative (University of Duisburg-Essen et al., 2017).

Yamauchi & Xiao, (2018) wanted to capture mouse movements during choice tasks by using music, clips, images. These different emotion approaches end up in a relationship between emotional states and mouse movements. Yamauchi and colleagues also introduce a series of cursor motion studies involving many people. These studies demonstrate that mouse motion analysis can predict computer users' emotional experiences (Yamauchi & Xiao, 2018).

In a field experiment, Khan et al. (2013) gathered mouse data as well as valence and arousal evaluations from 26 volunteers over the course of several days. They discovered that, on an individual level, usage data predicted emotional ratings, but not on a group level. Moreover, the use of the mouse has been linked to more specific emotional states such as fatigue or stress (Khan et al., 2013).

Pimenta et al. in a class experiment wanted to predict user fatigue level using mouse and keyboard usage. Based on their mouse usage during a simulated night shift, predicted participants' exhaustion levels with 62% accuracy (Freihaut & Göritz, 2021).

Kapoor et al. investigated the relationship between mouse usage and pleasant or unpleasant feelings. The researchers captured the average, the variation, and skewness of mouse pressure as participants learned to solve a puzzle-quiz. Mouse pressure was indicted the emotion of frustration (Kapoor et al., 2007).

Other researchers assessed Electroencephalography signals and mouse activities for example the total number of clicks, the distance traveled, and the click length during a lesson that has to do with algebra using a sophisticated tutoring system. The results showed that mouse activity can supplement EEG data with relevant information for emotion recognition (Azcarraga & Suarez, 2012).

Scheirer et al. studied the patterns of mouse clicking by 24 participants during an online game and discovered a link between mouse clicking and dissatisfaction. In their experiment, unpleasant events were generated by interrupting the mouse's action, and individuals were asked to play the puzzle by clicking a certain grid spot. As a result, interpreting their findings as proof of a connection between mood and cursor movements is difficult (Scheirer et al., 2002).

Maehr wanted to explore the link among cursor movement and positive or negative emotions. Respondents' mouse movement patterns like accuracy, clicks, movement efficiency, speed etc. were assessed while participants filled an online questionnaire after seeing some movie clips eliciting diverse feelings. He assessed the positive, negative, and neutral states (Maehr,. 2008.).

Participants in Mueller and Lockerd's (2001) study performed online purchasing tasks while their cursor actions were monitored. The researchers found "similarities" of cursor actions relevant to users' interest after reproducing the captured cursor activities for observational analysis(Mueller & Lockerd, 2001).

Guo and Agichtein (2008) used cursor movement patterns to determine users' intent in searches. The researchers manually assessed "user intent" and concluded that the average trajectory length of navigational inquiries was shorter than that of informative queries (Freihaut & Göritz, 2021).

To sum up, these investigations all point to an essential connection between emotion and cursor movements. As far as concerned the interconnection among mouse motion and emotion is primarily correlational, since, in some case scenarios inefficient statistical analysis is implemented, and in other cases, experiments are just confused by other outside influences. Furthermore, the multitude of surveys looked at broad aspects of emotion but no in other feelings (e.g., fear, attention, concentration) were looked at; the impact of emotion on cursor motion has been examined almost exclusively in within-subjects' conditions (Freihaut & Göritz, 2021).

2.4.1 Mouse tracking and the emotion of stress

Mouse tracking can be applied specific in tracking the emotion of stress. Stress is an ever-present feature of modern life in a lot of societies, with an increasing prevalence (Freihaut & Göritz, 2021).

There are numerous methods for measuring stress. Self-report may be the most common and straightforward method of assessing stress. A second method of measuring stress employs physiological indicators and is widely used in attempts at automatic stress or emotional state detection. The third approach, which is in our concern, employs behavioral measures, which is stress measurement using the computer mouse (Freihaut & Göritz, 2021)

The logic of this approach is that when using the mouse, the stress response manifests itself in psychomotor changes. Mouse cursor motion analysis first appeared in HCI field in 1970s, when people began comparing the performance of various devices. Behavioral approaches have been used far less frequently than physiological approaches in the past. Behavioral measures, like physiological measures, employ cameras to detect tiny changes that can be quantified as stress markers. Using the mouse for measuring stress has a significant advantage. More specifically, there is a sensor integrated into anyone's daily life that ensures regular data collection without the need for additional equipment, or the user does not change his or her daily behavior. As a result of this benefit, stress measurement via mouse is a low-cost tool, as is comfort measurement. On the other hand, there is a drawback when using mouse to measure stress and it is linked to computer usage, which limits its potential spread. However, the existence of work-related contexts and human computer interaction help the researchers to not consider this as a major drawback. As far as concerned the workplace, is one of the most common and important sources of stress, and it is also a context that frequently necessitates the use of computers. In a survey, nearly half of the respondents said that they use desktop or a laptop at work on a regular basis, which means that the use of mouse is frequent, and researchers have the possibility to get more insights. Another survey in which participants working in an office, revealed that they spend an average of 6.5 hours in front of the computer screen during a typical workday (Freihaut & Göritz, 2021). Although the computer mouse is not the only input device for computer navigation, ultimate usage figures show that a large majority of individuals use the mouse for a significant amount of time during the day in a context where stress assessment is essential. In the context of HCI, measuring the feeling of stress through the computer mouse can help in improving user experience (University of Duisburg-Essen et al., 2017). Another filed in which people are stressed and can be applied the mouse tracking technique is the e-learning field. For example, if the mouse usage patterns imply that the people who use the mouse is stressed, then the e-learning application may offer extra guidelines or recommend a break (Freihaut & Göritz, 2021).

The earliest empirical investigations proved the potential utility for stress assessment via mouse movement. Hebel et al. and Sun et al. demonstrated that individuals' anxiety and frustration during they are completing a simple task in the computer interface could be recorded in cursor activities like the speed of the mouse cursor using emotion elicitation through a task. Kaklauskas et al, (Kaklauskas et al., 2011; Yamauchi & Xiao, 2018) established a comprehensive software for stress detection that analyses users' behavioral and psychological input. The system tracks the location, speed, and distance traveled by a mouse, as well as hand shaking and force pressure (Yamauchi & Xiao, 2018). Participants in Sun et al.'s study completed normal mouse activities in either a stress or non-stress environment. They estimated that the mouse usage varied between different conditions (both metrics serve as substitutes for muscular stiffness). The authors used machine learning to classify the users' stress condition or non-stress condition on unseen mouse data with high accuracy. At last, other authors, in a laboratory study, investigated the relation among stress and mouse speed and a field study. People that participate in this study exposed into a stressful incident and into a control task. The results showed that mouse speed had significant differences among the two experiments when they were stressed, but not when they in the control condition. Variables such as mouse speed, valence, and arousal, measured and collected from 62 employees in the field at regular intervals during their working hours. The results showed that mouse speed predicted eustress, this means high level of the emotion of excitement with positive valence, and distress, which means low arousal with negative valence, based on a combination of arousal and valence ratings (Kowatsch et al., 2017). All in all, the evidence suggests that a person's mouse characteristics reflects his or her emotional state. However, it is essential to become further research in order to confirm and carve out effects because the literature's preliminary picture is foggy. In other words, there is a limitation in this part because the current studies did not offers a concrete link between emotional states and mouse usage, resulting in observable heterogeneity in the application of concepts, approaches, and results (Freihaut & Göritz, 2021).

2.5 Mouse tracking in relation to Education field

Observing students' learning engagement in the context of online education is not as easy as is the face-to face observation of students learning outcomes. Today there is a way to find the traces of user interaction with the learning system. For instance, behavioral engagement, it is the high-level involvement that a student has in online activities and can be measured using students' access logs and the number of articles in a blog. On the other hand, emotional engagement can be measured by students' facial expressions, head posture, and other factors (Zhang et al., 2020).

As a result, the importance of capturing the time spent on a learning experience in order to identify the user's behavior patterns has been emphasized. Koh et al. (2018) highlight the significance of documenting the time spent on a specific section of a learning task because the hours wasted on a whole page does not reflect the entire learning time because the time spent on different parts tends to vary. According to the researchers, mouse movements can be used to measure the average time spent on a particular part, but mouse tracking is more than just evaluating the amount of time spent on a particular part. Another application of mouse tracking is the recording of mouse cursor behaviors, which can then be used to assess a variety of factors, including mental demand. So far, the data that created by mouse movements might be overwhelming to analyze because of the quantity or quality, however the rapid development of data mining will be used to acquire useful insights (Poon et al., 2017).

There have been conducted a few intriguing studies in the subject of mouse tracking, which are listed here. In response to an English jumbled-word inquiry in which learners must match the mixed-words with the appropriate Japanese word a study conducted with the development of a web-based application that captures mouse movements. This study recorded the mouse events like durations, coordinates, recording events specific to their system such as English words activated. At the end of the experiment, they achieve their goal which was not only the analysis of the learning outcome but also the analysis of the learning process, which previous systems and experiments couldn't be able to manage it. Other researchers, underline the learning process and non-intrusive data collection, but their research focuses on identifying students' stress levels in e-learning. They used Moodle to track mouse and keyboard movements, recording mouse clicks, speed, click accuracy, mouse movement, amount of movement and keyboard strokes. They tried to set up a controlled experiment in which one group would be normal and the other would be stressed. Finally, they compared mouse and keyboard profiles for users who are stressed and non-stressed and discovered that stressed users performed significantly more actions than non-stressed users, including mouse movements mouse wheel and other. Salmeron-Majadas et al., (2014) measured emotional states (degree of valence, such as pleasure vs discontent) and behavioral changes in a comparable study. According to their findings, they claim that mouse and keyboard tracking methods are both non-intrusive and low-cost. Their goal was to utilize machine learning to produce automated emotional state and behavior change identifiers from mouse and keyboard logs. Finally, another survey conducted on Moodle, also a mouse and keyboard tracking experiment, but the goal of this experiment was to evaluate Moodle's usability, ease of use and other variables which has to do with user experience and not with the learning process analysis. As a result, they decided to add the number of clicks, the duration of each activity, mouse position, and completion rate to their measurements. The authors collected mouse and keyboard data from instructors while they were performing Moodle actions including signing in, entering the course area, and other actions in the Moodle platform (Purnama et al., 2020).

2.6 Mouse tracking and learners' engagement

Miller et al., conducted a study that backs up the landscape model which include the people who read more slowly (or faster) so that they can assimilate information and material more effectively. The participants, more specifically students read for various topics and discovered that, after controlling for fluency, the students that had the lowest speed of reading where those that they had a higher intention not participate in the study. Following to a conclusion, the individuals that have a higher concentration they tend to have a higher cognitive endeavor. To real time circumstances it is possible to use a camera to evaluate an online learning case. The scrolling speed of the page can be used to estimate the students' reading speed. Based on the results of a study, there is a correlation between the variables of the eye movement the movement of the mouse. It seems that people who would like to read a specific area would use at the same time the mouse. By using the hardware (mouse), researchers had the opportunity of a sensor that identifies the movements of the users as well as if for example the mouse was contributing to the user while he responds the questions. As it is mentioned before, mouse movement have a significant relation with the emotions of the users while contributing to several task like reading. Therefore, the mouse cursor movements are crucial for students' appraisal of their cognitive emotions because of this study. In summary, it is important to present that user's engagement regarding the comprehension of text and engagement is it commonly expressed by facial expression, and this is one way that people can contribute (Zhang et al., 2020).

In the specific research authors end up in some results that supported from the above graphic. They presumed that the first and third users review the full content page at a constant reading speed, whereas the second and fourth users read faster and scroll down the page with the content more often, particularly user four, who scrolled the content page from beginning to end in less than 100 seconds. Furthermore, in order to achieve good learning outcomes, students must measure their engagement condition and assign their cognitive and interest resources at any point during the learning experience. It is seeming from the fourth user scrolling track that he is familiar with the learning materials or that he only reads superficially and without exerting enough cognitive effort. As a result, we can conclude that Users one and three are more engaged in their learning than second user, even though second's user engagement is relatively high at the start of his learning process. The fourth user is less interested in learning (Zhang et al., 2020).

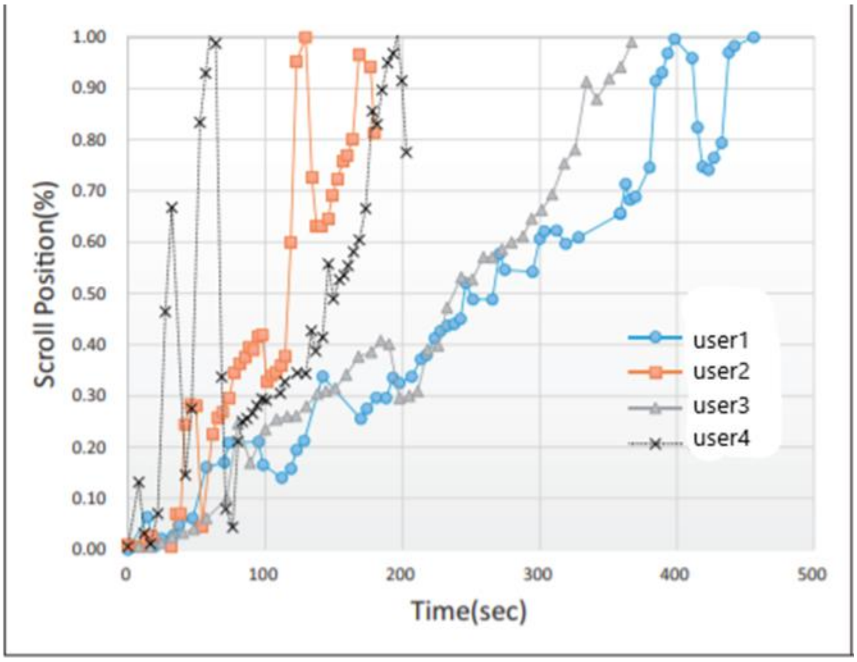

Figure 1 Comparison of 4 users' mouse movements Source:(Zhang et al., 2020)

According to author Miller, the more time users waste on a task, the more substantive effort they make, and we can consider a user to be engaged when the curve of his mouse movement on the graph gradually increases. However, the user's level of engagement was relatively low when his curve shifted dramatically in a brief span of time. Furthermore, according to Heather and Elaine's proposed model of engagement, the transition from engagement to disengagement will take a certain amount of time (2008). The curves of all four users steadily increased at first, and then some curves began to change significantly, as shown in the graph. This is continuous with the engagement model: most users were able to concentrate easily at the start of the study, but as time went on, some of them seem to be disturbed. They couldn't finish reading if they couldn't reengage; instead, they scrolled to the bottom of the content page (Zhang et al., 2020).

In this table we demonstrate a revision of key findings from the research that mentioned in the literature part

Key Findings	Reference
People who are watching emotionally charged images When compared to people who are viewing neutral images, subconsciously produce more force in the hand.	(Coombes et al., 2008)
The observation of an unpleasant image from the user, the velocity of the mouse movement are decreasing and also there is a significant expression of the emotions that the users have.	(Grimes et al., 2013)
When people see emotional images, their hands subconsciously produce more force than when they see neutral images. Even so, when compared to neutral images, emotional images do not increase the variance of force production.	(Naugle, et al. 2012)
Mouse movements are influenced by tightness caused by stress.	(Sun et al., 2014)
Based on the positive or negative emotions of an individual the movements are changing respectively.	(Zimmermann et al., 2003; Zimmermann, 2008)
Mouse characteristics (for example, random movements or hovers) are associated with self - reported ease of use, perceived usefulness, self-efficacy, learning behavior and attitude, and risk awareness.	(Tzafilkou & Protogeros 2018)
A decrease in mouse acceleration and velocity resulted in a reduction in learning and memory.	(Pimenta et al., 2013)
There is a significant relationship between mouse movement parameters	(Zimmermann, 2008)

like cursor movement and user-rated arousal.	
In the context of the relationship among valence and mouse distance and speed, whenever the valence was negative, mouse distance risen while mouse speed reduced.	(University of Duisburg-Essen et al., 2017)
On an individual level, usage data predicted emotional ratings, but not on a group level, and mouse use has been related to more precise emotional states such as exhaustion or anxiety.	(Khan et al., 2013)
There is an association between mouse clicking and dissatisfaction.	(Scheirer et al., 2002)
The use of a task to elicit emotion to show that a user is overwhelmed and frustrated during a simple challenge, which could be expressed in mouse motions.	(Sun et al., 2014; University of Duisburg-Essen et al., 2017)
When a user is stressed make more actions than a user that is not stressed such as mouse moves, mouse wheel moves and other actions.	(Rodrigues et al., 2013)
When a user devotes a significant amount of time to a task, the user exerts greater effort and may become more engaged. The curve of his mouse movement suggests this.	(Miller, 2015)

Table 1 Key findings from previous research

2.7 Use of mouse dynamics for user authentication

Mouse dynamics, like face and speech recognition, fingerprint, vein, handwriting, and keystroke dynamics, is considered a biometric user identification technique. People's muscles are firmly embedded with mouse gesture -biometrics, and the reaction to specific muscle movements is natural and hence safe. When compared to standard authentication techniques, mouse dynamics is regarded as one of the most secure (since it cannot be stolen from another person). Biometric characteristics might be physiological or. Because of their long-term stability, physiological characteristics are used in many security systems. The problem with characteristics of a behavior is that the samples of a single user might significantly change each time they are captured. A user has a specific typing rhythm or some pointer movements. However, the benefit of the mouse movements is that since they are natural types of biometrics, they don’t need additional technology. They are also less invasive than some other approaches, and it is feasible to record mouse settings when a user uses the computer (Kolakowska, 2013).

The user authentication, which demonstrates the viability of such a method yields promising results. By studying mouse-behavior features over the period of contact, researchers focus on the use of mouse dynamics for intrusion detection (i.e., identity monitoring or reauthentication). Most of these attempts provide moderate to excellent outcomes. However, most of these studies have significant research limitations, such as sample size and authentication time, and they frequently overlook environmental and human elements (e.g., point device, mood/affection) that influence mouse behavior (Kolakowska, 2013).

Many studies have been carried out in order to obtain high accuracy in user authentication using mouse dynamics. The study of Zheng et al. (2011), who used mouse angle-based features and produced a False-Rejection Rate (FRR) of 0.86% and a False-Acceptance Rate (FAR) of 2.96%, is noteworthy in terms of accuracy and sample size. They collected data from three groups: 30 users in three separate controlled computer settings, 94 users in the same controlled computing environment, and more than 1,017 people on a forum website gathering mouse data for one hour. They assessed the system's accuracy and speed of verification, resulting in an Equal Error Rate of 1.3 percent after just 20 mouse clicks. Other related studies include Kaixin et al. (2017), who achieved a high accuracy score of 84.1% and a FAR of 8.1% in user authentication machine learning tasks, as well as Mondal and Bours (2016) and Chen et al. (2014), who accomplished real-time user authentication (Kolakowska, 2013).

Distance, angle, and click-related metrics such as direction, angle of curvature, and curvature distance, average speed, travel distance, and angle of movement, acceleration, and curvature change rate are all popular mouse features for user authentication. Mouse motions are less commonly used as biometrics than keystrokes, however this group's techniques look at things like mouse speed, acceleration, direction, and number of clicks, among other things. Intruder detection has also been researched and deployed using a mix of keystroke and mouse motions (Kolakowska, 2013).

Presently, most of the researchers obtained technology utilization of data regarding the HCI for the end user to gather data and evaluate the several behaviors that the end user has. In several studies people must complete several challenging within a specific time for the researcher to evaluate their responses. For example, participants in research required to input their credentials using a mouse and a regular keyboard, after which their movement would be observed and recorded. Similar to this, another study group had participants travel a screen labyrinth using a mouse, and then by analyzing the data, the researchers were able to determine the velocity of the motions that the users had made themselves. Based on research that wanted to construct multiple level models to proceed to continuous authentication, researchers have separated the mouse movements into 3 levels to identify the movement of the hardware that the users are using, and in the end proceed to the classification. Even though mouse behavior authentication is accurate in an experimental context, we want to see if it is still accurate in an actual environment The motions that the user makes with his or her web mouse are thus very important to analyze. The detection in the real-world settings when the users using a mouse it is significant more difficult. On the other hand, based on the big data techniques, it is significantly more beneficial rather the traditional methods to identify the mouse patterns of the user that is evaluate. For several research is important to develop a secure hardware and a faith computed environment to apply in an information system to achieve reliability and authentication thus, enhance the overall integrity of the system. Secure network technology is currently improving computer security at all levels, including hardware, software, terminals, and network architecture. As a result, on a trust - worthy computing platform, the user's behavior always produces the desired outcome. In essence, trust between the user and the computer system is established to enhance the system's quality and protection to accomplish behavior predictability. During the engagement process, web users, on the other hand, are shaped by a myriad of factors. Establishing trusted interactions is challenging since it is difficult to ensure that a user's interaction behavior corresponds his or her behavior pattern. (Yi et al., 2020).

2.8 Mouse movements in relation to age

Several studies look at how age affects the user behavior and finds that older people perform worse on a variety of tasks. Relatively long movement times greater movement variation ,and more errors are all signs of aging (Smith et al., 1999). Enhanced reaction time and decreased muscle strength could be the cause of these differences (Hertzum & Hornbæk, 2010). While increasing the ID of tasks reduces performance for all users, high ID values have a greater impact on older adults' performance (Ketcham et al., 2002). A few studies have found that adults and older adults have different strategies, with older adults emphasizing accuracy over speed. There are also differences in performance between adults, younger adults, and children, according to the literature. (Hourcade et al., 2004) conducted a review and found several disparities between children and adults. They found out that children appear to process information slower than adults, impacting their response time and movement speed (Hertzum & Hornbæk, 2010).

To understand some differences in mouse movements we can use the cursor trajectories. Older adults, for example, make more sub movements and have lower peak velocity longer phases of deceleration, and longer cursor trajectories, according to studies of cursor trajectories. Some researchers investigated potential scenarios for the findings that older adults were slower in pointing tasks than younger adults. They used tasks that required both accuracy and a ballistic movement, with varying penalties for errors. They discovered that the relationship between peak acceleration and endpoint distribution variability in a movement varies with age. This is means that young adults have better average acceleration and relatively low endpoint variation than older adults. From their last sub movement to the mouse's release button, older adults devote considerable time than young adults, implying that cognitive feedback is processed more slowly. Walker et al. evaluated the effect of a point system on encouraging timely and efficient effectiveness as proof for strategy distinctions between age categories. Young adults used an optimization method, trying to adjust their moves to receive the most points possible, whereas older adults took a more conventional approach, not adapting their movements to the point system. To summarize, while some efforts have been made to illustrate age-related differences in pointing behavior by evaluating cursor trajectories, we are unaware of any detailed explanation of the users of young and young adults (Hertzum & Hornbæk, 2010).

The researchers investigated how three age groups accomplished on different mouse tasks, such as trying to point, going to click, dual times of clicking etc. Additionally, it is significant to identify several other tasks such as age-related changes in motor system processing speed etc., that affected the use of the mouse. They captured some specific mouse metrics for example traveled time and some errors in order to evaluate performance for every activity. The time of the movement considered as the time it took the pointing device from its center point to the mouse pointer destination, whereas movement distance was described as the distance covered the mouse moved to achieve the goal. Because the exact distance traveled would be included in the movement distance, if a user did not take the quickest direct path to the objective, the distance of the move that cursor does would be higher. The participant's movement speed was measured in terms of how quickly he or she could reach the target. As errors maybe considered the number of times that the cursor left the wanted object before accomplishing the task. According to the findings, the older groups performed significantly worse on the clicking and double-clicking tasks than the other age groups tested. Extended movement times, more discrepancies, and a greater number of cursor motions while the mouse button is pushed were all linked to poor performance. The task that included the double click was the most difficult for older people to complete effectively out of all the tasks tested. Another discovery was that the older group had longer move distances and made more slip errors when using a pointer (Oakley, n.d.).

2.9 Definitions of emotions

Also, in this part we demonstrate some definitions of emotions which are difficult to understand and that emotions may emerge when a user interacts with an online environment. In our survey we will analyze the emotion of self-efficacy, engagement, immersion, enjoyment, confusion, frustration, stress, and dissatisfaction. Some of them analyzed below.

2.9.1 Self-Efficacy

More especially, self-efficacy is a person's belief in his or her own ability to perform a specific action, behavior, or task. Bandura (1977) was the first to introduce it, and it was successfully incorporated into his social cognitive theory. Past successes are thought to have a positive impact on self-efficacy, whereas past failures are thought to have a negative effect. It is also inspired by the person's emotional situation, their perception of others performing the same action, and how others may have persuaded them that they can perform the action. This procedure is part of a larger self-regulation system in which a person's beliefs about their own character, abilities, and flaws, as well as how others perceive them, have a major impact on how they control their behavior and interact with their environment. As a result, self-efficacy influences not only how one perceives one's abilities, but also how one actions and makes decisions. People, in overall, avoid domains where they lack confidence (low self-efficacy) and jump into tasks where they think they are qualified (high self-efficacy). Perceptions of self-efficacy also anticipate how engaged a person is with a task, how much effort they put in, and how long they will adhere with it once they begin (Schunk & Pajares, 2002). As a result, a user's perceived self-efficacy for accomplishment in a virtual world educational environment influences how the user behaves in that environment, including their learning motivation and perseverance when faced with difficulties or failure (Cosgrove, 2016).

2.9.2 Engagement

The level of investment made by a user when engaging with a digital system defines user engagement as a user experience characteristic. The possibility to take part and preserve engagement in online environment, among other objects, is thought to lead to positive outcomes in citizen investigation and active participation, e-health, web search, and e-learning. Over the last two decades, human-computer interaction (HCI) growing interest in comprehension, developing for, and analyzing user engagement with a wide range of computer-mediated health, education, playing games, social and news media, and search applications. UE is highly context-dependent: each digital environment seems to have its own number of technological capabilities that interact with users' intentions to accomplish a desired goal. (O'Brien & Toms, 2008).

2.9.3 Immersion

Few studies have been conducted to check if there any relationship between the sense immersion and acquiring knowledge in GBL environments. Researchers found that immersion has a significant relationship with academic results. Other research finding claim that emotions like engagement, and immersion have a great effect on student learning process. When challenge and skill is high, they associated with greater rates of engagement engrossment, and they may all be correlated with greater learning without the mediated effects (Hamari et al., 2016).

3. Game-based learning

"Game-based learning or else GBL is a learning environment in which game material and game play contribute to the acquisition of information and skills, and game tasks include dilemmas-solving spaces and challenges that provide to users a sense of accomplishment". The methods and instruments used in online education have undergone significant changes. The use of game-based learning media to encourage and inspire online learners is becoming increasingly popular. These tools empower and motivate online learners, making the learning process more interesting (Ucar & Kumtepe, 2017).

Computer game-based learning is becoming increasingly popular in schools. Recently there has been a growing interest among researchers both in teaching methods and the capabilities of computer games as learning, as well as research into their use. The merger of wargaming, operations research and computer science, together with the rise of constructivist educational ideas emphasizing dynamic, experiential learning and reflection, led to the birth of educational gaming in the 1950s. Play is a significant effect on learning that is essential to both adult and child development, encouraging engagement and execution of developmental activities. According to Koster (2005), educational games are the key element of the growing human experience and the way we learn, offering the chance to practice and explore in a secure environment, teaching skills such as aiming, timing, planning, and power control (Liu et al., 2020).

People who advocate the computer game-based learning method claim that computer games could disrupt the way students learn until today, inspiring and empowering a new generation of learners for the future in ways that conventional schooling does not provide. Both adults and children can easily engage in using games for learning, because these kinds of games are inherently motivating, as stated in the literature.(Bin-Shyan Jong et al., 2013)

Course information is provided to learners while they are playing a game in game-based learning. This method's main objective is to boost the motivation of learner. This learning process does not focus on the game itself; its usage is simply one aspect of the teaching method. Students are encouraged to study and learn better when they are exposed to a plethora of sound effects, screen designs, and educational materials. Game-based learning has been used in several educational contexts by researchers and this has as result the observation of different game-based learning features. For example, students are motivated to evaluate their new learned knowledge when they play games, the gaming environment's rapid feedback allows teachers to monitor individual students' development and make appropriate comments in a timely way. Also, students can share their knowledge by playing games with one another, game play allows students to acquire knowledge in an informal environment, which keeps them from becoming bored and discussions and social activities are frequently accompanying game play (Bin-Shyan Jong et al., 2013).

A slightly different term for game-based learning is the “Digital game-based learning” which is considered a competitive activity in which students are given educational objectives to help them gain information. These games may be intended to encourage learning process or cognitive skill development, or they may take the form of simulations that enable students to perform their abilities in a virtual world. DGBL definitions have been proposed by several writers. A DGBL environment, according to Mayer & Johnson (2010), should include “a set of dynamic responses to the learners' behavior, a set of rules and constraints, appropriate challenges that allow learners to experience a sense of self-efficacy”. As Mayer and Johnson (2010) pointed out, this is a relatively wide term that may apply to both digital and conventional games, such as chess. (Mayer & Johnson, 2010). Prensky's research gives us a better understanding of what DGBL is all about. For Prensky, one of the major key characteristics is the combination of serious learning with participatory enjoyment. To some point, digital learning games may be considered as an amusement tool that aims to generate cognitive changes in its users (Erhel & Jamet, 2013).

In more details, GBL is a technique and that encourages learners to acquire knowledge through experience. Also, it provides learners with a learning experience in which they may experiment with various methods and decision-making procedures while chasing game goals. When they play a game help them to retain the learning topic and context through repetition, emotion, and immersion in the gaming environment. Teachers can use game-based learning approaches to create an environment in which complex systems, can be modeled and project events can be reproduced (Jääskä et al., 2021).

The impact of GBL approaches on educational objectives (effective learning), student participation (a student to be motivated and attachment), and learning together as sociocultural, it has been examined. It is a challenge of recognizing and assessing the efficiency of game-based learning, due to its multi-disciplinary structure. The impacts are frequently addressed in the literature from the viewpoints of education, gaming, neuroscience, and computer science, instead of a cross-disciplinary study and synthesis (Plass et al., 2015).

The most talked-about aspect of GBL is its impact on student motivation. Educational games amuse and arouse students' attention, tends to result in intense involvement with the subject material. Playing is a normal human behavior that is essential for cognitive growth and learning at any age. As a result of the use of games, player involvement has become a prominent subject. Engagement manifests itself cognitively as mental processing, emotional processes that result in effective engagement, and behavioral and social involvement. Game-based learning is also characterized by adaptivity to learners' prior knowledge and the concept of gracious failure as part of the learning process (Plass et al., 2015).

GBL offers learners with an environment in which to practice making decisions in complicated project contexts without jeopardizing the project or budget. Rumeser & Emsley, investigated the use of an educational game in the field of project management decision-making and discovered that both complicated and less complex project simulation games improved decision-making performance (Rumeser & Emsley, 2019).

Several studies show that practical actions in gamified scenarios and instructional games aid students in comprehending and applying theory. It has been found that simulation games to be helpful in improving class instruction and boosting awareness of lean building principles in engineering education. There was a positive impact on critical thinking skills development and student satisfaction. A quantitative and qualitative assessment of student involvement and challenge in a GBL environment revealed a beneficial influence on learning (Hamari et al., 2016).

Learners are said to be motivated by educational games either inherently (for pleasure or challenge) or extrinsically (for external incentives). Because of their novelty and active nature, gamified techniques in education are frequently appealing to both learners and educators. Collaboration and competitiveness are encouraged using gamified methods and games, which inspire students. Gaming in the classroom appears to have a beneficial impact on overall student motivation. GBL is said to be enjoyable, challenging, and motivating, resulting in increased student engagement and learning efficiency. According to previous study, the advantage of utilizing instructional games is that students may apply theory to simulated real-life scenarios. Students learn how to handle relationships between individuals and activities with integration and uncertainty in game contexts. In addition to discipline-based skills, this method may help the development of students' generic skills such as coordination with others, solving an issue, decision-making processes, all of which are necessary for project managers to master. In the case of creating and implementing game-based learning, there are several challenges and drawbacks to consider. Teachers must evaluate any possible or current impediments to the usage and dependability of game-related hardware and software, as well as support, resources, and expertise. It takes time and effort to manage students' various preferences and abilities in order to maintain their interest in and desire for studying. When employing game-based activities, one of the obstacles that must be overcome is determining how they relate to the subject matter covered in the course or class (Jääskä et al., 2021).

GBL is an effective method to attract students' emotional engagement. Most researchers believe that these games could be effective in learning because they can increase learners' engagement and learning achievement. Some early studies have found that when GBL methods are used in online education, learners perform better than students in face-to-face classes. Likewise, students who are take part in GBL activities have a greater score and they express pleasant feeling than students which are not participate in GBL tasks in traditional (face-to-face) education. GBL has also been shown in higher education research to significantly improve students' perceptions of the learning topic and their perspective about the learning process. Beyond academic achievement, it is believed that games can elicit feelings, which have been shown to improve learning outcomes in digital learning environments. Because of the pandemic situation, it is now even more important to examine the positive or negative effects that has the GBL method in distance education. Despite GBL's growing popularity in learning procedure, many authors agree that there is no conducted much research about the methods techniques that provide an improvement in learners' performance and emotional engagement. According to the authors, "future studies should examine extra audio and visual features (music, sound), gameplay elements, and other design features." Nevertheless, some researches have been conducted in order to investigate in depth the GBL environment in relation to education, there must be conducted further research on students' emotions or sentiment analysis in distance learning. Nowadays, due to the COVID-19 situation there has been an urgent and rapid transition to online learning, and this has the result of a massive shift to mobile learning, because it allows multiple people, for example, in a single household, to access information. As a result, mobile learning is an unavoidable option during COVID-19. (Tzafilkou & Economides, 2021).

3.1 Results of different studies

3.1.1 Immersion

A series of studies investigated the relationship between immersion and game-based learning environment have been conducted. Participants become more emotionally attached to a game as they become more immersed in it, and they may even develop an empathic connection with it as they become more immersed in it. More specifically, participants' emotions are directly influenced by the game when they are completely absorbed in it, and they are completely attached to the game characters, causing them to empathize with their situations. Games offer engaging learning environments that arouse a variety of emotions, but it's uncertain which emotions or sets of emotions have the most potential for GBL (Cheng et al., 2020).

According to research, higher levels of engagement and immersion are linked to increased challenge and skills, and challenges, skills, engagement, and immersion may also be linked to increased learning without the mediated effects. Some previous studies used structural research models to examine the interrelations and pathways of variables surrounding engagement and immersion to predict learning. This occurs because studies either explore the relation between game elements and learning without taking into account mediating personality traits, or explore the association between game elements and psychological factors without broadening the evaluation to include alternative educational outcomes (Faiola et al., 2013).

In the meantime, some studies have found a negative relationship between negative emotions and game-based science learning while others have found that they are beneficial to learning and immersion (Cheng et al., 2020)

3.1.2 Enjoyment

One of the most significant motivations for using games in educational contexts is to have fun. Much research has shown that students enjoy playing educational games. Nevertheless, when students in control conditions were given the opportunity to play a game that has not educational character, they also demonstrated a high level of likeability. As a result, rather than being instructive, games as a whole increase likeability (Cruz-Cunha, 2012).

3.1.3 Engagement

Few studies have attempted to quantify psychological engagement in the context of GBL. In a GBL environment, Pellas (2014) discovered that the three dimensions of engagement, behavioral, cognitive, and emotional engagement, were strongly linked. Students who completed homework and labs in a game-based format for an undergraduate engineering course were clearly more engaged in the activity than those who completed homework in a traditional format, according to Coller and Shernoff (2009). However, gaming experience and the nature of the learning tasks have been shown to moderate engagement in educational games. Previous research has found a link between engagement and learning, as well as that game engagement can redirect unwarranted attention away from grades and toward learning. For instance, Sabourin and Lester (2014) discovered that a GBL environment can both support education and enhance engagement. Others discovered that flow had a significant effect on students' game achievement but had no influence on learning results; nevertheless, the more students are learning when they participated in a group competition (Faiola et al., 2013).

More specifically, Huizenga et al., (2009), looked at the engagement impacts in addition to likeability. They use observation to explore the engagement background of a mobile game. According to the statistics, most students who were playing the mobile game were quite interested. Annetta et al. (2009b) also emphasized on engagement. The methodology for classroom observations was used to assess engagement. There were significant variations in the degree of involvement of the users when playing with the game; students who are included in the experimental group were more involved than students which re included in the control group (without games). Furthermore, other researchers observed that game-playing conditions were substantially more engrossed than in control conditions. The above findings show that many researchers' belief that instructional games have a beneficial influence on student engagement is true (Cruz-Cunha, 2012).

Ke and Grabowski (2007) studied the influence of game-playing on students' mathematic attitudes and discovered that game-playing had an overall significant impact on math attitudes. They also discovered that computer games had a substantial impact on favorable attitudes about math instruction. Fontana and Beckerman, (2004) also investigated if an online educational videogame could be a useful tool for teaching violence prevention, and whether such a game might help students appreciate prosocial ideas, attitudes, and behavior patterns highlighted in interactive technology materials. The findings revealed substantial shifts in students' perspectives of social behavior and how to deal with conflicting situations. Hence, these findings show that instructional games have a favorable effect on students' attitudes (Cruz-Cunha, 2012)

3.2 Learning outcomes in the cognitive domain

A significant portion of the research has been on the effects of games or game elements on cognitive learning results. In comparison to groups that did not play educational games, the majority claimed that groups that did play educational games had a significantly better outcome on posttests assessing their knowledge. Moreno and Mayer (2005), for example, used an interactive educational game to illustrate the benefits of assistance and reflection in scientific learning. In addition, Ke and Grabowski (2007) discovered that game-playing had a significant influence on arithmetic performance scores. Virvou et al. and Annetta et al. found that games with educational features (virtual reality games and MEGAs) improved students' posttest results significantly. In another study, Papastergiou (2009) found that the kind of intervention had a statistically significant influence on posttest results in favor of the game-application group. Furthermore, other researchers verified that the study participants surpassed the control group and this way of learning, via a vocabulary website with word-based games, was a little more successful than task-based learning. Huizenga et al. (2009) discovered equivalent results, reporting a substantial effect of the intervention (i.e. mobile city game) in favor of the experimental condition for understanding of medieval Amsterdam. According to Chuang and Chen (2009), the experimental group exceeded the control group in terms of differentiation and memory, as well as comprehension and problem-solving skills. There were no differences in analytical and comparison skills. Others discovered that playing the game produces the same learning effects as the traditional method, and therefore GBL method had no significant influence on knowledge enhancement when compared to the control circumstances. In accordance with this, Ke (2008) discovered no significant association in cognitive math exam achievement among computer games and paper-and-pencil exercises. Finally, Wrzesien and Raya (2010) found no statistically significant difference in educational objectives between the game-playing group and the conventional group (Cruz-Cunha, 2012)

4. Kahoot!

Kahoot! is a paradigm of a GBL platform that tests students' knowledge and can be used as a formative assessment tool or as a break from traditional teaching methods. Kahoot is a one-of-a-kind free GBL platform with the goal of making learning more enjoyable for students of all ages and in any language. It is easy to use and only requires a digital device with a browser and an existing infrastructure that includes a reliable internet connection. Also, through competitive learning games, the Kahoot platform allows educators and learners to interact in a variety of learning sessions of various sizes. Students will not be required to create a Kahoot! Account instead prior to participating in a specific game at https://kahoot.it/#/ their mentor will provide them with a game PIN. The asset of these games stems from the fact that learning happens naturally without the students even realizing it. Some of the characteristics of the Kahoot platform is that the time limits and scoring are used in order to create a competitive reviewing environment and the scores of each student are presented at the end of each game (Kalleny, 2020).

This game-based learning platform was the first student response system designed to give a gaming experience by applying game design ideas from intrinsic motivation theory and game flow. Therefore, Kahoot combines audience participation, the use of video and audiovisual aids and role-playing. Kahoot! is a new generation of digital game-based student response system that emphasizes student engagement and motivation while also assessing their grasp of a lesson. Kahoot include visual and audio features which are provide a gaming capability and can enhance engagement of users, can motivate the users to participate and learn. A study that conducted about Kahoot involving approximately 600 students discovered that the music features of Kahoot can positively affect students' enjoyment, motivation, engagement, and concentration. Furthermore, a significant asset that Kahoot! has is the feedback that provide into learners and teachers (Kalleny, 2020).

Kahoot! is a learning platform that wants to combine a student response system, existing school technological infrastructure, students bringing their own digital devices, social networking, and games. Kahoot's purpose is to enhance learning performance and classroom dynamics by increasing engagement, motivation, fun, and attention. The use of participatory educational tools was regarded to prevent student stress and loss of interest, which can result in a reduction in learning outcomes as a result of teaching methods. Student participation is critical to high-quality learning. Formative assessment tasks performed on a regular basis can assist students in developing positive attitudes and behaviors toward learning (Martín-Sómer et al., 2021). On the contrary, boredom can lead to poor learning and undesirable behavior in a computer learning environment. The success of Kahoot! can be attributed to the fact that its primary goal is to make learning enjoyable through a GBL platform (Martín-Sómer et al., 2021).

Kahoot is among the most popular GBL tools with 70 million monthly active unique users. Several studies on the impact of using Kahoot! in the classroom have been published since the platform's debut in 2013, but no comprehensive analysis of the data has been conducted. (Wang & Tahir, 2020).

During the literature research, four literature reviews about Kahoot were discovered. A review of the literature on trends in student response systems highlighted that the benefits of SRSs include as interaction, improving academic achievement, and involvement, while the problems include waiting time, lack of academic effectiveness, and practical limitations. Also, it is said that an SRS app like Kahoot! have combined the best elements of SRS and mobile phone apps by adding a competitive game element to SRS. A further study of the literature looked at the pros and cons of computer game-based foreign language learning and concluded that this method appears to be particularly successful in vocabulary development. Higher motivation and involvement were two of the benefits. In the meantime, drawbacks included students' absence of focus on vocabulary development and learning, incorrect game selection that was irrelevant, and instructors' unfamiliarity with computer games, as well as their hesitation and fear to utilize them. Kahoot! was described as a GBL that may be used to learn a foreign language (Wang & Tahir, 2020).

Furthermore, one study of the literature focused on online formative evaluations and their various delivery modalities as well as psychological advantages Kahoot! was defined in this research as a game-like SRS with capabilities such as music video images and scores so it is considered one of the more dynamic tools. Higher academic results and the ability to think critically cognitive tasks are two benefits of using online foundational assessment methods. Finally, one study of the literature on mobile-based evaluations included articles from 2009 to 2018 (Nikou & Economides, 2018). According to these findings, there is a significant positive impact on learners performance, motivation, and attitude, and that more research is required to investigate issues and concerns related to negative perceptions of mobile assessment, particularly from the perspective of teachers. This review includes one Kahoot! research that looked at the long-term effects of using a GSRS on a regular basis (Wang, 2015).

4.1 GBL and COVID-19

Due to COVID-19 Situation which has resulted in a global shift online learning. Furthermore, this increase is driven by the emergence of a new generation of students who learn differently than previous generations, as current students are becoming more tech-savvy, overburdened with non-academic tasks, and stressed by time constraints. Kahoot! also has the advantage of being usable in the current COVID-19 situation. Kahoot! can be used in a live virtual setting for distance learning in the same way it can be used in a face-to-face setting. For online courses, teachers should share their screen with students using any video conferencing tool with screen-sharing capability such as Zoom so that students from any place can join and enjoy the game (Kalleny, 2020).

Due to the shift from conventional schools to distance education caused By COVID-19 situation in 2020, Kahoot's use grew rapidly in Spain and it climbed more than 100 positions in educational application lists (Martín-Sómer et al., 2021).

The unexpected closure of schools and colleges compelled the digitization of education. As a result, teachers were faced with the unforeseen challenge of teaching solely online. Because of the need to redesign teaching activities, many obstacles arose, including maintaining student interest. Furthermore, according to some studies, online education causes stress in students, which should be avoided. Since the release of Kahoot in 2013, many studies examine this new platform with positive results. Because of the pandemic, Kahoot was chosen as the platform for the questionnaires. All lectures were held online, and Kahoot games were played after each topic. The results of the Kahoot! games were related to the exam results (carried out in onsite mode). Likewise, the results were compared to those obtained in a previous onsite teaching course that did not use Kahoot. On the other hand, two surveys were conducted to learn about the students' perspectives on Kahoot's utility and the students' perceptions of online teaching and how this change has affected them. Since a growing increase in students enrolled in online education activities was observed in the years prior to the COVID19 crisis, it appears obvious that the shift to online education is already necessary outside of the pandemic situation. Understanding the growth of the digital classes will be helpful not only because of the potential for new lockdowns, but also because it may be appropriate for future education that addresses some of the pre-existing challenges. It's important to remember that this study only involved a small number of students, so its findings should be interpreted with caution. The authors believe, however, that it is a representative sample that can be considered in a global context of online education. The main limitation of the study is that it was carried on a specific theoretical topic, and the results might be very distinct in other subjects with a more technical nature, for which the Kahoot platform may not be suitable (Orhan Göksün & Gürsoy, 2019).

5. Aims and Research objectives

The primary goal of this study is to look at bivariate possible relations between mouse behavioral and dynamic metrics and user emotions during a game-based learning quiz.

The examination of significant correlations will unveil highly promising research for the future of user's emotional assessment and the utility of mouse and keyboard tracking techniques as feedback gathering methods in a game-based learning environment.

Based on the above mentioned, our research questions can be stated as follows:

RQ1: Are behavioral mouse metrics significant correlated to users' emotions during a game-based learning task?

RQ2: Are dynamic mouse metrics significant correlated to users' emotions during a game-based learning task?

RQ3: Do demographic characteristics like gender, age educational field, educational level affect users' emotions during a game-based learning task?

RQ4: Do demographic characteristics like gender, age educational field, educational level affect mouse metrics?

RQ5: Are there any significant correlations between the used mouse device (mousepad, mouse input device) and expressed users' emotions during a game-based learning task?

RQ6: Are there any significant correlations between the used mouse device (mousepad, mouse input device) and mouse metrics?

RQ7: Are there any significant correlation between the level of familiarity of game-based learning method and users' emotions during a game-based learning task?

RQ8: Are there any significant correlation between the level of familiarity of game-based learning method and mouse metrics?

6. Research Methodology

The study method uses a four-step approach to investigate possible mouse and emotions correlations in a game-based learning environment during completing a game-based learning task with simple questions at the easy promos' platform.

To reach this goal, we need to define measurable mouse items as derived from similar research works, mentioned in the literature review.

The main research objectives are to measure the mouse-behavior movements and attributes during the time needed by a user to complete a game-based learning task. The time that needs a user to complete a task varies depending on the user and is defined as "task duration/completion time." As a result, the time-related mouse metrics (e.g., mean time between movements, count movements, count speed total count of time short or long pauses, etc.) for each user are divided by the task duration time, and this ratio is used as the main mouse metric.

The first step is the presentation of the tool that was used for this experiment. Then we describe the mouse and keyboard monitoring mechanism and demonstrate its implementation as well as the data extraction method. Following that, we describe the field test, including sample and procedure details, the user task, performance calculation, and measured dependent variables, as well as the questionnaire. The last step is to display the data analysis procedure and the part that we discuss the main findings.

A game-based learning quiz was conducted by 33 participants to monitor their mouse behavior during their interaction with a game-based learning environment. The users were asked to watch a video about physics and after that to complete a set of simple questions. After the completeness of the quiz, they must reply on a questionnaire about their emotions that they felt during playing the game. The sample consist of both males and females, and they varied to their age, the education degree, and the level of their familiarity with that kind of learning method.

6.1 Easypromos platform

The Easypromos is an online platform in which users can create and manage digital campaigns. The Easypromos include also contests, puzzles, surveys giveaways quizzes etc. We chose this platform for our experiment because it is easy to create a quiz like the quiz we wanted for our experiment and users can interact with the platform in a quick and easy way. To create our quiz, we had to create an account in which all the participants had to log in to participate to the GBL quiz. Then we created a new promotion from the editor button which is at the right side of the platform, and we chose from the variety of options that it offers the knowledge quiz because it is the most appropriate for our experiment. The creation of the quiz wasn't requiring much time and the steps for the creation was simple. The next step was to embed the questions and the possible answers that participants had been called to choose. To make the quiz more interactive, we put some photos relative with the topic. The instructions for the quiz been given to the participants via e-mail and included the link with the video that they had to saw, the link with the platform, the email and password in order to log in in the platform and some screenshots that showed the two buttons that they had to click in order to be sure that their mouse movements will be captured. When participants logged into quiz all they had to do was to "Click here to test the promotion" to begin the quiz and users moved to the quiz interface.

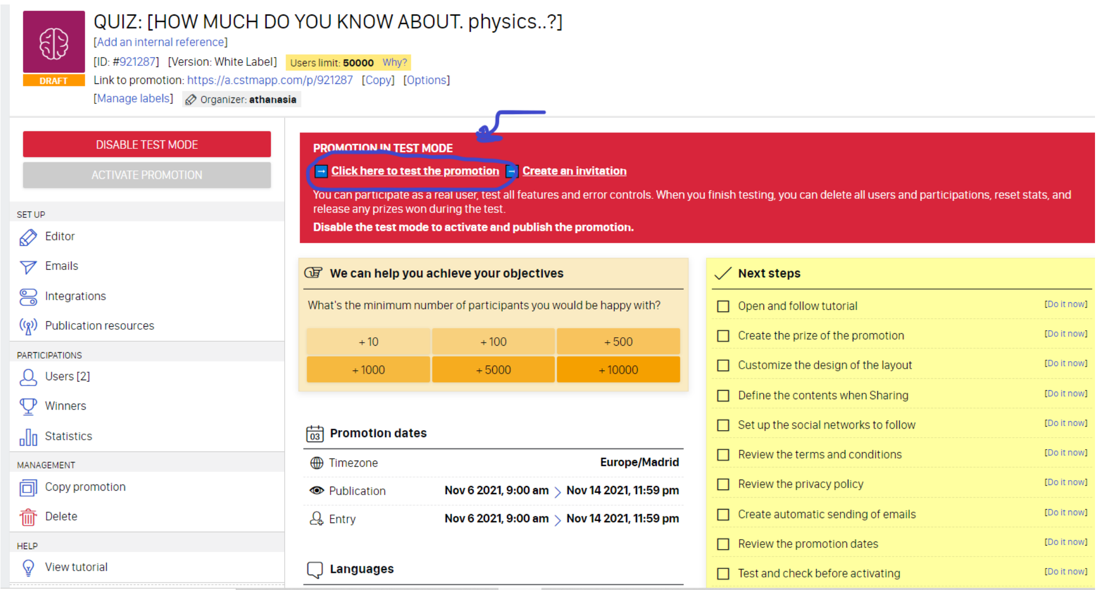

Figure 2 The Easypromos platform

After finishing the quiz all the participants had to click the button "click me when you finish" to save their mouse movements. They could fill their name or their email to see their scores. Most of them thy didn't.

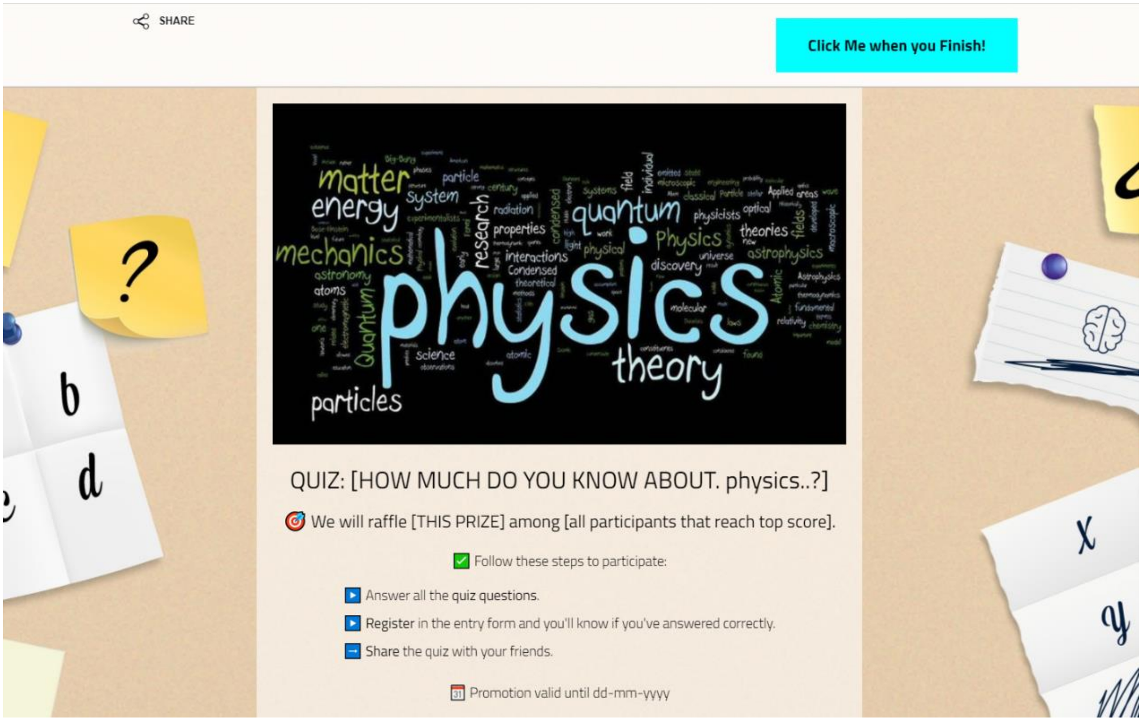

Figure 3 The Easypromos quiz

6.2 Mouse monitoring mechanism and data extraction

The technology used to record mouse data was based on an existing JavaScript-based mouse tracking code, which was developed to capture user mouse behavior in real time during the user online interaction and store the captured events of: i) speed_ speed, ii) speed_ acceleration iii) moves_ Move_CoordX, v) moves_ Move_CoordY, iv) moves_ TimeSince and in some users the following events: clicks__Clicked Element, clicks__Click_CoordX, clicks__Click_CoordY, clicks__Click_Timestamp, clicks__TimeSince_lastClick . We must mention that the tool had to measure the clicks, the time between clicks that user did during the game, but not clicks from all the sample size captured so, we couldn't achieve to measure the clicks and as far as clicks are concerned. The JavaScript code was embedded in the Easy promos platform and was able to monitor mouse events on the developed GBL task and store them in JSON files on a remote server. One JSON file per users was stored in the server through AJAX

(Asynchronous JavaScript and XML.) request, upon completing the game. The captured metrics were converted into csv files through an online converter (https://data.page/json/csv), to process the data and extract the mouse features to be used in the statistical analysis. The Figure4 below depicts in an aggregated manner the mouse metrics that were extracted, calculated, and examined in the current research. As depicted, these are categorized into behavioral and dynamic mouse metrics, as derived from the literature review.

As mentioned, we linked the monitoring tool to the easy promos quiz to monitor the user's mouse behavior while they are fulfilling the given game-based learning task.

To connect the questionnaire responses to each user's mouse and behavior we developed a special user id for every user, and we stored it in every database table and in a questionnaire's answer field.

The below tables depict the excel file with all the data that we extracted from the game-based learning task.

User id	Gender	Age	Device	VAR1 Self effica	VAR2 Engagement	VAR3 Immersion	VAR4 Enjoyment	VAR5 Frust	VAR6 Conf	VAR7 Stres	VAR8 Dislikness
giota	f	35+	Mousepad	1	1	1	1,7	5	4,7	4,2	5
kostas	m	35+	mouse input device	2,5	1,25	2	1	5	3,3	4,4	5
nasia	f	25-35	Mousepad	3,5	2	1,3	2	3	2,7	3	4
xristinag	f	25-35	mouse input device	2,5	1,5	2	2,3	2,5	2	2,6	5
mpif	f	18-24	mouse input device	3,5	3,5	3,3	4	5	4,7	2,6	5
sevasti	f	25-35	mouse input device	4	4	4	4	1	1	1	1
gianniotis	m	25-35	Mousepad	1,5	1,25	1	1,7	4,5	4,7	4	5
loukoumas	f	25-35	Mousepad	2	1,25	2,3	1	3,5	3	3,4	5
MariaLiakou	f	25-35	mouse input device	1,5	2,25	2	2,3	5	5	5	5
TSARASATHAN	m	25-35	mouse input device	4,5	4,25	5	4,7	3	3,7	1,8	4
VASILIS	m	25-35	mouse input device	1,5	1,25	1,7	1	4	4,3	5	5
Nikoleta Makri	f	25-35	Mousepad	2,5	3,25	3,3	3	1	2,7	1	1
mama mpif	f	35+	mouse input device	1	2,5	1,7	2,3	4,5	3,7	4,8	5
troumanis	m	25-35	Mousepad	1	1,5	1,7	1	3	5	5	5
vivi	f	25-35	mouse input device	1,5	1,25	1	1,7	4,5	3,3	3,6	5

Table 2 Data extracted from GBL task (variables and demographics)

Mean speed/Var speed	Mean speed/Va	Time Btw Movements	Total Count	Total Co	Total Count	Count spee	Task completion	Count movements/t	count speed=0/ta	count pauses>2	count pauses>5/task
5,88397E-17	-3,81268E-18	1,18022E-16	70	61	12	49	8,96804E+17	7,8055E-17	5,46385E-17	6,80193E-17	1,33809E-17
4,59463E-17	5,11247E-18	1,47206E-16	72	66	9	45	9,03922E+17	7,96529E-17	4,97831E-17	7,30151E-17	9,95661E-18
3,58157E-17	-5,83293E-18	1,88849E-16	78	64	17	59	7,2571E+17	1,07481E-16	8,12997E-17	8,81895E-17	8,12997E-17
5,91083E-17	3,70824E-18	1,67281E-16	142	106	41	115	1,62473E+18	8,7399E-17	7,07809E-17	6,52415E-17	2,52349E-17
5,31341E-17	1,23199E-18	9,79002E-17	522	345	988	127	5,63507E+18	9,26341E-17	2,25374E-17	6,12237E-17	1,75331E-16
4,35044E-17	-4,44263E-18	1,84468E-16	374	324	57	77	4,78067E+18	7,82318E-17	1,61065E-17	6,7773E-17	1,1923E-17
4,8596E-17	6,72618E-18	9,60053E-17	410	26	385	117	2,264E+17	1,81095E-15	5,16784E-16	1,14841E-16	1,70053E-15
3,92915E-17	-5,05395E-18	1,30321E-16	367	273	119	110	3,33461E+18	1,10058E-16	3,29873E-17	8,18686E-17	3,29873E-17
5,53276E-17	-6,79586E-18	1,13539E-16	126	85	45	97	1,37185E+18	9,18468E-17	7,07074E-17	6,19601E-17	3,28024E-17
4,42521E-17	-4,8256E-18	9,43637E-17	328	279	57	81	4,405E+18	7,44609E-17	1,83882E-17	6,33372E-17	1,29399E-17
5,30965E-17	4,02982E-18	1,06588E-16	611	486	140	95	7,5747E+18	8,06633E-17	1,25418E-17	6,4161E-17	1,85E-17
5,01806E-17	-2,85144E-17	5,73797E-17	198	6	192	131	7,5E+16	2,64E-15	1,74667E-15	8,00E-17	2,56E-15
5,73733E-17	-8,41945E-18	1,03116E-16	73	41	33	54	6,70063E+17	1,08945E-16	8,05894E-17	6,11883E-17	4,92491E-17
3,70587E-17	-7,43985E-19	1,41225E-16	154	22	132	134	1,8E+17	8,55556E-16	7,44444E-16	1,22222E-16	7,33333E-16
4,88997E-17	1,12623E-17	1,90025E-16	97	77	25	78	1,11793E+18	8,67671E-17	6,97715E-17	6,8877E-17	2,23627E-17

Table 3 Data extracted from GBL task (mouse metrics)

As we mentioned before in the literature there are a plethora of mouse attributes that help us to analyze the basic mouse behaviors of the users. In the below schema (Figure 4) we summarize the measurable mouse attributes we gathered from mouse behavioral patterns and mouse dynamics literature review, and we are going to measure and analyze below. These metrics will define the independent variables that will be statistically analyzed to examine the RQs the before stated research objectives.

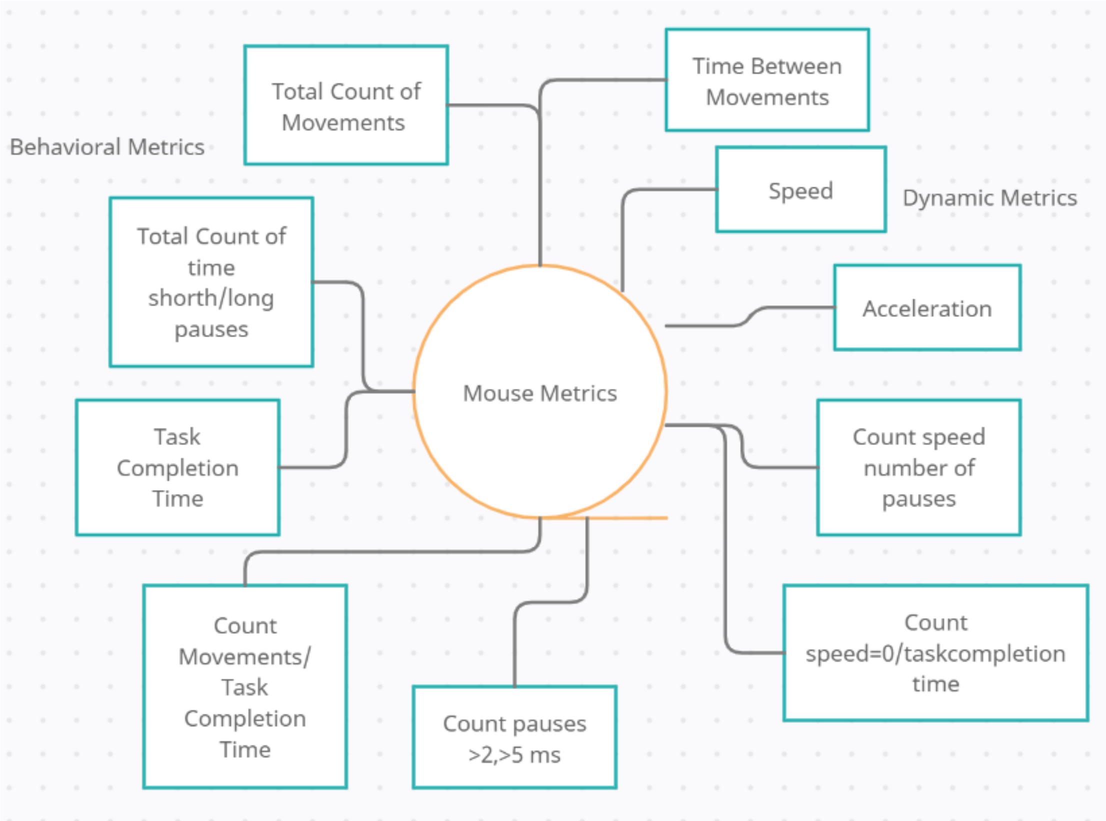

Figure 4 Mouse behavioral and dynamic metrics

Following is the list of the mouse features that were calculated from the raw JSON stored metrics:

1. Speed Mean/ Var: Which is the Average/Variance of mouse speed (px/milliseconds) between consecutive points for a given user/session.
2. Acceleration Mean/ Var: Which is the Average/Variance of all possible accelerations for every three points detected for a given user/session.
3. Time between Movements: Average/Variance of time difference (milliseconds) between mouse moves for a given user/session.
4. Total Count of Movements: Number (count) of mouse movements for a given user/session.
5. Total Count of time Between movements short pauses: The time that a user needs to move from a point to another point. When the user does short pauses
6. Total Count of time Between movements long pauses: The time that a user needs to move from a point to another point. When the user does long pauses
7. Count speed number of pauses: The total number of speed pauses

8. Task completion Time: Total time milliseconds for completing the web tasks for a given user/ session
9. Count movements/task completion time:
10. Count speed=0/task completion: Total count of speed in a task.
11. Count pauses>2/task completion time: Number of short pauses (time elapsed since last movement >2000ms) in a task
12. Count pauses>5/task completion time(hesitation) Number of long pauses (time elapsed since last movement >5000ms) in a task

6.3 Field test

6.3.1 Participants and procedure

The participants' initial population was 36 volunteers, and the final sample consists of 33 participants,14 male and 19 female. The sample size was reduced to 33 users because two of them did the quiz from a mobile device and we couldn't track their mouse movements and the mouse movements of the third ones did not measure, possibly because the user didn't click the button "click me when you finish". So, their data could not be used in the analysis process.

The participants were given a game-based learning task to solve, in the form of a quiz demanding to answer some questions according to a video that they saw at the beginning of the experiment. The use of easy promos platform was simple, and the interface text was in Greek. The instructions of the quiz send to participants by e-mail, as we stated above, and include step by step the procedure that they will follow, meaning the link of the video, the link from easy promos platform and the passwords for their connection to quiz and the form of the questionnaire from Goggle forms. Few users who were unfamiliar with the computing device sought assistance and were given additional detailed instructions. Finally, participants could be informed about their performance and discuss their experiences and difficulties, as well as ask any additional questions. The most common question was "How did I do?" and if they did right (there weren't sure if they click right the button "click me when you finish").

Drawing from all of this, the targeted group population ranged in age from 18 to 35+; they were Greek users with no disabilities, typical computer training and expertise (e.g., computer use and web surfing); some were comfortable with game-based learning tasks, while others were not.

To confirm these criteria, some personally identifiable information (gender, age, educational background) was gathered, and as previously stated, after accomplishing the game-based learning task, respondents were also instructed to perform a short questionnaire about their level of experience with similar games and their emotions while carrying out the task. Their experience level was measured in a scale from 1 to 5, "strongly agree" to "strongly disagree" as depicted in the below diagram. (Figure 12)

Demographics in more detailed:

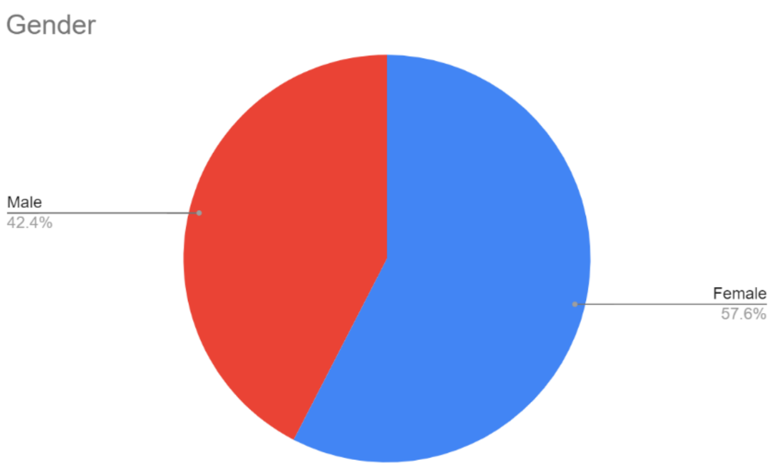

Figure 5 Pie chart Gender

The sample size that was invited to participate in this experiment were 33 unique participants. Participants are both males and females. 57,6% was female and 42,4% was male.

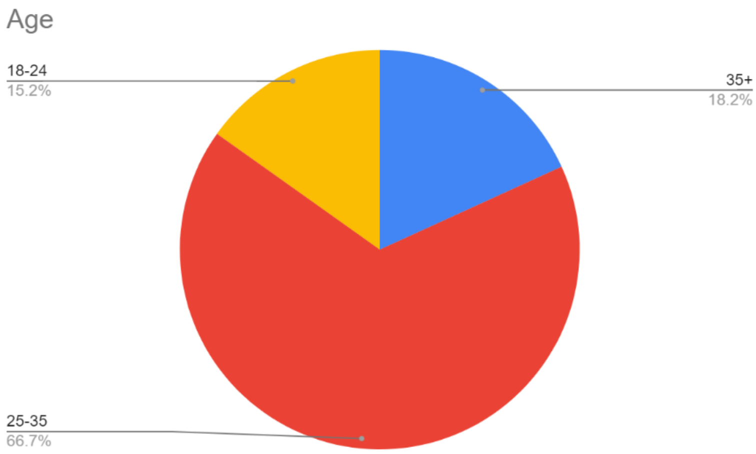

Figure 6 Pie chart Age groups

As far as concerned the age of participants 15,2% were 18-24, 66,7% were 25-35 and 18,2% were 35+.

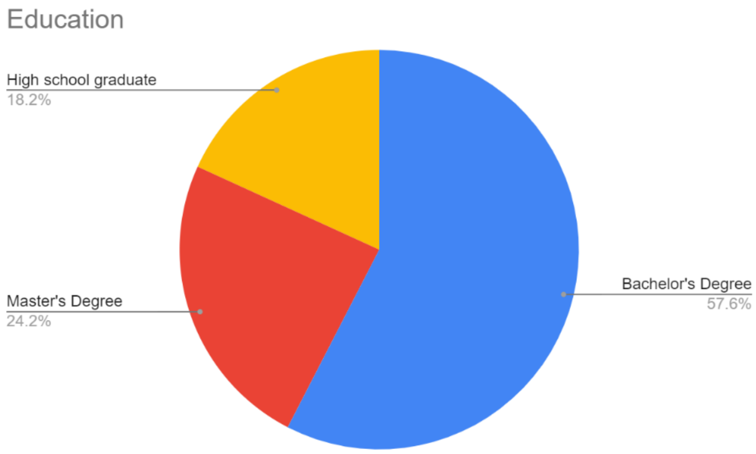

Figure 7 Pie chart Education

The educational level of participants was varied 57,6% had a bachelor's degree, 24,2% had a master's degree and 18,2% were graduated from high school.

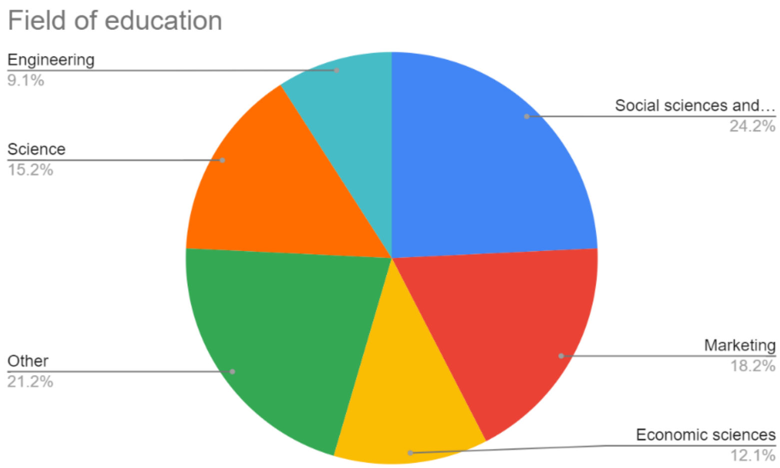

Figure 8 Pie chart Field of Education

The field of education of participants was varied the most of participants 24,2% concern people from social sciences and humanities field, 21,2% was involved in different field of education, 18,2% concerned people who has to do with marketing, 15,2% involved in science, 12,1% involved in economic sciences and 9,1% has to do with engineering.

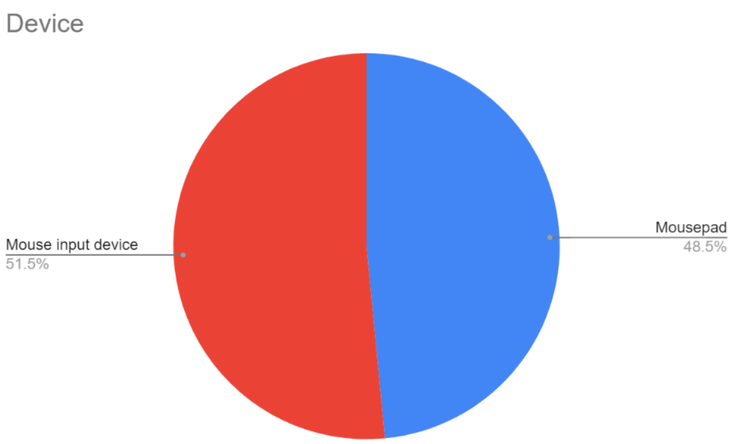

Figure 9 Pie chart Device

Every user needed to complete a task only by a computer or laptop device (not a mobile phone). Of those, 48,5% mouse data samples were provided via mousepad and 51,5% sample were of an external (classic) mouse device.

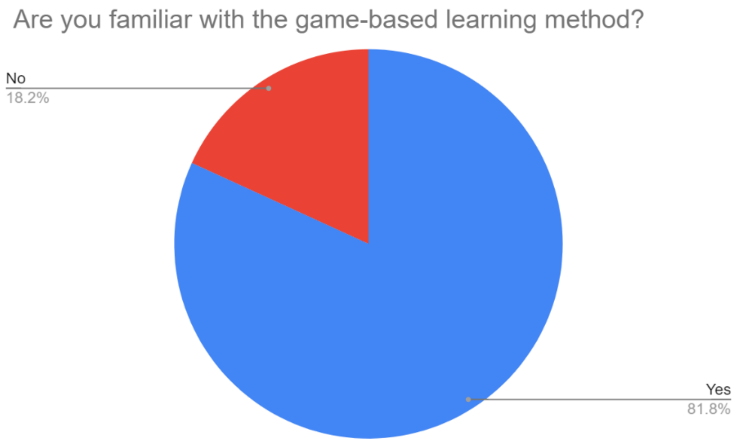

Figure 10 Pie chart familiarity of the user in relation to game

Another question that user had to answer after finishing the game-based learning task was concern their familiarity with the game-based learning method. Most of them more particular 81,8% were familiar with the method and 18,2% weren't.

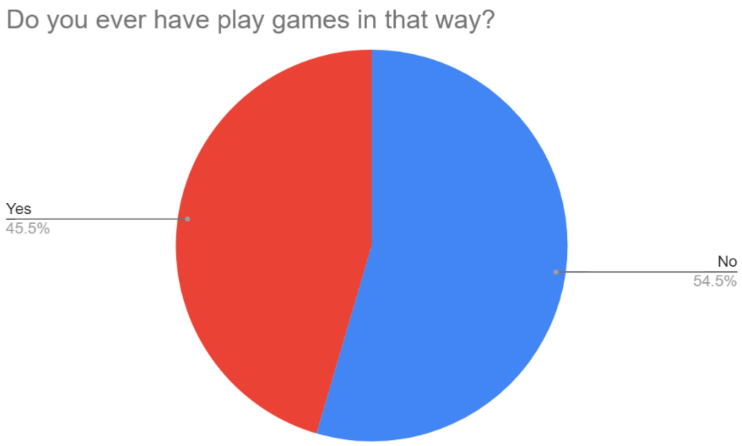

Figure 11 Pie chart "Do you ever have played this kind of games?"

Also, almost half of the participants, 45,5% had played in the past that kind of games and the other half 54,5% didn't play a game like that.

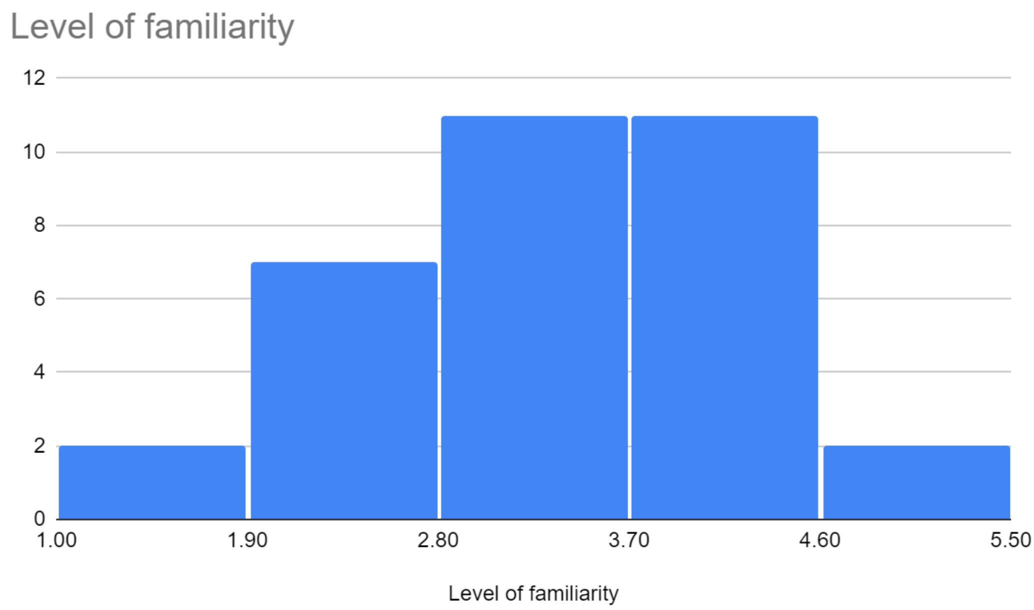

Figure 12 Chart Level of familiarity

The above histogram shows us the level of familiarity of participants playing the game-based learning quiz. The answers were in a licker scale "Strongly agree". "Agree", "Neither agree nor disagree", "Disagree", "Strongly disagree".

	Descriptive Statistics				
	N	Minimum	Maximum	Mean	Std. Deviation
Level of familiarity	33	1	5	3,1212	1,0234
Valid N	33				

Table 4 Descriptive Statistics for level of familiarity (the mean value)

6.3.2 User task and performance measure

Users were called to watch an educational video which concerned physics as we mentioned before. More specifically, after watching this video, they had to play a game-based learning quiz and answer to the questions based on the video that they saw. Following that, users were asked to complete an online background questionnaire in gathering pertinent demographic information and to answer some other additional questions. After of the completion of the user task, each participant was required to complete a self-report questionnaire-based survey consisting of 22 items measuring a specific emotion variable. The questionnaire was made available to users in the form of an online survey form.

The game-based learning quiz (user task) had to be small enough for participants to complete in a brief amount of time while also being as accurate as possible to acquire a logical amount of mouse moves and other cursor metrics. The example of the quiz is simple and comprehensive since the easy promos interface are easy to use from the most of users and its completion is simple as well. The only thing to do is to answer a question and go to the next question. So, the exercise given to the participants was to play a quiz in accordance with what they saw from a video.

6.3.3 Variables and questionnaire

The set of user-oriented variables measured for each user from the post-task questionnaire survey is listed below.

Emotion Variables:

- Self-efficacy
- Engagement
- Immersion
- Enjoyment
- Confusion
- Frustration
- Stress
- Dissatisfaction

The questionnaire survey included 24 queries (items) that measured the six independent variables mentioned above. The items were measured using a five-point Likert-type scale ranging from 1 "strongly agree" to 5 "strongly disagree." Our questionnaire structure was derived from previous studies of computer perceived notion and acceptance questionnaires, but we modified and enlarged the questions to support all the survey attributes listed below.

6.3.4 Data Analysis

6.3.4.1 Sample characteristics

A normality distribution test was performed to determine whether the eight variables under consideration were approximately normally distributed across the entire sample. Six of the eight variables do not follow a normal distribution (engagement, immersion, enjoyment, frustration, stress, dissatisfaction), according to a Shapiro-test Wilk's (Shapiro & Wilk, 1965) and visual inspection of box plots (engagement, immersion, enjoyment, frustration, stress, dissatisfaction) (confusion, self-efficacy). So, the six variables follow a statistical analysis which performed using non-parametric tests and the two variables follows a parametric method.

Test of Normality				
	Statistic	Sig	Statistic	Sig.
VAR2 Engagement	,195	,003	,850	<,001
VAR3 Immersion	,188	,004	,875	,001
VAR4 Enjoyment	,188	,005	,885	,002
VAR5 Frustration	,214	<,001	,800	<,001
VAR7 Stress	,174	,013	,849	<,001
VAR8 Dissatisfaction	,427	<,001	,486	<,001

Table 5 Test of normality N=33

Test of Normality				
	Statistic	Sig	Statistic	Sig.
VAR1 Self-Efficacy	,181	,007	,913	,012
VAR6 Confusion	,154	,045	,919	,017

Table 6 Test of normality N=33

6.3.4.2 Data analysis method

Also, the construct validity of the results has been checked to determine that they are accurate and stable. We assessed construct validity by calculating Cronbach's alpha. This metric assesses internal consistency by implying how several objects are relevant and form a group. Nunnally (1967) suggests that a Cronbach's alpha (a) value of 0.70 is acceptable, though a slightly lower value may be acceptable in some cases. In the below table Cronbach's a values for all factors are greater than 0,70, denoting that all measures used in this study have acceptable internal reliability and that the measurement model is supported.

Variables	Questions	Cronbach α(>=0,70)
Self-Efficacy		0,80
Q1	I felt that I was trying my best	
Q2	I felt very confident playing the game	
Engagemnet		0,90
Q1	The video and the game questions were attractive	
Q2	There was something interesting of the game that captured my attention	
Q3	I would like to play the game again	
Q4	I liked the game because contributed to my learning too	
Immersion		0,82
Q1	I have been fully concentrated in the game	
Q2	I didn't notice the time pass while playing	
Q3	I was completely engrossed in the game when playing it	
Enjoyment		0,93
Q1	I find the game exciting	
Q2	I find it enjoyable	
Q3	I had fun with the game	
Confusion		0,85
Q1	I was felt I couldn't remember anything from the video that I saw	
Q2	There were 4 possible answers, and it was difficult to choose	
Q3	I wasn't sure about my choice	

Frustration		0,89
Q1	I was annoyed because of the complex questions	
Q2	I was annoyed because of the distracting photos of the quiz	
Q3	I was annoyed because I didn't understand exactly the question	
Stress		0,93
Q1	I was anxious because I might have chosen the wrong answer	
Q2	I choose by chance the answers because I was stressed	
Q3	When I finished the quiz, I was anxious about the results	
Q4	I was anxious about the next question	
Dissatisfaction		0,94
Q1	I didn't like it at all	
Q2	I felt that I was wanted to quit the game	

Table 7 Questionnaire survey and results for validity of the measurement model

7. Results and Discussion

7.1 Descriptive Statistics

The Pearson correlation analysis was used to measure the bivariate interrelations between the normally distributed measured variables because it is an appropriate method for defining the degree of correlation among a set of continuous variables. The Spearman correlation analysis is another method we use for non-normally distributed variables to measure bivariate correlations between the measured variables.

We used descriptive statistics to present the overall results for each measured variable. (Tables 8,9,10,11) The mean values and standard deviations of the sample's demographic data, perceived emotions, and mouse metrics were presented using descriptive statistics. Spearman's rank correlation was used to calculate bivariate correlations between mouse metrics and our eight variables. The effects of education and age were investigated using the Kruskal-Wallis rank sum test, and gender and mouse device differences in user expressed emotions were investigated using the Man Whitney (Wilcoxon test for independent samples). We highlight our main findings and discuss several potential limitations of the current experimental design in the Discussion section.

The table 8 below shows us the descriptive statistics of demographic characteristics of the participants. The table 9 presents the values of descriptive statistics results for our measured variables. The next tables 10 and 11 depict the descriptive statistics extracted values for behavioral and dynamic mouse metrics correspondingly.

This type of statistics allows for easy quantitative summaries of data and the identification of patterns. In our analysis, we used two types of descriptive statistics: measures of central tendency and measures of spread. The first category describes the frequency distribution's central position in our dataset. Such examples in our feature set are the mean. The second category describes how spread the scores in a dataset are distributed. The standard deviation was used to calculate the spread. Finally, we looked at simpler statistics like demographics' minimum, maximum, and sum of values, each emotion variable, and each mouse cursor trail.

	Descriptive Statistics				
	N	Minimum	Maximum	Mean	Std. Deviation
Gender	33	1,00	2,00	1,4242	,50189
Age	33	1,00	3,00	2,0303	,58549
Education	33	1,00	3,00	1,6061	,78817
Valid N	33				

Table 8 Descriptive statistics from demographic data

	Descriptive Statistics				
	N	Minimum	Maximum	Mean	Std. Deviation
VAR1 Self-efficacy	33	1,00	4,50	2,1970	,99953
VAR2 Engagement	33	1,00	4,50	2,0076	,96518
VAR3 Immersion	33	1,00	5,00	2,0515	,94575
VAR4 Enjoyment	33	1,00	4,70	2,1333	,94593
VAR5 Frustration	33	1,00	5,00	3,9697	1,21796
VAR6 Confusion	33	1,00	5,00	3,6970	1,09815
VAR7 Stress	33	1,00	5,00	3,7818	1,29553
VAR8 Dissatisfaction	33	1,00	5,00	4,4848	1,17583
Valid N	33	1,00			

Table 9 Descriptive Statistics for emotion variables N=33

	Descriptive Statistics				
	N	Minimum	Maximum	Mean	Std. Deviation
Total Count of Movements	33	25,00	718,00	221,00000	187,08588
Mean Time Between Movements	33	55,11	1,50000000	1,0607000	4,1777590000
Var Time Between Movements	33	113203,32	2,37000000	8,4104000	4,9453300000
Total Count of Time Between Movements long pauses	33	,00	519,00	144,3939	140,39697
Total Count of Time Between Movements short pauses	33	9,00	988,00	159,3333	223,24617
Task Completion Time	33	13171,00	8,01000000	2,1238000	2,168840000
Count Movements/ Task Completion Time	33	,00	,02	,0063	,00404
Count pauses>2	33	,00	8,82	6,4225	2,02138
Count pauses>5	33	,00	9,96	3,2429	2,53036
Valid N	33				

Table 10 Descriptive Statistics for Behavioral mouse metrics N=33

	Descriptive Statistics				
	N	Minimum	Maximum	Mean	Std. Deviation
Mean Average Speed	33	6,930000000	9,7400000000	3,6190000	2,341380000000
Var Speed	33	1,480000000	2,7200000000	7,5365000	5,347400000000
Mean Acceleration	33	-3,95000000	1,4000000000	-5,4477000	1,086840000000
Var Acceleration	33	8,510000000	2,7400000000	9,86090000	6,748130000000
Count speed= 0 (number of pauses)	33	16,00	136,00	84,6970	33,36492
Valid N	33				

Table 11 Descriptive Statistics for Dynamic mouse metrics N=33

7.2 Correlations between mouse features and emotions

The main findings for each of the above-mentioned research questions are summarized below. The Pearson correlations (r) between each extracted mouse metric and EUD behavioral attribute are shown in the tables below. Several significant correlations have been discovered, as shown. The Tables 12, 13 and 18 depicts the Spearman correlation between activity level of mouse movements and behavioral variables. The Pearson correlations (r) between each mouse metric and users' behavioral attributes are shown in Table 17. Some significant correlations have been discovered, as shown.

RQ1: Are behavioral mouse metrics significant correlated to users’ emotions?

Results in the above table show that the variance of time between movements (“behavioral mouse metric” Movement variance means you do the same foundational movement, but slightly change it.) is significantly correlated with frustration. This means that users that were frustrated during the game-based learning task they didn’t follow a particular movement but changing it during the quiz. This may happen because when a user is frustrated the movements of his mouse didn’t follow a calm and specific direction, therefore the variance time between movements it is possible to related with the feeling of frustration. As we mentioned above, Hibbeln et al. (University of

Duisburg-Essen et al., 2017) and Sun et al. (Sun et al., 2014) used the emotion elicitation through a task to demonstrate if a user is stresses or frustrated during a simple interface manipulation challenge could be reflected in cursor activities like traveled distance and direction change.

Also, as we mentioned above another article supports that "random mouse movement" is a response to either slow user interface elements or high cognitive loads. It appears in both cases in the same way: rapid back-and-forth or circular movements with no functional intent or connection to targets on the page. (Tim Rotolo, 2008).

			Var Frustration	Var Time Between Movements
Spearman's rho	VAR Frustration	Correlation Coefficient	1,000	,365*
		Sig (2-tailed)		,037
		N	33	33
	Var Time Between Movements	Correlation Coefficient	,365*	1,000
		Sig. (2-tailed)	,037	
		N	33	33
*Correlation is significant at the 0,05 level (2-tailed)				

Table 12 Spearman Correlation test of the variable's "frustration" and "var time between movements"

RQ2: Are dynamic mouse metrics significant correlated to users' emotions?

Results in the below table show that engagement of users during the game-based learning task significantly associated with mean acceleration. The emotion of engagement correlated negatively with mean acceleration, which is means that when engagement increases the mean acceleration decreases. A possible reason for that correlation could be the fact that engagement is a positive emotion that a user feels when interact in this case with a game-based learning environment and mouse acceleration happens usually when a user feels negative emotions like anger, frustration, and stress because of the convulsive movements. So, we may conclude that when a user feels the emotion of engagement with the game-based learning task the mean acceleration of mouse movement decreases.

As we mentioned above, according to research, the more time users spend on a specific task or activity the better effort they make, and we can consider a user has a high level of engagement when we see a gradual increase in the curve of his mouse movement on the graph (above graph). On the other hand, we assume the user's level of engagement was relatively low when his curve shifted dramatically in a brief span of time. Furthermore, according to Heather and Elaine's proposed model of engagement, the transition from engagement to disengagement will take a certain amount of time (2008). The curves of all four users steadily increased at first, and then some curves began to change significantly, as shown in the graph. This is continuous with the engagement model: most users were able to concentrate easily at the start of the study, but as time went on, some of them seem to be disturbed. They couldn't finish reading if they couldn't reengage; instead, they scrolled to the bottom of the content page (Zhang et al., 2020).

			Var Engagement	Mean Acceleration
Spearman's rho	VAR Engagement	Correlation Coefficient	1,000	-,350*
		Sig (2-tailed)		,046
		N	33	33
	Mean Acceleration	Correlation Coefficient	-,350*	1,000
		Sig. (2-tailed)	,046	
		N	33	33
*Correlation is significant at the 0,05 level (2-tailed)				

Table 13 Spearman Correlation test of the variable's "engagement" and "mean acceleration"

Q3: Do demographic characteristics like gender, age educational field, educational level affect users' emotions?

Results of Kruskal Wallis test between demographic characteristics like gender, age, educational field, educational level construct show no evidence of affecting users' emotions.

RQ4: Do demographic characteristics like gender, age educational field, educational level affect mouse metrics?

On the other hand, we can see in the above table that age has a significant correlation with total count of movements. A conclusion that may occurs for that correlation is that users according to their age behave different in accordance with their total movements when it comes to complete a task.

Cursor trajectories can also be used to explain age-related differences in movement. Older adults, for example, make more sub movements and have lower peak velocity, longer phases of deceleration and longer cursor trajectories, according to studies of cursor trajectories. As we mentioned above, there is a relationship between peak acceleration and endpoint distribution variability in a ballistic movement varies with age. This is means that young adults have a greater acceleration and relatively low endpoint variation than older adults (Hertzum & Hornbæk, 2010).

Other researchers investigated the relationship between three age groups and performance on four different mouse tasks, including pointing, clicking, double-clicking, and dragging, as well as how age-related changes in motor control, processing speed, and visuo-spatial skills influenced mouse use. A variety of physiological and cognitive tests were used to assess abstractions, spatial ability, processing speed, visuo-motor ability, perceptual speed, and motor coordination. To evaluate performance, the researchers recorded movement time, movement distance, movement speed, sub-movements, and slip errors for each task. The time it took the mouse to move from its home position to the cursor target was measured in movement time, while movement distance was defined as the total distance the mouse traveled to achieve the goal. Because the movement distance includes the exact distance traveled, if a user does not take the shortest direct route to the target, the movement distance will be greater. The older groups performed significantly worse on the clicking and double-clicking tasks than the other age groups tested, according to the findings. Lower performance was associated with longer movement times, more frequent errors, and a greater number of cursor movements while the mouse button was pressed. (Oakley, 2009).

	Age	N	Mean Rank
Total Count of Movements	1,00	5	25,40
	2,00	22	18,41
	3,00	6	4,83
	Total	33	

	Total count of movements
Kruskal-Wallis H	13,740
df	2
Asymp.Sig	,001

Table 14 Kruskal-Wallis test with variables "age" and "total count of movements"

The below table shows us that age has a significant correlation with the count speed=0 (number of pauses). As mentioned before, according to some surveys as it is mentioned in the literature review relatively long movement times greater movement variation, and more errors are all signs of aging. Enhanced reaction time and decreased muscle strength could be the cause of these differences. While increasing the ID of tasks reduces performance for all users, high ID values have a greater impact on older adults' performance. A few studies have found that adults and older adults have different strategies, with older adults emphasizing accuracy over speed. As we mentioned above in the literature part there are differences between children and young adults, it is seemed to process information slower than adults, impacting their response time and movement speed (Hertzum & Hornbæk, 2010).

	Age	N	Mean Rank
Count speed=0 (num of pauses)	1,00	5	23,70
	2,00	22	18,73
	3,00	6	5,08
	Total	33	

	Count speed=0 (num of pauses)
Kruskal-Wallis H	12,230
df	2
Asymp.Sig	,002

Table 15 Kruskal-Wallis test with variables "age" and count speed=0"

The below table shows us that age has a significant correlation with total count of time between movements (short pauses).

	Age	N	Mean Rank
Total count of time between movements short pauses	1,00	5	28,40
	2,00	22	17,57
	3,00	6	5,42
	Total	33	

	Total count of time between movements short pauses
Kruskal-Wallis H	15,641
df	2
Asymp.Sig	<,001

Table 16 Kruscal-Wallis test variables "age" and total count of time between movements short pauses"

RQ5: Are there any significant correlations between the used mouse device (mousepad, mouse input device) and expressed users' emotions?

According to our finding we must mention that no significant correlation was found between the used mouse device (mousepad, mouse input device) and expressed users' emotions, so we must conclude that the used mouse device (mousepad, mouse input device) does not affect the expressed users' emotions.

RQ6: Are there any significant correlations between the used mouse device (mousepad, mouse input device) and mouse metrics?

Also, as far as concerned the mouse metrics and the device that users used, no significant correlation was found. So, according to this research findings we have to mention that the used mouse device (mousepad, mouse input device) does not affect the mouse metrics.

RQ7: Are there any significant correlation between the level of familiarity of game-based learning method and users' emotions?

The below table declare that a significant correlation was fount between level of familiarity and self-efficacy. This is obviously means that when users are familiar with a task, in that case with a game-based learning environment, are feeling more confident about their answers and their performance during the game.

The emotion of self-efficacy as stated in the literature part of this paper is an individual's perception of his or her ability to perform some action, behavior, or task. It is considered that successful past experiences have a positive impact on self-efficacy, while past failures have a negative impact. It's also influenced by the person's emotional state, their assessment of others performing the same action, and how others may have convinced them that they can accomplish the action (Schunk & Pajares, 2005). As a result, self-efficacy affects not only one's perceptions of one's abilities, but also how one acts and makes decisions. In general, people avoid domains in which they lack confidence (low self-efficacy) and jump right into tasks in which they believe they are competent (high self-efficacy). Self-efficacy perceptions also predict how engaged a person is with a task, how much effort they put in, and how long they will stick with it once they start it (Pajares, 1997, 2002). As a result, a user's perceived self-efficacy for achievement in the virtual world learning environment impacts how the user acts in that environment, including their learning motivation and their perseverance when encounter difficulties or failure (Cosgrove, 2016).

		Level of familiarity	VAR1 Self-efficacy
Level of familiarity	Pearson Correlation	1	,404*
	Sig (2-tailed)		,020
	N	33	33
VAR1 Self-efficacy	Pearson Correlation	,404*	1
	Sig. (2-tailed)	,020	
	N	33	33
*Correlation is significant at the 0,05 level (2-tailed)			

Table 17 Pearson Correlation for "level of familiarity" and self-efficacy

RQ8: Are there any significant correlation between the level of familiarity of game-based learning method and mouse metrics?

In the RQ8 as we can see in the below table a negative significant correlation was founded, which means that when level of familiarity increases the count speed=0(number of pauses) decreases. A possible explanation of that negative correlation maybe the fact that when a user is familiar with a task it is more possible to move their mouse with a greater speed that a user that process the interface. Also, as far as concern the number of pauses a familiar user it is more possible to control their mouse and make a specific number of pauses than a user that does not feel comfortable with the mouse device.

According to the study, advanced users who understand what the computer can do and how it works are less likely to be disaffected than less advanced users.

Prior research into novice-expert differences has strongly suggested that changes to user interfaces that benefit novices tend to negatively affect experts and vice versa. Expertise studies have revealed that skilled users' standards and responses diverge from those of inexperienced users. NASA Space Station mission experiments, according to Burns et al., discovered significant improvements in speed and accuracy for inexperienced users on some types of displays. On alphanumeric displays, experts made fewer mistakes but showed no difference in response time. Although this study did not compare different display types, it's possible that the two groups' overall performance tolerance levels vary. Experienced users may have a better understanding of the mechanism and be more prepared to receive longer response times. (Hoxmeier, 2000)

			Level of familiarity	Count speed=0 (num of pauses)
Spearman's rho	Level of familiarity	Correlation Coefficient	1,000	-,411*
		Sig (2-tailed)		,018
		N	33	33
	Count speed=0 (num of pauses)	Correlation Coefficient	-,411*	1,000
		Sig. (2-tailed)	,018	
		N	33	33
*Correlation is significant at the 0,05 level (2-tailed)				

Table 18 Spearman Correlation between level of familiarity and count speed=0

8. Possible issues and limitations

This study has some limitations because it is one of the few in the field of mouse tracking and user experience in a game-based learning environment.

First, the method uses a limited set of behavioral and dynamic mouse metrics, and additional research could include additional important emotions (e.g., willingness to learn, perceived ease of use, etc.) as well as mouse metrics (e.g., total number of clicks and many others) or even keyboard incidents.

The matter of generalization is a second significant limitation. The field test selected is based on a small sample size, which may limit the ability to generalize the results. The current study assesses the sample representation based on a group of users who interact with a game-based learning environment, rather than the general group of users. As previously stated, we refer to a population group because the survey participants are not coherent and are divided into groups with different goals, tasks, and activities. The sample size varies by cultural, educational, training, and employment background, computer use experience, age, and types of (dis)abilities, among other factors. While the findings were consistent with other studies on user emotions, the users in this survey may not be indicative of all game-based learning users who complete a task. The user was also not subjected to any time constraints during the experiment. The addition of these components could have a big impact on the outcome.

Furthermore, because this study has a small number of participants, it should be considered a preliminary study, and larger sample size studies should be conducted in the future.

Also, this is essentially experimental research, and the observed differences do not confirm causal relations; our findings should only be regarded as hypothesis generating.

Finally, there may be another possible limitation involved the tool that measure the mouse movement metrics such as time between movements etc. Other tool design maybe captured more precisely the mouse movements and possibly we didn’t lose track of user’s clicks during the game-based learning task. Also, another tool maybe led to differentiated results.

9.Conclusions and Future Work

We looked at the relationship between a set of mouse metrics, both behavioral and dynamic, and users' emotions during a game-based learning task in this paper. Using mouse tracking data, we presented a generalized solution for measuring users' emotions during a game-based learning task. Our work is influenced by the fact that millions of users interact with online content on a daily basis, and that many changes have occurred and distance learning has emerged as a result of the COVID-19 condition in the field of education, without supplying any clear and specific insight into the quality of their sentiments. As a result, any effort to gain a better understanding of user online behavior is regarded as a high-value task. Mouse tracking can meet this need in a cost-effective and scalable way, without removing users from their natural environment. To that end, we detailed a method for extracting deliberate mouse movements from cursor coordinates, which is a high-level representation of cursor interactions. In a game-based learning environment, we wanted to see if users' emotions were reflected in their mouse behavioral and dynamic mouse movements. The measured perceived emotions were self-efficacy, engagement, immersion, enjoyment, confusion, frustration, stress, and dissatisfaction. The mouse behavioral movements we examined were mean speed, variation of speed, mean acceleration, acceleration variation, time between movements, total count of movements, total count of time between movements for short and long pauses, the number of speed pauses, the total time in milliseconds for completing the given task from each user, the count of movements in relation to task completion time, the total count of speed in a task, the number of short and long pauses. To structure the research objectives and distinguish the measured variables, a set of research questions was created. We conducted a small-scale, controlled user study and captured the cursor data of users who interacted with a game-based learning task to explore the survey's research objective. A total of 33 participants (out of a total of 36 users) had their mouse movements monitored. Our research into cursor interactions reveals some interesting connections between mouse movements and user emotion. The results of the field test revealed a significant link between mouse behavioral measurable attributes and users' emotion when interacting with a game-based learning environment. More specifically, we noticed that the variance of time between movements ("behavioral mouse metric" Movement variance means you do the same foundational movement, but slightly change it.) is significantly correlated with frustration, engagement of users during the game-based learning task associated with mean acceleration, the emotion of engagement correlated negatively with mean acceleration, which is means that when engagement increases the mean acceleration decreases, then, age has a significant correlation with total count of movements, speed=0 (number of pauses and total count of time between movements, also, a correlation was founded between level of familiarity and self-efficacy and finally a negative correlation was founded between the level of familiarity and the count speed=0 , which means that when level of familiarity increases the count speed=0(number of pauses) decreases. The purpose of this work is to provide a fundamental research background and inspiration to study further and recognize user behavior in game-based learning environments, and also the correlation among mouse movements and users' emotions while users interact with all these environments, to the HCI science community and to the current field of game-based learning. This survey can be considered as a preliminary work towards the implementation of game-based learning method in education filed for example and explore how users feel with a game-based leaning interface. The findings of this study reveal some intriguing links between mouse movements and pleasant and unpleasant emotions such as self-efficacy, engagement, frustration, stress, and so on. Unlike previous mouse tracking data analysis efforts, our method does not require any manual or expensive efforts (e.g., eye tracking). Additionally, this study makes a significant contribution to the practical assessment of the mouse metrics that have so far been gathered, indicating which ones are or can be useful for future research.

Mouse tracking method as mentioned before is a relative new approach but we consider that mouse movements should researched even more in game-based learning environments to analyze user behavior. As previously stated, there are several other important user behavioral attributes and emotions like user experience, ease of use of a task willingness to learn, curiosity, memorability etc. as well as mouse metrics that could be included in future studies. Another exciting prospect area of study could be combining mouse/keyboard monitoring and eye tracking methodologies to explore user behavior. Furthermore, as stated earlier in the Discussion part, user-modeling methodologies could be established to adapt/personalize game-based learning environments in the field of education, with the aim of boosting user performance and experience, by trying to capture the users' behavior. Finally, as aforementioned, this is preliminary research, and related studies with larger sample sizes are required to resolve generalizability issues and reflect broader populations (such as the student population). Our findings should, hopefully, shed light on the importance of similar human-centered behavioral analyses in the evolution of EUDs and spur future research.

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