Modeling Cognitive Load and Affect in Interactive Game-based Learning Using Physiological Features

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Media use in educational environments has been rapidly developing with the increasing availability and diversity of interactive elements. By understanding how student cognitive load changes when interacting with learning technologies, we can make sense of their learning process and how to provide appropriate, personalized media design to enhance the learning experience. Recent developments in sensing technologies makes it possible to capture learner's dynamic physiological reactions. In this thesis research, we will identify learner's cognitive load when interacting with educational media. We will explore how affective reactions contribute to the modeling of cognitive load and how real-time cognitive load changes alongside learning activities. We focus on modeling such information using physiological reactions that include pupillary, cardiovascular, and electrodermal responses. We are conducting this work in a game-based learning (GBL) environment for reading comprehension. We have implemented a sensing pipeline that will enable the modelling of learner affect and cognitive load. The modeling and analysis from this project could enable the design of interactive learning media that provides real-time adaptation to support learning processes.

Additional Keywords and Phrases: Game-based Learning, Cognitive Load, Affect, Eye Tracking, Physiological Features

1 INTRODUCTION

The widespread use of affordable communication and information technology has stimulated the development of learning media. The use of digital media allows learners to participate from anywhere through virtual learning environments. Media also allow students to access learning materials with richer interactive elements (e.g., animated slides [28], learning games [19], immersive virtual environments [8]), thus improving their learning experiences [24]. However, such diversification has created a challenge surrounding how to design and present personalized support that enhances learning experiences.

Researchers have suggested that complex materials and interactive design features might tax cognitive resources and unnecessarily increase learner cognitive load [22, 23]. Cognitive load has a complex relationship with learning performance [15]. According to cognitive load theory (CLT) [17, 26] and the cognitive theory of multimedia learning [13], the presentation format of information is related to learning performance because the employed formats influence students' working memory and through that their cognitive load. Therefore, how student cognitive load reacts to interacting with learning media is a key component to understanding design for new learning technologies. While prior studies have shown some implications of interactive learning on cognitive load, the exploration of its real-time changes alongside learning activity design has yet to be completed.

Prior work with multimedia learning has begun to consider emotions during the learning process and their influence on learning outcomes [14, 31]. More recent research has suggested this implication of emotion can be explained by its potential contribution to changes in user cognitive load during learning [8, 10, 16]. Such potential interactivity suggests there may be value in jointly measuring these constructs.

Our long-time research goal is to support the design of adaptive learning media. In this thesis project, we will advance this goal by building user models that predict learner's real-time cognitive load reactions to interactive learning media. While prior user modeling studies only focused on either the cognitive or affective responses of learners, we highlight how a learner's affective reactions contribute to cognitive load. To understand this phenomenon and create models that

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capture it, we will conduct user studies with a game-based learning (GBL) platform. The selected environment is an online educational game that is used to develop children's literacy. To collect user data, we have built a sensing platform that can extract and synchronize different types of physiological data. After the experiment, we will perform multimodal analysis to detect learner cognitive load and affect.

2 RELATED WORK

In this section, we describe related studies about cognitive load and affect in learning and discuss how these might be measured.

2.1 Cognitive Load and Affect in Learning

CLT has been applied to improve learning activity and material design for children, teens [27], and older adults [22]. However, it does not explain an important part of the learner experience that is tied to the motivation behind introducing games and multimedia into learning processes: learner affect and motivation.

More recently, neuroscience research has shown that affect and cognition are interrelated rather than independent processes as previously believed [18]. Studies suggest that cognitive and affective behaviors have rich interactions [11]. While considerable research has been performed on the role of affect [30], most have considered affect independently from cognitive load. For example, prior work found a relationship between longer periods of boredom and lower scores [3]. However, the type of negative affect is important; students might have better learning performance when given erroneous examples even though those examples produced confusion and frustration [2].

While some argue the interrelatedness of affect and cognition, there is no consensus on how to incorporate affect into cognitive load modeling. Some argue affect could increase extraneous cognitive load because emotion regulation may add non-task-related processing that consumes extra cognitive resources [6]. Others have suggested that affect could be considered beneficial as it can foster motivation so that learners invest more cognitive effort [9].

2.2 Measurement of Cognitive Load and Affect

Subjective rating scales as well as task- and performance-based methods have often been used to measure cognitive load. However, each of these methods is limited in its ability to capture this information. Subjective rating scales (e.g., NASA task load index [7]), which are grounded in a belief that people can report the amount of mental effort they have expended, are not always well suited to capturing automatic or unconscious processes. In task- and performance-based methods, the introduced measurement tasks may interfere with the primary task when a reaction is necessary despite their requiring the use of few additional cognitive resources [4]. What's more, these methods have relied on post-experiment data analysis so they typically fail to support continuous monitoring.

Recently, methods that rely on physiological data have presented the potential to address this issue. Among them, eye-tracking technology provides information about pupillary response, which is considered a reliable source that enables the investigation of cognitive processes [10]. Moreover, increased cognitive load is generally associated with increases in pupil diameter [1], and user gaze trajectory data is considered a reliable indicator of reading behavior [24, 30]. Such visual information is the key to investigating learner attention patterns and strategic processes.

In the context of affect measurement, psychometric methods (i.e., self-reports) have been used but they rely on the user's ability to understand and communicate their affective responses. New physiological sensing approaches address this problem by allowing researchers to capture proxies that can be used to infer user affect [21]. While brain-activity-based methods, such as electroencephalography (EEG), require wearing complex instruments that can be obtrusive to users, physiological arousal data, such as Electrodermal activity (EDA) and skin temperature, can be extracted with light wearable sensors. Thus, they are considered more suitable for this project.

In this thesis project, user physiological features (i.e., eye-tracking data and EDA responses) will be incorporated with questionnaires that measure cognitive load and affect.

3 RESEARCH QUESTIONS AND APPROACH

Considering that we do not know how cognitive load and affect interact during game play, we will *model students' cognitive load and affect in a game-based learning environment.* Learner data will be collected during gameplay and models will be developed using this data to answer the questions below.

3.1 What does affect contribute to the modeling of cognitive load during GBL?

In this project, hidden Markov models (HMM) will be used to model dynamic cognitive load. Learner physiological reactions will be used as observable signals to estimate the hidden cognitive load state. Two HMMs will be developed. The first will use physiological features, i.e., heart rate and pupil dilation (PD). The second will build on the first by adding EDA information as input. These models will be supervised using participant responses to the cognitive load and affect questionnaires. The performance of these two models will be compared to see how including affect information affects the modelling of cognitive load.

3.2 How does learner affect and cognitive load change alongside their learning when interacting with a GBL environment?

To answer this question, we will investigate cognitive load and affect dynamics across learning activities. This analysis will focus on how the media and game design contribute to changes in affect and cognitive load. We are particularly interested in how the user interface design contributes to these latent states.

Analyses for this question will include linking gameplay behaviors and performance (i.e., score, task completion) to their affective states and cognitive load. We will use two types of behavioral data: (a) gaze information (i.e., trajectory and gaze point) and (b) system interaction logs (i.e., questions answered and mouse clicks). The interaction logs will provide information about how learning-activity design contributes to these latent states. The eye-gaze data will provide information about what contributes to increasing cognitive load or changes in affect. These two sources of data can be triangulated to better understand what is happening at critical moments (the moment when cognitive load or affect change).

Ideally, we will also compare the cognitive load and affect of students who performed similarly. This comparison will be across learning session(s) to explore whether those students have similar behavioral patterns.

4 PROGRESS TO DATE AND FUTURE WORK

So far, we have implemented our sensing platform and designed the case study. Our institutional Research Ethics Board (REB) has approved our case study plan, and we have begun piloting. Our next step is to collect data and build models. In the future, we will investigate how our modeling can explain student learning trajectories and use our models to inform learning media design.

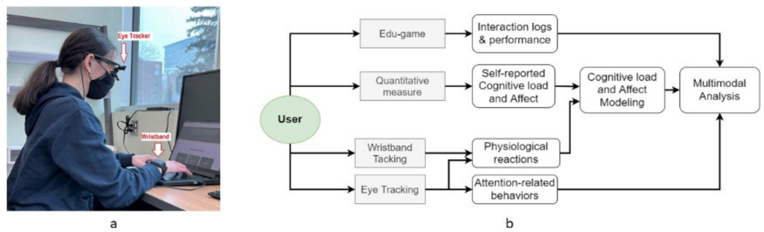

Figure 1. Study Overview: (a) shows the device set up and (b) shows the overall process

4.1 Sensing System

We will use multimodal analysis to support the recognition of cognitive load and affect. We built a sensing platform that reliably collects data while allowing users to remain relatively comfortable (Figure 1-a). Our platform captures learners' physiological reactions. The captured sensor data can then be used to infer cognitive load and current affective states. Two classes of real-time physiological features will be collected: (a) pupil dynamics from an eye tracker and (b) cardiovascular and EDA data from non-invasive wearable sensors. Part of the developed system synchronizes the time-series data from these different sensors to facilitate later analyses. The sensing platform supports real-time data streaming, recording, and synchronization.

4.2 User Study

In addition to participant demographics, we will collect three types of data (Figure 1-b): (a) learner performance and interaction from the game, (b) physiological data from sensors, and (c) self-reports.

We will recruit 35 students from an English as an additional language course. Each student's participation will involve approximately 60 minutes of gameplay (Figure 2) and an additional 30 minutes of other activities. The base-building game integrates literacy and English language arts tasks as a mechanic to enable learners to defend their virtual home from invaders. This helps create an interactive and potentially engaging learning experience.

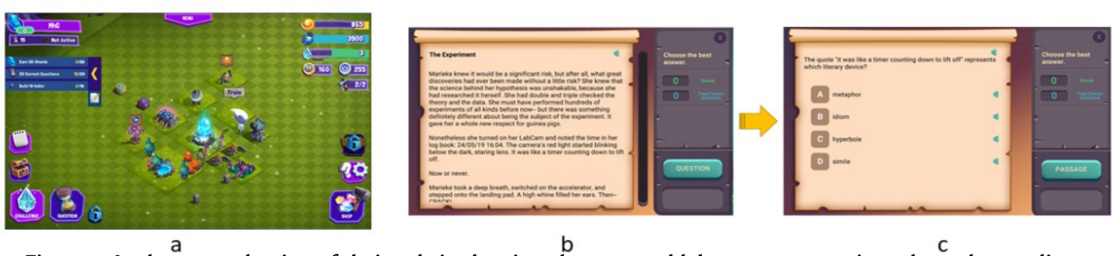

Figure 2. In the strengthening of their role in the virtual game world, learners are motivated to solve reading tasks with appropriate difficulty levels. In the (a) game interface, users click the question button and try to get game points by reading a (b) passage and answering a comprehension question. Users also answer (c) English-language arts questions to earn points.

Sensor calibration will follow consent. During game play, sensors will be used to collect data and self-report measures of cognitive load and affect at regular intervals (~ every 7 min). We will collect demographics at the end.

The self-report measures will be used to verify our sensor-based measurement. We follow the definition of CLT [26], dividing cognitive load into three types: intrinsic, extraneous, and germane. Based on prior work [12], we developed

Likert-scale items to measure all three types of cognitive load. For affect, we adopt an established scale – the international positive and negative affect schedule short-form (I-PANAS-SF) [29] – to measure learner affect.

We will collect participants' demographic information using a questionnaire. In addition to basic information (e.g., age, gender), we will collect information about participants' language-learning background (e.g., mother tongue, IELTS/TOEFL scores).

4.3 Future Work

In our further work, we plan to explore if our modeling of cognitive load helps predict the learner's knowledge during GBL. If our modeling can better explain student learning trajectories, we will incorporate these models so that they inform learning media design.

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