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Overcoming foreign language anxiety in an emotionally intelligent tutoring system

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OVERCOMING FOREIGN LANGUAGE ANXIETY IN AN EMOTIONALLY INTELLIGENT TUTORING SYSTEM

BY

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OVERCOMING FOREIGN LANGUAGE ANXIETY IN AN EMOTIONALLY INTELLIGENT TUTORING SYSTEM

Abstract

Learning a foreign language entails cognitive and emotional obstacles. It involves complicated mental processes that affect learning and emotions. Positive emotions such as motivation, encouragement, and satisfaction increase learning achievement, while negative emotions like anxiety, frustration, and confusion may reduce performance. Foreign Language Anxiety (FLA) is a specific type of anxiety accompanying learning a foreign language. It is considered a main impediment that hinders learning, reduces achievements, and diminishes interest in learning.

Detecting FLA is the first step toward reducing and eventually overcoming it. Previously, researchers have been detecting FLA using physical measurements and self-reports. Using physical measures is direct and less regulated by the learner, but it is uncomfortable and requires the learner to be in the lab. Employing self-reports is scalable because it is easy to administer in the lab and online. However, it interrupts the learning flow, and people sometimes respond inaccurately. Using sensor-free human behavioral metrics is a scalable and practical measurement because it is feasible online or in class with minimum adjustments.

To overcome FLA, researchers have studied the use of robots, games, or intelligent tutoring systems (ITS). Within these technologies, they applied soothing music, difficulty reduction, or storytelling. These methods lessened FLA but had limitations such as distracting the learner, not improving performance, and producing cognitive overload. Using an animated agent that provides motivational supportive feedback could reduce FLA and increase learning.

It is necessary to measure FLA effectively with minimal interruption and then successfully reduce it. In the context of an e-learning system, I investigated ways to detect FLA using sensor-free human behavioral metrics. This scalable and practical method allows us to recognize FLA without being obtrusive. To reduce FLA, I studied applying emotionally adaptive feedback that offers motivational supportive feedback by an animated agent.

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My most extraordinary dedication is to our God. Without your support, this work wouldn't be possible. You stood with me on my good and bad days. You provided me with countless blessings. All my praises and thanks are to you.

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Chapter 1

Introduction

1.1 Overview

Learning can be significantly affected by emotions. If the learner has positive emotions, that can encourage learning and enhance interest in studying, while if the learner has negative emotions, that can reduce achievement and lessen self-confidence. Foreign language learners especially encounter cognitive and emotional challenges, such as anxiety, that influence their learning success.

Foreign Language Anxiety (FLA) is a feeling of tension, stress, or worry when learning a foreign language (Hayasaki & Ryan, 2022; Horwitz et al., 1986; MacIntyre & Gardner, 1994). It is a situation-specific anxiety with similar manifestations to test or math anxiety, but it appears when learning a foreign language. As will be detailed in Section 2.2.2, FLA affects learners' physical, psychological, and learning performance. It also interferes with motivation and interest in learning a foreign language. Significantly, FLA obstructs cognition and attention. Furthermore, it hinders foreign language proficiency development and the ability to master the language. Therefore, there is a need to study methods to detect and overcome FLA.

Accurately detecting FLA is the first step to recognizing it and, eventually, reducing and overcoming it. Identifying FLA from user behavior would be an advance that would allow us to detect FLA with minimal interruptions. Once best measuring techniques have been identified, finding approaches to alleviate FLA and defeat it is an important contribution that would produce a positive learning environment and improve learning. Moreover, it would boost interest to learn, raise motivation, increase confidence in communicating in a foreign language, and improve mental and physical health.

1.2 Problem Statement

Learning a foreign language is challenging because there are cognitive and emotional obstacles. Therefore, understanding learners' behaviors and emotional states is essential to enhance foreign language learning. Discovering techniques to identify and reduce FLA would allow us to build an effective learning environment full of positive emotions and educational achievements.

To detect FLA, researchers have used various methods such as physical measures (see Section 2.3.1), self-reports (see Section 2.3.2), and facial recognition (see Section 2.3.4). The benefits and limitations of these approaches will also be discussed in Section 2.3. In general, physical metrics, also called sensor-full metrics, can provide more reliable results because they are more direct. However, such techniques can bother the learners and make them uncomfortable (see Section 2.3.1). Self-reports are practical because they are easy to administer and it can be easy to analyze the results. However, they can also be unreliable because some people provide inaccurate answers, hiding their feelings, whether intentionally or not (see Section 2.3.2). Finally, existing facial recognition applications reliably detect only basic emotions, not anxiety, which may result in inaccurate interpretation (see Section 2.3.4). To better capture FLA in the context of an e-learning system, this study investigated using sensor-free human behavioral measures, which detect FLA with minimal user interruption and without obstructing the learning process.

To reduce FLA, several approaches have been used, such as intelligent tutoring systems (Section 2.4.1), games (Section 2.4.2), or robots (Section 2.4.3). These interventions sometimes, but not always, reduce anxiety. They can also produce side effects that reduce learning. Full details of these interventions, their advantages, and drawbacks are also described in Section 2.4. Furthermore, adaptive difficulty could lower anxiety, but it is insufficient for high learning gain (see Section 2.4.1.1). Animated agents that provide coping messages have been shown to reduce math anxiety (see Section 2.4.4.2). My research transferred that approach to alleviating FLA, focusing on an adaptive animated agent that provides motivational supportive feedback. This method is not disruptive to learning and is scalable because it can be deployed in a web-based system.

The main objectives of this research are:

- To investigate different approaches for detecting FLA using sensor-free human behavioral measures.
- To determine effective ways to alleviate FLA.
- To establish the effectiveness of an adaptive, emotionally intelligent tutoring system for reducing FLA.

Measuring FLA within an e-learning system is essential because online educational platforms have become a prime source for knowledge acquisition. Reducing FLA is beneficial for increasing learning and positive emotion.

1.3 Research Questions

The ultimate outcome of this research is to find ways to detect and alleviate FLA in the context of an e-learning system. The research questions are described below.

1.3.1 Detecting FLA

Research Question 1: Can FLA be detected using sensor-free human behavioral metrics in an e-learning context?

Sensor-free human behavioral metrics detect emotions without using any physical sensor. I created three sub-questions to address research question 1. The first sub-question is focused on understanding the relationship between in-class and online FLA. As will be discussed in Section 2.2.2, there are interrelationships among anxiety-producing situations, and investigating these relationships would help researchers detect and reduce anxiety. So, the first question is:

RQ 1.1: Do metrics for classroom FLA help predict FLA in an online system?

As will be discussed in Section 2.2.2, task complexity is one of the main factors that affect FLA. However, there are some researchers who did not find a significant interaction between task complexity and anxiety (Kim & Tracy-Ventura, 2011). To understand the relationship between FLA and task complexity I created the following Research Question:

RQ 1.2: What is the relationship between FLA and the difficulty of the exercise?

Using sensor-free human behavioral metrics to detect FLA has potential benefits because they are practical and scalable measurements. It has been successfully used to detect emotions like motivation, frustration, and confusion, but not yet FLA (see Section 2.3.5). To find out how to detect FLA using sensor-free human behavioral metrics I created the following Research Question:

RQ 1.3: Can FLA be identified by the learner's interaction with the system?

1.3.2 Interventions to Reduce FLA

Research Question 2: Can FLA be effectively reduced by different types of feedback, different modalities of feedback presentation, or a combination of the two?

This research compared two types of feedback: explanatory feedback alone and explanatory feedback with motivational support. In addition, it examined three modalities of feedback presentation: text only, voice with text, and animated agent with text and voice. Because the answer to this research question might depend on the learner and their context, there are four sub-questions. The first sub-question asked whether user answers could impact the effectiveness of the motivational supportive feedback. Getting benefits from motivational supportive feedback is subject to various factors, such as the learner's academic achievement (see Section 2.4.5). Considering these facts, Research Question 2.1 is:

RQ 2.1: Does the correctness of the learner's answer impact the effectiveness of motivational, supportive feedback?

Reducing FLA will increase learning, boost positive emotion, improve grittiness, and promote a growth mindset (see Section 2.2.2). An animated agent can reduce shyness and worry and improve the willingness to communicate in a foreign language, which alleviates anxiety. Moreover, animated agents that provide coping motivational feedback have been shown to reduce anxiety in a math context. Similarly, using conversational agents that provide empathetic feedback could reduce FLA (see Section 2.4.4.2). To understand the effectiveness of an animated agent that provides motivational supportive feedback to reduce FLA, I created the following Research Question:

RQ 2.2: Are there interactions between feedback type and modality when reducing FLA?

Learners' anxiety levels and performance differ by gender. Gender differences impact individual emotions and learning achievements. Males and females react differently in class (see Section 2.2.2). Understanding gender differences is essential for learning success (see Section 2.4.5). To find whether there is an interaction effect between gender, feedback type, and modality I created the following Research Question:

RQ 2.3: Are there interactions between gender, feedback type, and modality when reducing FLA?

FLA is affected by various situational variables such as teacher behavior or course difficulty and learner variables like gender or age. Also, the learner's academic achievement and performance affect their FLA (see Section 2.2.2). Understanding the relationship among anxiety variables would help to reduce it and eventually overcome it. To address these factors, I created the following Research Question:

RQ 2.4: Are there interactions between gender, performance, feedback type, and modality for reducing FLA?

1.3.3 Adaptive Feedback

Research Question 3: Is an adaptive motivational feedback strategy more effective than a fixed feedback strategy?

To find whether an adaptive feedback approach sensitive to the learner's emotion is more effective than a fixed feedback approach, I created the following four sub-questions. Studying the effectiveness of an emotionally adaptive system — i.e., one that responds to the learner's anxiety level — could help provide better FLA reduction. It is beneficial to offer adaptive emotional support because it helps alleviate negative emotions when learning (see Section 2.4.5). As will be discussed in Section 2.4.1, adaptive systems can increase learning gain. To figure out how effective adaptive feedback is for reducing FLA, and for increasing learning, I created Research Questions 3.1 and 3.2:

RQ 3.1: How effective is an adaptive feedback approach relative to a fixed feedback approach for reducing FLA?

RQ 3.2: How effective is an adaptive feedback approach relative to a fixed feedback approach for increasing learning?

Prior-knowledge could affect the learner's anxiety levels (see Section 2.2.2). Low-knowledge learners often benefit from the cognitive adaptive feedback more than high-knowledge learners (see Section 2.4.1). To find out if adaptive motivational supportive feedback is effective for low-knowledge learners, I created the following Research Question:

RQ 3.3: Is there a difference between the effectiveness of adaptive emotionally supportive feedback on low vs. high knowledge learners?

Anxious and non-anxious learners behave differently in foreign language learning classes (see Section 2.2.2). To understand whether adaptive motivational supportive feedback is effective for anxious and non-anxious learners, I created the following Research Question:

RQ 3.4: Is there a difference between the effectiveness of adaptive emotionally supportive feedback on anxious vs. non-anxious learners?

1.4 Contributions of this Work

This work attempts to identify effective means of detecting learners' FLA from their behaviors; it further attempts to identify effective means of lessening learners' FLA. Through this study, I investigated the effectiveness of detecting FLA using human behavioral metrics. I studied multiple interventions that could reduce and eventually overcome FLA within an e-learning system. To my knowledge, this is the first study to detect FLA using sensor-free human behavioral measures. Also, I examined interventions to reduce FLA when learning English as a second language, using a combination of various feedback types and modalities. Finally, I studied the effectiveness of adaptive feedback in reducing FLA.

1.5 Potential Applications

The system detects FLA using sensor-free human behavioral metrics. The features I used to recognize FLA can be applied to any e-learning system. Developers can incorporate the emotionally intelligent tutoring system into any foreign language education system to help detect FLA. It can help teachers/researchers to recognize learners' emotional state and provide support when needed in addition to assisting the learners in reducing their FLA.

Another potential application of the emotionally intelligent tutoring system is to reduce FLA. The system uses adaptive feedback varied between motivational supportive, and explanatory feedback presented by text, voice, or agent. This can assist learners in learning a foreign language without experiencing negative emotions, and can improve their learning.

Chapter 2

Related Work

The three research questions offered in the previous chapter address the identification and reduction of foreign language anxiety within an adaptive system. In this chapter, I will discuss the previous literature on emotions in learning environments by examining the relationships between emotions and cognition and discussing the impact of emotions on learners' behavior. I will focus on anxiety as a special case of negative emotions, specifically foreign language anxiety. I will describe how to measure emotions using physical measures, self-reports, expert observers, facial expressions, and human behavioral metrics. Also, I will examine how to reduce foreign language anxiety using intelligent tutoring systems, games, robots, animated agents, and emotional support.

2.1 Emotions and Learning

Emotions play a critical role in forming human cognition, actions, and decisions (Lopatovska & Arapakis, 2011), affecting physiological, psychological, behavioral, expressive, and motivational functions (Plass & Kaplan, 2016; Solomon, 2004). There is an interrelation between emotion and cognition, which affects learning (C.-M. Chen & Wang, 2011; Lopatovska & Arapakis, 2011; Trigwell et al., 2012). This relationship is bidirectional. Students who experience positive emotions are more likely to succeed. High achiever students mostly tend to encounter positive emotions. Conversely, learners who experience negative emotions would be more likely to fail. Students with trouble learning tend to have negative emotions (Trigwell et al., 2012). Motivation, engagement, and pride enhance learning, while frustration, confusion, and anxiety may reduce it (Harley et al., 2016; Trigwell et al., 2012).

Various aspects such as the topic, difficulty of the material, or medium for content delivery affect emotional status. For example, extremely easy material could produce boredom, while challenging elements could result in frustration and anxiety (Chaffar & Frasson, 2010). E-learning systems that are difficult to use and access can induce negative emotions (Ismail & Hastings, 2019).

Defining emotions as simple "negative" and "positive" emotions does not help us to identify the root of the problem or to find effective solutions. Researchers have classified emotions into families based on their characteristics and the nature in which emotions occur (Ekman, 1992).

2.1.1 Emotion Theories

There are various emotion theories based on manifestation and the structure of how emotion appears. Cognitive theories of emotions, a manifestation sub-group, explain how the mind organizes conscious and unconscious information to perceive emotions (Oatley & Johnson-Laird, 2014). It expresses how beliefs, judgments, desires, and behavior affect emotional experience (Ortony et al., 2022; Reisenzein, 2020).

Psychologists developed variants of cognitive emotion theories, such as appraisal theory, action readiness theory, or communicative theory of emotion. *Appraisal theory*, first proposed by Arnold (1960), explains how emotions are directed by events and situations. This state depends on factual beliefs and evaluation (Reisenzein, 2020). According to Arnold (1960), emotions are driven to or from the object appraised based upon whether an individual has had positive or negative past experiences with the object. The improved versions of the appraisal theory include appraisal plus additional assumptions or components (Reisenzein, 2020). The causal interpretation considers emotions as a separate noncognitive state like feeling pleasure (Ortony et al., 1988; Reisenzein, 2020).

Action readiness theory of emotions refers to the states behind the actions that prioritize a specific goal, emotional feeling, and expressive behavior (Frijda & Parrott, 2011; Oatley & Johnson-Laird, 2014). Specifically, it describes the motive behind action tendencies and emotional responses, either with physiological or psychological indicators. Emotion-relevant appraisals generate the goals of these actions by influencing an integrated structure based on the intensity of the emotions through desirability, praiseworthiness, and appealingness (Frijda & Parrott, 2011; Ortony et al., 2022).

The communicative theory of emotion assumes a connection between emotion and cognition in the nervous system, which affects actions and behaviors (Oatley & Johnson-Laird, 1987). Particularly, it provides explanations about emotional developments and their role in cognition, reasoning, and relationships (Oatley & Johnson-Laird, 1987, 2011).

Emotions are feelings that explain individual emotional responses based on action dispositions (Frijda & Parrott, 2011; Kallinen & Ravaja, 2006). These responses can communicate to others through facial and vocal expressions, gestures, and postures (Oatley & Johnson-Laird, 2014).

Some researchers categorize emotions based on the structure as discrete or continuous. The discrete approach is divided into basic emotions or combinations of basic emotions. The basic emotions are happiness, surprise, disgust, sadness, fear, and anger (Du et al., 2014; Ekman, 1992; Imani & Montazer, 2019; Johnson-Laird & Oatley, 1989; Levenson, 2011). The combination of emotions (Ekman, 1992; Imani & Montazer, 2019) includes anxiety, a variant of fear.

Some researchers argued that categorizing emotions as basic emotions is vague and limited because Ekman (1992) theory could not explain emotion disorders, behavioral genetics, or temperament psychology (Posner et al., 2005). Also, Ekman (1992) only identified these six basic emotions while all emotions are distinct, equally important, and researchers can recognize them (Frijda

& Parrott, 2011; Hume, 2012; Ortony et al., 2022; Russell, 2009; Wehrle & Kaiser, 1999). Given this evidence, researchers suggest classifying emotions not as discrete but as continuous along two or more dimensions (Frijda & Parrott, 2011; Imani & Montazer, 2019; Russell, 2009).

One of the suggestions proposes the circumplex model of emotion, which is a two-dimensional circular space with valence (pleasantness) and arousal (activation) dimensions (Imani & Montazer, 2019; Posner et al., 2005; Russell, 1980). This model can represent any emotion at all levels, from low to neutral to high activation and pleasant. Psychologists use it to assess emotional self-report and cognitive structure (Russell, 1980). Other researchers represent emotions as groups that have similar characteristics and form identical reactions to events, agents, and objects. These reactions generate three classes of emotions: pleased vs. displeased, approving vs. disapproving, and liking vs. disliking (Ortony et al., 2022).

Other researchers define emotions as combinations of cognition- and learning-centered emotions that learners may encounter in a learning context. They include positive and negative emotions such as motivation, engagement, boredom, confusion, and frustration (D'Mello & Graesser, 2013; A. Graesser & D'Mello, 2012; Tettegah & Gartmeier, 2016). These usually happen during problem-solving contexts. Some researchers count anxiety as a learning-centered emotion because it often fluctuates from moment-to-moment while learning. However, since anxiety mainly occurs in high-stakes situations, such as testing (A. Graesser & D'Mello, 2012) or starting a new job, it is often viewed as a separate category.

2.1.2 Emotions and Cognition

Emotion, cognition, and learning interact in many ways. In this section, I will describe how important it is to understand learners' emotional states to provide an effective learning environment. Also, I will elucidate the integration between emotions and cognition in the brain, especially when people feel fear or anxiety. Finally, I will highlight emotional intelligence and how it helps to reduce negative emotions such as anxiety.

2.1.2.1 Relationship Between Emotion and Mind

Researchers have studied the psycho-physiological state, which involves understanding the relationship between emotion, body, and mind. The psycho-physiological state of learners influences their behavior and performance. An imbalance of the psycho-physiological state negatively affects the learner's body and mind. For example, when a person is feeling anxious, it will reflect on their heart rate and cognitive processes. Understanding learners' psycho-physiological state can help provide an effective learning environment. If teachers recognize learners' mental and emotional status, they can react according to their needs (Bigdeli, 2010). Experiencing an emotion arouses the mind, which may react by producing physical actions. The environment, of course, also can affect the body (Bigdeli, 2010).

From a psychological perspective, these workings of the mind are generally categorized into what Kahneman (2011) referred to as System One and System Two. System One is the unconscious part that is responsible for perception and behavior. It helps in deciding if a situation is good or bad. System Two is the rational mind, the conscious part that monitors operations with self-awareness, solves problems, and analyzes an event. Both systems work tightly together and guide each other to react to certain behaviors and environments. An equilibrium between the two systems helps the mind make wise decisions, while their imbalance may produce irrational behaviors such as anxiety and fear (Eagleman, 2011; J. Johnson, 2020; Kahneman, 2011; Oatley & Johnson-Laird, 2011).

From a neuroscience perspective, specifically neurophysiology, there are complex interactions between emotion and cognition (Izard, 1984; Oatley & Johnson-Laird, 2014; Scult & Hariri, 2018). The brain's architecture works in integration across the neural networks (Bolls et al., 2019). Each brain region is sensitive to a wide spectrum of signals. Each of them affects and is affected by another (Pessoa et al., 2019). This connection creates a comprehensive communication between emotions and cognition, which impacts behavior (Oatley & Johnson-Laird, 2014).

Neurophysiology is the domain that studies this brain process (Tyng et al., 2017). Different emotions spark distinct neural circuits in the brain that are reflected in expression, behavior, and feeling. There would be no cognition as we know it if no neurophysiological processes boost emotion (Izard, 1984). Some brain structures and neural activities are more connected to emotional and cognitive behavior (Izard, 1984).

There are activation and inhibition of specific areas in the brain when experiencing FLA. For instance, the "limbic system" mainly manages this emotional and cognitive process. It consists of the "hippocampus" and the "amygdala". The hippocampus is the brain structure that processes learning and memory. Also, it is the key element for the motivational basis for selective attention (Izard, 1984; Tyng et al., 2017), which makes learners focus on specific tasks. The amygdala is part of the brain that is responsible for emotional activities and interoceptive awareness (Eagleman, 2011; Knight et al., 2019; Oatley & Johnson-Laird, 2011; Okon-Singer et al., 2015; Tyng et al., 2017), which helps people to be mindful and aware of what they are experiencing or feeling. It reacts to strong emotions like fear (Eagleman, 2011; Oatley & Johnson-Laird, 2011) and anxiety (H. Jeong et al., 2015) by sending alarm signals to various parts of the brain, which reflect in the activation of hormones, the cardiovascular system, or immobilization of muscles.

This reaction causes an effect called *amygdala hijacking*. In other words, when people experience fear, they act rashly, unexpectedly, and sometimes negatively. This behavior can impact daily activities like learning (Goleman, 2011, 2012), including learning a foreign language (H. Jeong et al., 2015). To prevent amygdala hijacking, researchers suggest using emotional intelligence techniques such as empathy, self-awareness, and self-management (Goleman, 2011, 2012).

For example, foreign language anxiety causes hyper-activation in the insular cortex, especially during communication or interpersonal tasks (H. Jeong et al., 2015). At the same time, there was deactivation in the left insula and orbitofrontal cortex (H. Jeong et al., 2015). The "insular cortex" is another part of the brain that also connects the emotional and cognitive processes

(Berntson et al., 2011). There is a reciprocal connection between the insular cortex and the limbic system (Berntson et al., 2011; Gogolla, 2017), defined as processual and structural relationships (Gogolla, 2017). Within the insular cortex, specifically, the "anterior insula" serves as the basic node in the brain, which is responsible for cognitive-emotional interactions (Gu et al., 2013). It is associated with valence/arousal activation, recognition, attention, decision-making, perception, and processing (Berntson et al., 2011; Gu et al., 2013).

When looking at brain activation using FMRI techniques while processing a foreign language task, researchers found high activation in the right insula (Tai et al., 2020). This activation is connected to anxiety and risk-taking, also linked to cognitive overload (Tai et al., 2020). Specifically, students with high foreign language anxiety had high activation of the left superior temporal gyrus and left precentral gyrus (Weekes, 2020). While the low anxious group had high activation of the ventral anterior cingulate cortex (Weekes, 2020).

2.1.2.2 Emotional Intelligence

Emotional intelligence refers to perceiving and recognizing emotions (one's own or another's) to facilitate thoughts (Berenson et al., 2008; Brackett et al., 2004; Gkonou et al., 2017; Law et al., 2020; Matthews, 2005) and ultimately regulate them to assist problem-solving and reasoning (Brackett et al., 2004). Emotional intelligence's main role is to balance cognition and emotions (Brackett et al., 2004).

Emotionally intelligent learners have self-perceptions which allow them to regulate, control, and express their emotions. They know how to show empathy and adaptability and manage stress (Berenson et al., 2008; Dewaele et al., 2008; Goleman, 2012; Law et al., 2020; Matthews, 2005). Being aware of self and others' emotions promotes positive reactions. Individual differences in emotional intelligence positively correlate with success, while negativity correlates with failure. In particular, higher emotional intelligence is associated with calmness and negatively correlated with anxiety. In short, high levels of emotional intelligence promote healthy well-being and a successful life (Brackett et al., 2004; Gkonou et al., 2017; Goleman, 2012; Mohanan et al., 2017; Pishghadam, 2009).

Teaching students social-emotional skills provides them with the tools to be emotionally intelligent, helping them to develop their learning achievements and future success. The fostering of learners' soial-emotional skills allows them to regulate their negative emotions and to improve their academic performance (Berenson et al., 2008; MacCann et al., 2020; Matthews, 2005). Moreover, it increases the learner's self- and social awareness, which results in understanding oneself's and others' emotions (MacCann et al., 2020). Finally, it improves self-control, self-efficacy, and resilience, which results in higher achievement (Berenson et al., 2008; MacCann et al., 2020; Pishghadam, 2009). Educators should also be interested in teaching social and emotional learning because it promotes equity and tolerance by inducing acceptance and diversity (Matthews, 2005).

Some researchers have used emotional intelligence to predict learner achievement (Berenson et al., 2008; Pishghadam, 2009). Regarding foreign language learning, they have found that emotional intelligence plays a critical role in achievement (Pishghadam, 2009), especially when looking at the intrapersonal and stress management factors. The intrapersonal dimension includes self-awareness, self-regard, self-actualization, assertiveness, and independence. Stress management provides stress tolerance and self-control (Pishghadam, 2009). The ability to practice emotional intelligence may reduce anxiety and stress because the learner will focus on the task and practice recognition and control. Indeed, students who lack emotional intelligence tend to have high foreign language anxiety (Dewaele et al., 2008). Therefore, researchers suggest teaching foreign language learners emotional competence to reduce anxiety (Pishghadam, 2009).

Since emotional intelligence is beneficial within and outside learning, researchers have attempted to simulate it in robots and animated agents to provide an affective, responsive, real-time learning experience. Researchers used emotional intelligence to support learning performance, learners' emotional states, and perception (Romero-Hall et al., 2016). Their system can show emotional intelligence by perceiving and understanding learners' emotional state, then communicating in empathic ways (Law et al., 2020; Romero-Hall et al., 2016). Robots with high emotional intelligence are more favorably accepted and trusted by learners (Law et al., 2020). Emotional intelligence has been coded into animated agents; these agents increase the interest to learn, encourage the learners to do more exercises, and improve their confidence (Karumbaiah et al., 2017). Therefore, systems that provide emotional intelligence and empathetic feedback to the learner improve the system interaction and learning performance (Karumbaiah et al., 2017).

2.1.3 Impact of Emotions on Learning

2.1.3.1 Impact of Positive Emotions on Learning

Emotions affect attention, cognition, perception, and memory recall (Izard, 1984; Tyng et al., 2017). Sometimes, experiencing positive emotions could distract learners' attention, hinder working memory resources, and reduce their enthusiasm to work hard (Pekrun et al., 2002). For example, relief impairs learning because sometimes, when learners feel a lack of concern they do not work hard which decreases their performance (Pekrun et al., 2002). On the other hand, experiencing joy or pride induces learning and improves the emotional state. Experiencing positive emotions increases long-term memory performance and organizes working memory activities (Ammar & Neji, 2007; C.-M. Chen & Wang, 2011; Tyng et al., 2017).

Specifically, positive moods, such as enjoyment or pride, enhance self-regulation, which fosters problem-solving, encourages creative thinking, and facilitates performance (Pekrun et al., 2002). Other positive emotions such as delight, excitement, and eureka improve cognitive processes and increase learning performance (Shute et al., 2015). Moreover, some positive emotions, such as motivation, engagement, and interest, promote cognition and motivate research and investigation(Izard, 1984). Precisely, a learner's affective state is associated with motivation. When learners become interested in learning, they also become motivated. That stimulates cognition and promotes exploring and active engagement (Craig et al., 2004; Izard, 1984).

Highly motivated learners receive boosts in their self-efficacy to learn (Van der Meij et al., 2015; N. Wang & Johnson, 2008). Experiencing enjoyment or pride fosters effort, motivation to learn, and achievement (Pekrun et al., 2002).

In conclusion, while some positive emotions can have negative impacts on learners, overall, they tend to promote learning achievements and produce a successful learning environment (Craig et al., 2004; Harley et al., 2016; Küçük et al., 2014). Activating positive emotions improves recognition (Tyng et al., 2017), induces critical thinking, promotes an enjoyable learning environment, and supports elaboration and organization (Pekrun et al., 2002).

2.1.3.2 Impact of Negative Emotions on Learning

There are conflicting opinions about the impact of negative emotions in learning environments. Negative emotions, like confusion, may motivate learners to seek help, search, and investigate to obtain clarification (Petrovica & Ekene, 2016; Tyng et al., 2017; Wixon et al., 2014). Although moderate negative emotions, such as anxiety and stress, might promote attentive, dedicated learning, having too many negative emotions might produce an opposite effect (C.-M. Chen & Wang, 2011; Tyng et al., 2017). However, other researchers claim that all negative emotions in learning can limit the learned information, hinder memory recall, and reduce retention (Tyng et al., 2017).

Negative emotions affect cognition and perception negatively (Ammar & Neji, 2007). For example, anger reduces confidence and productivity (Izard, 1984). Anxiety impairs learning and memory, which can cause negative consequences such as mental insufficiencies, attention deficit, and lack of enthusiasm (Tyng et al., 2017). A negative emotion reduces motivation and confidence (Lai & Wen, 2012). Students who face confusion may consequently experience frustration when they cannot solve problems, follow up, or tackle challenging material, which produces a desire to give up on learning and thus reduces their learning achievement (Y.-M. Huang & Huang, 2015).

Researchers have found that a negative emotional state reduces learning performance and cognitive processes (C.-M. Chen & Wang, 2011; Wixon et al., 2014). Therefore, reducing negative emotions can increase cognition, learning acquisition, and training (C.-M. Chen & Lee, 2011).

2.2 Anxiety

2.2.1 Anxiety in General

This dissertation focuses on anxiety because of its significant effect on foreign language learning. Anxiety is considered a special case of negative emotions associated with worry, discomfort, fear, nervousness, or stress (Bigdeli, 2010; Bletzer, 1986; Horwitz et al., 1986; Kazdin, 2000). Based on the Yerkes-Dodson law, experiencing moderate anxiety or stress could improve performance, while encountering high anxiety is disruptive. Having minimal anxiety would block enthusiasm to learn and work hard because it eliminates the stimulus to improve, pay attention, and maintain interest. Previous research has suggested that high anxiety hinders learning and cognitive activities because it blocks memory recall, shifts focus and hinders basic brain functions (Gkonou et al., 2017; M. Liu, 2006; Tyng et al., 2017). Thus, while moderate anxiety is beneficial because it motivates the learner to focus and endeavor, neither low nor high anxiety is sufficient or encouraged (Bigdeli, 2010; Hayasaki, 2018; Hayasaki & Ryan, 2022; Levitt, 2015; Marlow, 2021).

High levels of anxiety can evolve to become a psychiatric disorder, which affects mental health and causes speech dysfunction and immobilization (Bletzer, 1986). Some researchers consider anxiety an emotional disorder (Ekman, 1992) because it causes a behavioral disturbance (American Psychiatric Association, 2014). It affects various physiological and psychological components (Jansen et al., 2018) by increasing activity in the autonomic nervous system, which can cause sweating, difficulty in breathing, heart palpitations (Bigdeli, 2010), muscle tension, or fatigue (Barlow et al., 2020; Jansen et al., 2018). Other cognitive and behavioral elements associated with anxiety include insufficient inductive reasoning, hindered recall, impaired attention, and situation avoidance (Bigdeli, 2010; Jansen et al., 2018; MacIntyre & Gardner, 1994). Unlike some emotions, anxiety does not go away when the stressor is removed and lasts for an extended time, depending on the stressor's impact (Bigdeli, 2010).

Physical impacts of high anxiety in humans are headaches, fatigue, tension (Kralova & Petrova, 2017), chest pain, abdominal pain, and heart palpitations (Bigdeli, 2010). Anxiety can also produce physical illness and emotional disturbance (Bigdeli, 2010). It affects human well-being and health, manifesting in increased heart rate, blood pressure, and respiration (Bigdeli, 2010; Kazdin, 2000; Weekes, 2020). Furthermore, it activates hormones such as noradrenaline, steroids, and adrenaline, which affect the brain and the nervous system (Bigdeli, 2010).

There are internal factors that can cause anxiety: physiological (Bigdeli, 2010; Levitt, 2015), psychological (Bigdeli, 2010), genetic (Bigdeli, 2010; Bletzer, 1986; Hettema et al., 2001; Scult & Hariri, 2018), and neurobiological etiologies (Barlow et al., 2020). Biological problems such as disease, pain, or medications' side effects can cause anxiety; likewise, fear combined with anger, guilt, or shame can lead to anxiety (Bletzer, 1986; Levitt, 2015). Some genetic factors can make someone more vulnerable to anxiety (Barlow et al., 2020; Bigdeli, 2010; Bletzer, 1986; Hettema et al., 2001; Scult & Hariri, 2018). Also, external factors such as negative life experiences, stressors, and uncontrollable events, can impact anxiety (Bletzer, 1986; Levitt, 2015).

According to Kazdin (2000), anxiety can be studied from three approaches: trait anxiety, state anxiety, and situational-specific anxiety. Trait anxiety is habitual, reoccurring (Harley et al., 2016), and long-lasting (Spielberger, 1983). State anxiety is temporary (Spielberger, 1983) and occurs in response to a particularly threatening event (H. T. D. Huang, 2018; Quigley et al., 2012). Situational-specific anxiety is a kind of trait anxiety that only happens for a specific reason (Kazdin, 2000) and influences specific factors (H. T. D. Huang, 2018), such as test anxiety (Gopang et al., 2015; H. T. D. Huang, 2018), math anxiety (Ashcraft, 2002; H. T. D. Huang, 2018; X. Huang & Mayer, 2019; Im, 2012), and foreign language anxiety (Dewaele et al., 2008; Horwitz et al., 1986; H. T. D. Huang, 2018; Ismail & Hastings, 2019; MacIntyre & Gardner, 1994).

The general impact of high anxiety levels on cognition is similar for all approaches. Anxiety interferes with cognitive processes such as problem-solving, verbal communication, and incidental learning. It hinders the total capacity of the working memory (Eysenck et al., 2007; Levitt, 2015; Okon-Singer et al., 2015; Woolf et al., 2007), distracts the goal-directed attentional system, and produces inhibition (Eysenck et al., 2007). Also, it minimizes the attention towards the goal and directs it toward the threatening stimuli (Eysenck et al., 2007; Okon-Singer et al., 2015). It promotes task shifting (Eysenck et al., 2007; Quigley et al., 2012), produces insufficient inductive reasoning (Ammar & Neji, 2007; Gower, 2004), reduces the attentional control (Ammar & Neji, 2007; Eysenck et al., 2007; Gower, 2004), and decreases storage capacity (Ammar & Neji, 2007). Moreover, it impairs learning performance (X. Huang & Mayer, 2016; J. C. Yang & Quadir, 2018), especially when there is a dual task or there is a need for task switching (Eysenck et al., 2007). Because of these adverse effects, reducing anxiety would increase learning self-efficacy; correspondingly, it is likely to increase learning performance (X. Huang & Mayer, 2019).

2.2.2 Foreign Language Anxiety (FLA)

As mentioned above, situational-specific anxiety includes foreign language anxiety, which is also known as Xenoglossophobia. It is a combination of feelings, behaviors, self-perceptions, and beliefs about learning a new non-native language (Hayasaki & Ryan, 2022; Horwitz et al., 1986; H. T. D. Huang, 2018; Park, 2014). Specifically, it is a feeling of worry, tension, stress, nervousness, or apprehension (Hasan & Fatimah, 2014; Hashemi, 2011; Ismail & Hastings, 2019; MacIntyre & Gardner, 1994; J. C. Yang & Quadir, 2018). People who experience FLA tend to avoid speaking and studying a foreign language, which could limit daily life activities and cause severe anxiety (Böttger & Költzsch, 2020). FLA is a continuous feeling changeable within a short period to the degree that we can measure moment-to-moment fluctuations (Gregersen et al., 2014).

Different factors affect FLA, such as task complexity (C.-M. Chen & Lee, 2011; Hashemi, 2011; Levitt, 2015; Robinson, 2007), self-perception (Al Mamun, 2021; Hashemi, 2011; Onwuegbuzie et al., 1999), socio-cultural elements (Al Mamun, 2021; Hashemi, 2011; J. C. Yang & Quadir, 2018), experience with the foreign language (Latif & Binti, 2015), lack of emotional intelligence (Shao et al., 2013), and native language proficiency (Dewaele et al., 2008; Gregersen, 2006; H.-j. Liu, 2013). The dominant components that influence FLA are:

- **Communication apprehension:** Many situational and personality factors can induce communication apprehension, such as being unprepared, afraid, or shy about speaking a foreign language. It mainly occurs with interpersonal interactions such as oral communication, public speaking, or listening to messages because of the need for more vocabulary or difficulty understanding others. (Al Mamun, 2021; Dewaele et al., 2008; Gopang et al., 2015; Horwitz et al., 1986; Latif & Binti, 2015; Szyszka & Szyszka, 2017).

- **Test anxiety:** Many factors also affect test anxiety, such as being aware of the consequences of the test, self-deprecating thoughts, or concerns about inadequate competence. It appears with performance evaluations such as quizzes or tests because the learners put themselves under pressure by setting a high standard, and when they do not reach it, they feel like failures (Al Mamun, 2021; Horwitz et al., 1986; Latif & Binti, 2015; Szyszka & Szyszka, 2017).

- **Fear of negative evaluation:** Among the variables associated with the reasons that produce fear of negative evaluation are fear of a teacher or peers' judgments, bad pronunciation, or incapability to express ideas. It mostly appears with speaking and social interaction. (Al Mamun, 2021; Alemi et al., 2014; Gopang et al., 2015; Gregersen & Horwitz, 2002; Hayasaki & Ryan, 2022; Horwitz et al., 1986; Latif & Binti, 2015; Szyszka & Szyszka, 2017).

There is an interpersonal interaction among these: learners who are scared of peers' or teachers' negative assessments may also feel shy or worried about speaking a foreign language. This could produce test anxiety, especially for oral exams (Horwitz et al., 1986). Based on the DASS-21, Depression Anxiety and Stress Scale questionnaire, the 'Scared without any good reason' variable is the most important on the anxiety scale (Priya et al., 2020).

Multiple situational and learner variables impact FLA. Examples of situational variables are course difficulty, teachers' behaviors, or peer interactions (Al Mamun, 2021; Genç, 2016; Hashemi, 2011; Ismail & Hastings, 2019; Kralova & Petrova, 2017; Williams & Andrade, 2008). Learner's variables are age, gender, culture, and attitude (Genç, 2016; Hashemi, 2011; Kralova & Petrova, 2017; Williams & Andrade, 2008). Interaction among these variables affects foreign language anxiety (Williams & Andrade, 2008). Unsuccessful learners are likely to feel more anxious than successful students (Genç, 2016; Gkonou et al., 2017). Accomplished students may need different treatment than underachievers to ensure low anxiety for all students. Also, in a complex task, learners with low anxiety may perform better than highly anxious learners (Kim & Tracy-Ventura, 2011).

There are mixed results about the impact of gender on FLA. Some researchers found that females are more anxious (Genç, 2016); other researchers found that males are more anxious (Fariadian et al., 2014); while others found no significant differences (Taghinezhad et al., 2016). Some possible explanations for the contradictory results are: Females apply different strategies and approaches during foreign language classes than males. For instance, females tend to be more socially oriented, while males are more analytic (Skelton et al., 2006). Females answer short, more frequent questions, while males answer fewer questions in more detail (Chavez, 2000). Therefore, applying different strategies affects learners' social-emotional status, which impacts their vulnerability to foreign language anxiety, with gender serving as a possible intervening variable.

Anxious and non-anxious learners differ in their reaction in foreign language class. Anxious learners get disturbed by their errors, while non-anxious learners stay calm even when they make mistakes. Also, anxious learners may feel unsatisfied with their performance, while non-anxious learners celebrate small achievements (Gkonou et al., 2017; Gregersen & Horwitz, 2002).

The impact of FLA extends beyond the classroom. It has a long-term effect on willingness to communicate in a foreign language (Ayedoun et al., 2019; Gkonou et al., 2017; M. Liu, 2006; M. Liu & Jackson, 2008), which results in the avoidance of social activities (Ayedoun et al., 2015; Horwitz et al., 1986) and employment (Horwitz et al., 1986). FLA inhibits language acquisition, especially by increasing the learner's reluctance to practice (Dewaele et al., 2008; Hasan & Fatimah, 2014; M. Liu, 2006; M. Liu & Huang, 2011). It splits attention (Kralova & Petrova, 2017), interferes with retention (Rafada, Madini, et al., 2017), and blocks recall (M. Liu, 2006). Moreover, it decreases motivation to learn (M. Liu & Huang, 2011; Lu et al., 2007; Marlow, 2021), reduces engagement (Alemi et al., 2014; Lu et al., 2007), and impairs both confidence (Gkonou et al., 2017; Lai & Wen, 2012; Lu et al., 2007), grittiness (Y. Liu, 2022). Also, it hinders performance (Bigdeli, 2010; H. T. D. Huang, 2018; M. Liu, 2006; M. Liu & Huang, 2011; Marlow, 2021; Salehi & Marefat, 2014; Sparks et al., 2018; J. C. Yang & Quadir, 2018), production (Rafada, Madini, et al., 2017), and achievement (Farid, 2021; Gkonou et al., 2017; Y.-M. Huang & Huang, 2015; Shao et al., 2013) because anxious learners procrastinate fearing of making errors or getting negative evaluations (Gregersen & Horwitz, 2002). Furthermore, it affects physiological behavior such as pounding heart, rapid breathing, and stomach distress (Böttger & Költzsch, 2020; Gkonou et al., 2017).

2.3 Measuring Emotions

Detecting the learner's emotions is essential to provide an adaptive learning environment, which can improve the learner's achievement (Gkonou et al., 2017; Henderson et al., 2020). There are multiple ways to measure emotions. The selection of tools is based on the study objectives, although some researchers suggest using a combination of measuring techniques to provide accurate results (Dzedzickis et al., 2020; Henderson et al., 2020; Ismail & Hastings, 2019; Kazdin, 2000; Lopatovska & Arapakis, 2011). In this section, I will discuss ways to measure emotions in general and some methods to detect FLA. Specifically, I will elaborate on direct physical measures, self-reports, expert observers, facial expressions, and human behavioral metrics. Each measure has advantages and limitations, which I will discuss in detail in the following sections.

2.3.1 Direct (Physical) Measures

Direct physical measures, also referred to as sensor-full measures, use sensor-based metrics such as physiological data (Paquette et al., 2016) to indicate the emotional state (Dzedzickis et al., 2020). Some direct methods used to measure anxiety are blood pressure, heart rate, eye fixation, respiration, muscle tone, and brain activity (Kazdin, 2000).

Using physical measures to detect emotions is direct, reliable, and less regulated by the learner, which provides an accurate reading of anxiety (Dzedzickis et al., 2020; Kazdin, 2000). These measurements are precise, especially when combined with other techniques (Imani & Montazer, 2019).

However, using physical measurements to detect emotions has limitations, like requiring the participants to be available at the lab and not in their normal environment (Imani & Montazer, 2019). Moreover, using a physical tool requires special hardware, which may not be available for the learner (Dzedzickis et al., 2020; Imani & Montazer, 2019). Wearing these devices may also make the learner uncomfortable and induce more anxiety (Imani & Montazer, 2019; Picard, 2008). Using physical measures to detect biological signals could also be affected by age, gender, physical activity, or culture, which don't relate to emotion (Dzedzickis et al., 2020).

Anxiety has been measured using blood pressure, heart rate, and eye fixation. Unfortunately, there aren't many conclusive results. Some researchers found that blood pressure is positively correlated with anxiety (Bigdeli, 2010; Ismail & Hastings, 2019; Kelly, 1980; Levitt, 2015; Z. Zhang et al., 2011), while others found no significant relationship between anxiety and blood pressure (Howell et al., 2007; Shinn et al., 2001).

Heart rate could be used to identify anxiety, but researchers found variability in the relationship between anxiety and heart rate (Chalmers et al., 2014). Some researchers found that heart rate is positively correlated with anxiety (Bigdeli, 2010; Gotardi et al., 2018; Gregersen et al., 2014; Ismail & Hastings, 2019; Kantor et al., 2001; Kelly, 1980; Levitt, 2015; Weekes, 2020; Z. Zhang et al., 2011), while others found a reduction in heart rate variability for general anxiety disorder (Chalmers et al., 2014).

Eye fixation has also been used to measure anxiety. For example, eye fixation duration and saccadic eye movement have been used to give the teacher an indication of the learner's emotional state, whether the learner is focused, anxious, or tired (Ivanović et al., 2017). People with trait anxiety have a longer average fixation duration when looking at threatening images (Quigley et al., 2012). Similarly, subjects with social anxiety disorder have shorter first fixation latency and shorter first fixation duration compared to healthy people (Keil et al., 2018). Socially anxious individuals experience gaze avoidance (Weeks et al., 2013) and dwell longer on threatening faces (Lazarov et al., 2016). Some researchers found a significant positive correlation between FLA and the number of fixations (Ismail & Hastings, 2019). On the other hand, others found no significant correlation between anxiety levels and saccadic eye movement (Gotardi et al., 2018), eye fixation (Fernandes et al., 2018; Lazarov et al., 2016), and dwell time (Fernandes et al., 2018). Therefore, there is no evidence for constructive effectiveness in measuring anxiety through eye fixation, generally physical measures.

2.3.2 Self-Report Measures

Emotion self-report is used to detect learners' affective states by asking them about their emotional state (Bigdeli, 2010; A. Graesser et al., 2007; Imani & Montazer, 2019; Lopatovska & Arapakis, 2011). The self-report measure has been used for clinical and research purposes to assess anxiety (Jansen et al., 2018). Reporting emotions can be retrospective, current, or prospective, depending on whether the learner is reporting on experiential knowledge, episodic memory, situational-specific beliefs, or identity-related beliefs (Ortony et al., 2022).

The validity of self-reports has been proven by comparing them against physical measures (Gogolla, 2017; Ismail & Hastings, 2019; Kantor et al., 2001; Picard, 2008). There are several advantages and benefits. For example, self-reporting to measure emotion is easy to administer, and there is no need for additional tools (Imani & Montazer, 2019). Retrospective self-report is unlikely to disturb the learning flow (Baker et al., 2015). There is a lesser chance of misinterpretation because the participants express their feelings (Baker et al., 2015).

While some researchers argue that self-report is unreliable because people may unintentionally tend to hide their emotions (American Psychiatric Association, 2014; Dzedzickis et al., 2020; Imani & Montazer, 2019), within the context of an e-learning system, self-report is more effective than other measurements (Cunha-Perez et al., 2018; Imani & Montazer, 2019; Lopatovska & Arapakis, 2011). On the other hand, learners may not recognize their own emotions or might not be willing to share them (Dzedzickis et al., 2020). It may be annoying to ask the learner multiple times (Baker et al., 2015), but emotions can change during the session (Imani & Montazer, 2019). Furthermore, some cultural differences affect the expression of emotions (Baker et al., 2015).

There are various types of self-reports to measure emotions (Imani & Montazer, 2019). Researchers have used Likert scales to assess learners' motivation (Carlotto & Jaques, 2016), anxiety (Horwitz et al., 1986), and willingness to communicate (Ayedoun et al., 2015, 2019). Other researchers used the Self-Assessment Manikin (SAM) test, a pictorial questionnaire to express arousal, valence, and dominance (Cunha-Perez et al., 2018). Another form of pictorial questionnaire is a slider with emojis, which measures foreign language anxiety (Ismail & Hastings, 2019), arousal, and pleasure (Betella & Verschure, 2016). Other researchers used self-explanation by using journals or log data to express the affective state (Bilal & Kirby, 2002; H.-C. K. Lin et al., 2015; Lopatovska & Arapakis, 2011).

The Foreign Language Classroom Anxiety Scale (FLCAS) see Appendix D was designed for measuring foreign language anxiety in a classroom context. It was initially developed and validated by Horwitz et al. (1986) for English speakers studying Spanish as a foreign language. Subsequently, it was translated into a number of different languages, primarily for learners of English as a second language (Alrabai, 2014; Ismail & Hastings, 2019; Shao et al., 2013). The self-report has 33 questions with a 5-point Likert scale ranging from strongly agree to strongly disagree. The questions about negative behavior attributes gave 5 points to the "strongly agree" answers. Questions about positive attributes were reverse-scored. Each of the 33 questions was related to one of the three main components of FLA: communication apprehension, fear of negative evaluation, and test anxiety (Horwitz et al., 1986). Researchers classify FLCAS scores into three levels: below 90: "not anxious"; 90-110: "mildly anxious", and above 110: "anxious" (Al Mamun, 2021; Guo et al., 2018). The FLCAS has been used as a pre-test in some experiments (Alemi et al., 2014; C.-M. Chen & Lee, 2011; Ismail & Hastings, 2019, 2020;

H.-C. K. Lin et al., 2015) or as a standalone measure (Rafada & Madini, 2017; Shao et al., 2013).

2.3.3 Expert Observers

Expert observers are trained coders who observe learners to detect their emotions. They look for holistic physical and verbal cues based on consistent evidence rather than a single occurrence (Baker et al., 2015). Researchers suggest observing learners for abnormal anxiety levels to provide support when needed (Bigdeli, 2010). Some observers have identified emotions such as boredom, frustration, confusion, engagement, and off-task behavior while learners use an e-learning system (Craig et al., 2004; Jiang et al., 2018).

Trained judges are reliable in coding those learners' emotions based on facial expressions and tutorial dialogue (D'Mello et al., 2008). Although expert observers may be an expensive measuring tool, they are least obtrusive to learners (Lopatovska & Arapakis, 2011). The benefit of detecting affect using expert field observers is using the results to build a sensor-free affect detector (Jiang et al., 2018; Paquette et al., 2014).

Employing expert observers to detect emotions has some disadvantages, such as requiring the learners to be in the lab, which does not simulate the exact emotional state that occurs in a normal situation (Lopatovska & Arapakis, 2011). As mentioned before, using human experts is expensive. Also, depending on the human could be biased and misleading because some observed behavior may not be emotional (Lopatovska & Arapakis, 2011). Learners may feel uncomfortable because they know they are being observed. There could also be cross-cultural differences (Imani & Montazer, 2019; Lopatovska & Arapakis, 2011) which affect learners' behavior, which results in incompatibility between learner, teacher, and trained judge emotion detector (D'Mello et al., 2008).

2.3.4 Facial Expression

Facial expression has been used to identify emotions. Some researchers used a combination of facial recognition, posture, and conversational cues to detect boredom, confusion, frustration, and engagement (D'Mello & Graesser, 2013).

Facial expression is used with biological signals such as heart pulse, respiration, and temperature to classify emotions on dimensions of boring–interesting, confused–comprehending, and tired–concentrating (Nosu & Kurokawa, 2006). Speech and face recognition have been used to detect emotions such as fatigue, interest, or understanding (Z. Wang et al., 2010). Other emotions, such as joy, surprise, fear, disgust, anger, and sadness, were recognized from facial expressions within a tutoring system(Ammar & Neji, 2007). For detecting foreign language anxiety, Guo et al. (2018) suggested focusing on facial expressions, voice, gesture, learner performance, and diary journal feedback. Similarly, facial recognition and self-reporting are used to recognize FLA (H.-C. K. Lin et al., 2015). Facial recognition applications could help researchers detect basic emotions through a built-in web camera (Imani & Montazer, 2019).

There are some disadvantages of using facial expressions. Subtle facial changes can be challenging to track (Imani & Montazer, 2019). Moreover, sometimes emotions do not manifest as visible facial expressions. Felt emotion could be different from expressed emotions. People sometimes exhibit signs of emotion while experiencing something else (Hume, 2012). Finally, existing facial recognition applications best operate on basic emotions and struggle to detect complex ones. Some researchers used applications that detect basic emotions such as sad and fear in an attempt to track non-basic emotions such as anxiety (H.-C. K. Lin et al., 2015), but it resulted in inaccurate recognition.

2.3.5 Human Behavior

Various studies have shown that behavioral metrics can be used to identify emotions. Imani and Montazer (2019) showed that using human behavioral measures to feed the internet of things, deep learning, and information fusion technology with essential data to create an affective application like Cognitive Tutor Algebra (Baker et al., 2012), Inq-ITS (Paquette et al., 2014), and Affective AutoTutor (D'Mello & Graesser, 2014). Human behavioral measures incorporate sensor-lite and sensor-free metrics. Sensor-lite metrics measure emotions with minimal physical tools, such as a computer's built-in camera or microphone (D'Mello & Graesser, 2014). Sensor-free emotion detectors measure emotions using user interactions with the system without additional physical tools (D'Mello & Graesser, 2014; Ismail & Hastings, 2020; Lan et al., 2020). Examples of sensor-free behavioral metrics are typing speed (Hernandez et al., 2014), mouse movements (Macaulay, 2004), correct/ incorrect answers, time on task, or the number of times pressing a hint button (Baker et al., 2012).

Using sensor-free metrics could allow ultimate benefits of affect detection (Baker et al., 2012) because there is a minimum interruption, disturbance, or distraction to the participants (Dzedzickis et al., 2020; Lan et al., 2020). Sensor-free behavioral metrics are cost-effective and scalable because they could be expanded to a large environment without additional tools (D'Mello & Graesser, 2014; Imani & Montazer, 2019; T.-Y. Yang et al., 2019). Researchers can avoid accidental failure or mistracking of the physical tools (Henderson et al., 2020). There are no privacy invasions because the data is anonymized, unlike with facial expression (T.-Y. Yang et al., 2019). Moreover, it is practical because the learner can be in their own environment without the need to be in a lab (D'Mello & Graesser, 2014; Dzedzickis et al., 2020). Furthermore, using a sensor-free interaction detector to detect learner affect can be more effective than physical detection (Paquette et al., 2016).

It is still a new field that needs more studies to provide more accurate predictions (Imani & Montazer, 2019). Because there are no physical sensors, there could be a lack of precision (Imani & Montazer, 2019), accuracy, and latency (Dzedzickis et al., 2020). Furthermore, there is a need to record a large amount of data to get accurate predictions (Imani & Montazer, 2019).

2.3.5.1 Features for Detecting Emotion

To measure emotions using sensor-free metrics, researchers have used various features and machine-learning approaches to reach accurate detection.

Multiple features have been used by researchers to detect emotions. An example of using sensor-free behavioral metrics is keyboard typing pressure to detect stress. Researchers studied the relationship between stress and typing pressure. While using a pressure-sensitive keyboard and self-report as the ground truth, they found that about 92% of the participants had more keyboard pressure when feeling stressed (Hernandez et al., 2014). However, there were no significant relation between stress and task duration or typing speed (Hernandez et al., 2014).

Also, prior research studied the relationship between mouse capacitance and work stress; they found a significant contact between the participant and the mouse surface when the stressor was present (Hernandez et al., 2014). Other researchers studied mouse tracking and anxiety when searching for medical symptoms online. They found a significant correlation between the severity of the symptom, which affects the anxiety level, and the search behavior (Youngmann & Yom-Tov, 2018). Contrarily, other researchers found no correlation between state anxiety and the speed of the mouse click (Macaulay, 2004).

Other researchers detected emotions such as confusion, frustration, boredom, and engagement using sensor-free metrics because it overcame the limitation of the self-report, expert observer, and physical measures in addition to providing accurate detection Baker et al. (2012). For example, to detect confusion while using Cognitive Tutor Algebra, Baker et al. (2012) used the following features: the percentage of actions that took more than five seconds after two incorrect answers, the percentage of hints requested, the minimum number of incorrect answers, and the average time spent on task unitized by the time spent by all the participants within sequences of five correct answers.

Other researchers used 47 features, such as calculating the average, max, min, median, standard deviation, and the sum of the time spent on each task to detect the emotional state of boredom, concentration, confusion, and frustration while using Inq-ITS (Paquette et al., 2014).

To detect the same emotions, Wixon et al. (2014) used a combination of features to build a sensor-free affect detection that uses mathematics application based on three main components: pre-test responses, other students' responses, and the student's responses. Each component had several associated features, such as total hint requests, total incorrect answers over the last three questions, and the logarithm of the time spent. The ground truth for accuracy comparison was emotional self-report. Jiang et al. (2018) used another approach to detect these emotions while learning science. They used three main features: Basic features, for example, the percentage of correct or incorrect answers; sequence features, which indicate student actions over time; and threshold features, which are determined by choosing the best threshold.

Other research used sensor-free approaches to detect pleasure, arousal, and dominance. Arevalillo-Herráez et al. (2017) propose an interaction between self-report and sensor-free metrics to increase the results' prediction, accuracy, and reliability.

Regarding FLA in particular, Onwuegbuzie et al. (1999) found seven factors that account for 40% of the variance: "age, academic achievement, number of times visiting foreign countries, high school experience with foreign languages, expected average for the current language course, perceived scholastic competence, and perceived self-worth (Onwuegbuzie et al., 1999, p. 217)." These, however, were used as general indicators to consider pre- or post-evaluation, not moment-to-moment predictors for measuring overall FLA.

2.3.5.2 Machine Learning Methods

Machine learning has been used to predict emotions such as anxiety, stress (Priya et al., 2020), confusion, frustration (Jiang et al., 2018), sadness, and anger (Balamurali et al., 2022). It uses computational methods to improve the system's performance (Zhou, 2021). Researchers choose between regression or classification methods (Kyriakides & Margaritis, 2019) based on the targeted value. Regression is used for continuous independent value, while classification is used for categorical targets (Kyriakides & Margaritis, 2019). Both methods consider multiple factors and learn through experience to provide predictions (Jordan & Mitchell, 2015; Kyriakides & Margaritis, 2019). Ensemble learning is a procedure that uses multiple machine learning algorithms to improve prediction accuracy and reduce overfitting (Brown et al., 2010; Kyriakides & Margaritis, 2019).

One effective ensemble method is Random Forest, which uses bagging to create sets of trees to produce the final prediction. It is used for classification and regression to reduce bias and variance (Breiman, 2001; Kyriakides & Margaritis, 2019). Also, the algorithm works parallel between the training and testing data, requiring less hyperparameter fine-tuning (Breiman, 2001;

Kyriakides & Margaritis, 2019). XGBoost is a highly efficient ensemble model that uses boosting with parallel trees to generate a prediction. In addition to providing a flexible, stable, and portable model, XGBoost avoids overfitting (Breiman, 2001; Hueniken et al., 2021; Kyriakides & Margaritis, 2019). Another ensemble method, Gradient Boosting Regressors, provides an agile prediction helpful for clean or imperfect data (Friedman, 2001). Support Vector Machines (SVMs) separate the training data by two hyperplanes with maximum distance to generate the prediction (Kyriakides & Margaritis, 2019; Priya et al., 2020). They deliver high accuracy and generalization (Awad & Khanna, 2015). Bayesian Ridge Regression estimates the prediction based on the probability of the distribution. It can overcome poorly distributed datasets by estimating a probabilistic model with common variance coefficients (Da Silva et al., 2021). Linear Regression is the most widely used regression method because it is a simple, easy, parametric method that generally provides satisfactory predictions (Montgomery et al., 2021). Also, it is practical and applicable to various fields, such as psychology, science, and economics (Montgomery et al., 2021).

Bayesian Ridge Regression has produced modest results in predicting emotions such as anxiety, contentment, and sadness (Hutt et al., 2019). Random Forest, XGBoost, and SVMs have been used to predict General Anxiety Disorder (GAD) (Byeon, 2021; Hueniken et al., 2021; Priya et al., 2020). Also, Gradient Boosting Trees, Random Forests, and SVMs have been used to classify Public Speaking Anxiety (PSA) and Foreign Language Anxiety (FLA) using electrodermal activity features (H. Lee et al., 2020). Linear Regression provided a low level of prediction of FLA using sensor-free metrics (Ismail & Hastings, 2020). Some researchers used Random Forest Tree (RFT), the Support Vector Machine (SVM), and the Convolution Neural Network (CNN) to predict anxiety (Priya et al., 2020). Other researchers predicted public speaking anxiety and Foreign Language Anxiety (FLA) using Decision Tree, Auto Multilayer Perceptron, Gradient Boosted Tree, Random Forest, and Support Vector Machine (H. Lee et al., 2020). They used features from physiological arousal of electrodermal activity (EDA).

When comparing Random forest with other machine learning methods, it produced the best accuracy among Bayesian Network (BN), logistic, multiple layer perceptron (MLP), Naïve Bayes (NB), random tree (RT), J48, sequential minimal optimization (SMO), random sub-space (RS), and K Star (KS) to predict anxiety and depression among the older people using medical factors and demographic information (Sau & Bhakta, 2017). Some researchers also showed that Random forest performs well in real-life applications (Zhou, 2021). Often, ensemble models offer better predictions, but sometimes, single models can outperform them. Ultimately, choosing the machine learning model is based on the dataset size, features, and quality (Kyriakides & Margaritis, 2019).

To model a machine learning application, Python is mainly used (Priya et al., 2020). Some researchers used R programming language to model Decision Trees, Random Forest Trees, Naïve Bayes, Support Vector Machine, and KNN to detect anxiety. They found that random forest is the best model to predict Anxiety (Priya et al., 2020).

There are contradictory views about the best affect prediction method. Botelho et al. (2017) found that deep learning methods such as Recurrent Neural Networks (RNN), Gated Recurrent Unit networks (GRU), and Long Short-Term Memory networks (LSTM) are more effective than machine learning approaches in predicting affect states. Similarly, when Lan et al. (2020) compared Logistic Regression (LR), Random Forest (RF), Fully-Connected Neural networks, and Monotonic Neural Networks, they found that both neural networks outperformed LR and RF. While Jiang et al. (2018) compared feature engineering and deep learning approaches to detect affect when learning, they found that feature engineering, such as Logistic Regression and Step Regression, was better than deep learning methods, such as GRU and LSTM. Therefore, there is no consensus on the best affect prediction method.

2.4 Decreasing FLA

Recognizing students' emotional state and providing interventions to reduce negative emotions could help overcome their effects (Elliott et al., 1999). Providing interventions to reduce anxiety is essential to ensure academic success (X. Huang & Mayer, 2016) and to build a positive learning environment (H.-C. K. Lin et al., 2015). Moreover, reducing anxiety can increase self-efficacy (Im, 2012), motivation (M. Liu & Huang, 2011; Lu et al., 2007; Onwuegbuzie et al., 1999; Z. Wang et al., 2010), and interest in learning (M. Liu, 2006; Lu et al., 2007). To improve foreign language reading, writing, speaking, and listening, researchers have used different technologies such as intelligent tutoring systems (H.-C. K. Lin et al., 2015), games (Vallejo Balduque, 2018), or robots (Alemi et al., 2014). Within these technologies, researchers have employed music (H.-C. K. Lin et al., 2015), adaptive difficulty (Abu Ghali et al., 2018; Alhabbash et al., 2016; C.-M. Chen & Lee, 2011; H.-C. K. Lin et al., 2015), gamification (Vallejo Balduque, 2018),storytelling (Lu et al., 2007), and motivational support (Deloatch et al., 2017; Hayasaki & Ryan, 2022; Heilmann et al., 2016; Jin & Dewaele, 2018) to improve learning and reduce FLA. Also, they used an animated agent to increase learners' willingness to communicate in the foreign language (Ayedoun et al., 2019). For my research, I have also considered using animated agents, emotional support, and shifting emotional attention as viable methods to overcome FLA.

2.4.1 Intelligent Tutoring Systems

An Intelligent Tutoring System (ITS) is an e-learning platform that provides individualized teaching, adaptive emotional, and/or cognitive support using artificial intelligence (Arroyo et al., 2014; H.-C. K. Lin et al., 2015; Phobun & Vicheanpanya, 2010). ITS provides customized instruction or direct feedback for students by being able to adapt to the learner's knowledge or emotional state. It uses learners' information to provide a high level of adaptability and personalization to guide them (Erümit & Çetin, 2020). Also, it determines teaching content and offers personalized instruction based on learners' traits (Alhabbash et al., 2016; D'Mello & Graesser, 2013). Many ITSs have been built for STEM-related topics (Cunha-Perez et al., 2018; D'Mello & Graesser, 2013; A. C. Graesser et al., 2014), but some are language-related (Abu Ghali et al., 2018; Alhabbash et al., 2016; Kaur et al., 2019). Specifically, ITSs have been developed to improve math (Arroyo et al., 2014; Harley et al., 2016), programming (Latham et al., 2014; Latham et al., 2012), and foreign language learning (Bradac & Walek, 2017; Gutierrez & Atkinson, 2011; Heift, 2015), by providing pedagogical support (Arroyo et al., 2014), personalized learning styles (Latham et al., 2014), or adaptive multi-strategy feedback (Gutierrez & Atkinson, 2011).

Using an adaptive system increases learning achievements, facilitates learning, and raises productivity (Bimba et al., 2021; Faivre et al., 2002; Harley et al., 2016). Specifically, using an adaptive tutor within a math e-learning system improves the learners' performance (Arroyo et al., 2014; S. Wang et al., 2023; Yu et al., 2023). Also, adaptive systems increase learners' motivation and enjoyment, reducing anxiety when learning math (Hwang et al., 2020; Jebur et al., 2022). Moreover, ITSs help to boost confidence and induce positive learning experience (Hwang et al., 2020; Latham et al., 2012; Yu et al., 2023). However, it should be noted that low achievers' confidence and performance increased more than high achievers because they benefited from the adaptive encouraging motivational support (Arroyo et al., 2014).

On the other hand, high achievers got engaged with a math adaptive tutoring system and became interested in learning, while low achievers stayed neutral or, worse, became bored. Specifically, high achievers benefited more from the metacognitive adaptive feedback (Arroyo et al., 2014).

2.4.1.1 ITSs for FLA

Researchers have built ITSs for foreign language learning to serve several purposes, such as adaptive ITSs to classify the text complexity (Kurdi, 2020), overcome FLA (H.-C. K. Lin et al., 2015), or analyze the cognitive thinking level (Kaur et al., 2019).

To overcome FLA within an ITS, some researchers analyzed the learner's mental model, then provided relevant feedback, guided the learner to the appropriate learning level, and played soothing music (H.-C. K. Lin et al., 2015). Other researchers developed an ITS that uses politeness strategies to induce a positive learning environment and reduce adverse affects (N. Wang & Johnson, 2008).

Using ITS increases learning achievement (Z. Wang et al., 2010), improves performance (Kulik & Fletcher, 2016), and reduces anxiety (H.-C. K. Lin et al., 2015). An ITS can provide an individualized learning environment that suits the learners' knowledge level and emotions at a convenient time and place (Latham et al., 2014).

Building an ITS is relatively expensive (Corbett et al., 1997) because researchers need to design and implement ITSs expertly and carefully to foster a significant increase in learning performance (Kulik & Fletcher, 2016). The interventions used to reduce anxiety within some ITSs do not decrease FLA permanently and can have some side effects. For instance, H.-C. K. Lin et al. (2015) used soothing music, which can produce a peaceful environment but may generate a cognitive overload (Clark & Mayer, 2016) because the extraneous audio may cause a working memory overload which distracts the learner. Also, H.-C. K. Lin et al. (2015) used lower difficulty, which may reduce anxiety but prevent teaching challenging materials.

2.4.1.2 Affective User Modeling

Affective user models, or as some people call them, learning models, are emotionally intelligent tutoring systems that recognize learners' emotional states and act adaptively to facilitate and enhance learners' affective states (Elliott et al., 1999; Hudlicka, 2020; Martinho et al., 1999). It simulates a human tutor, which helps the learner to perform better and reach a positive emotional state (Mohanan et al., 2017). Through an affective user model, the interaction between the learner and the e-learning system is empowered by the affective component. An adaptive system, which considers the current anxiety level can and reduces it (Kim et al., 2017). Adapting to a learner's emotional state is as important as accurately detecting a learner's emotions. A successful learning environment is built on cognitive and affective support because all individuals are different and adapt to various emotional support, needs, and personalities (Petrovica & Ekene, 2016).

To build an emotionally responsive system, some researchers incorporated animated agents with an affective reasoning system (Elliott et al., 1999). This system appraises the environment and provides feedback based on the student's emotions. For example, if the students are anxious, the agent will express sympathy (Elliott et al., 1999). It is essential to build an ongoing relationship between the agent/system and the student (Elliott et al., 1997; K. Lee et al., 2020; Picard, 2008). Such a relationship would convince the learners about the agent's responses and make them more believable, which would help regulate their emotions. An accurate affective user model can help to provide practical, emotional support that regulates emotions (Hudlicka, 2020; Picard, 2008).

To build an affective user model, researchers used multiple methods, including written programs (Elliott et al., 1997), or machine learning approaches such as Bayesian network or Hidden Markov models (Grawemeyer et al., 2017; Woolf et al., 2007). Others used rule-based expert systems to build the models (D'Mello & Graesser, 2013; Qianli et al., 2011; L. Zhang et al., 2007). They provide these models from various input sources such as behavioral characteristics (Katsionis & Virvou, 2004), facial expression recognition (Elliott et al., 1997; Wehrle & Kaiser, 1999), mouse pressure, posture sensing devices, or skin conductance wristband (Woolf et al., 2007).

Microsoft Clippit ("Clippy") was retired because of the many complaints to the effect that it was ineffective and even irritating (Picard, 2008). Clippy was an intelligent agent that provided hints for learning and intended to reduce users' frustration while using Windows. However, it did not support emotions and was worse when displaying inappropriate emotions. Instead of supporting the user's emotions, it annoyed and frustrated them because it ignored the users' emotional state and provided unnecessary advice (Bahr et al., 2007; K. Lee et al., 2020; Picard, 2008).

2.4.2 Games

Games are designed for entertainment and non-entertainment purposes, such as education and emotional support, to improve language proficiency and increase positive emotions (H.-J. H. Chen & Yang, 2013; Gaetan et al., 2016; Isbister et al., 2012; Rankin, 2016). Games have advantages in dealing with anxiety, but there are some drawbacks.

Overall, educational games improve foreign language learning acquisition (Y.-M. Huang & Huang, 2015; J. C. Yang & Quadir, 2018), and promote positive emotions such as motivation, confidence, and interest in learning (H.-J. H. Chen & Yang, 2013; Lai & Wen, 2012; Sampayo-Vargas et al., 2013). From learners' perspectives, using games to learn a foreign language makes learning easy, helpful, and attractive (Lai & Wen, 2012). Furthermore, gamification elevates self-competence, engagement, and enjoyment (Vallejo Balduque, 2018). Using gamification provides a fun (Lyu, 2019), encouraging, and relaxed atmosphere that reduces FLA (Vallejo Balduque, 2018). The environment created by educational games is friendly and free of criticism (Vallejo Balduque, 2018), which helps defeat negative emotions like anxiety (Lai & Wen, 2012; Vallejo Balduque, 2018; J. C. Yang & Quadir, 2018).

To improve learning English as a foreign language and reduce FLA, some researchers have also used augmented reality (AR), which helps to lower the cognitive load and promotes effective learning (Küçük et al., 2014). Researchers also used virtual reality (VR) to reduce anxiety, such as general anxiety disorder or public speaking anxiety. These games reduce the risk of children's anxiety disorder (Van Rooij et al., 2016) and can treat generalized anxiety disorder (Repetto et al., 2013). Using virtual reality cognitive behavioral therapy decreases public speaking anxiety (Anderson et al., 2005; Kahlon et al., 2019) and, when used as a distraction tool, reduces anxiety and pain (Schwartz et al., 2020).

Some drawbacks of using games to reduce anxiety include shifting subjects' focus from learning to winning the games (H.-J. H. Chen & Yang, 2013), addiction, and worsened eyesight (Lai & Wen, 2012). Also, some games could help retrieve vocabulary from short-term memory, but not long-term memory (Y.-M. Huang & Huang, 2015). Even though the experiment's results by Lyu (2019) increased the learner's motivation, there was no obvious evidence for reducing anxiety and improving confidence. Also, online role-playing games did not reduce anxiety for learners with low English proficiency levels (J. C. Yang & Quadir, 2018). Furthermore, using augmented reality requires high skill to gain learning and benefit from application support (Küçük et al., 2014).

2.4.3 Robots

Robots are used for various emotion-related purposes, especially to improve human well-being (Breazeal, 2003; S. Jeong et al., 2020). Some researchers used robots to interact with learners and reduce their FLA (Alemi et al., 2014; Alemi et al., 2017; Lu et al., 2007). There are both advantages and limitations to using robots.

Using robots to support learning increases cognition (Alemi et al., 2014), which could boost performance (Lu et al., 2007). Interacting with a robot to learn a foreign language could reduce anxiety (Alemi et al., 2014; Alemi et al., 2017; Hong et al., 2016; Lu et al., 2007) because learners are aware that it is an object, not a human (Tafazoli & Gómez Parra, 2017). Also, a robot enhances motivation to learn and self-esteem, which improves confidence (Hong et al., 2016). A survey about using a robot as an assistant in a foreign language classroom found that a robot could reduce anxiety and increase engagement (Randall, 2019).

Robots that use a synthetic voice decrease a learner's trust and acceptance of a robot's emotional intelligence (Law et al., 2020). Also, using robots may frighten and upset young learners, although the teacher's emotional support could help (Alemi et al., 2017). Moreover, robots perform similarly to human teachers in reducing anxiety but lack social ability (Wallbridge et al., 2018). Integrating an ITS with a robot to teach English vocabulary as a foreign language did not support the learning process (De Wit et al., 2019). Even though theoretically, robots could reduce anxiety, further research is required to investigate the effect of robots on anxiety levels in real life (Randall, 2019).

2.4.4 Animated Agents

Animated agents are used to facilitate learning (Al-Kaisi et al., 2020; Clark & Mayer, 2016; Romero-Hall, 2016) and provide emotional support (Van der Meij et al., 2015). Animated agents can be voice assistants or animated characters with bodies and voices (Al-Kaisi et al., 2020). To facilitate learning, animated agents should consider the student's emotional state (Elliott et al., 1997).

2.4.4.1 Animated Agents and Learning

Animated pedagogical agents promote information processing and can reduce cognitive load (Beege & Schneider, 2023; Dunsworth & Atkinson, 2007; L. Lin et al., 2013). They help the learner focus, pay attention, and engage in cognitive processes (Dunsworth & Atkinson, 2007). Using animated agents with narration can also improve communication skills when learning a foreign language (Al-Kaisi et al., 2020). Similarly, using conversational agents, communicating strategies, and expressing interest or sympathy could increase the willingness to communicate in the foreign language (Ayedoun et al., 2015, 2019). Therefore, applying animated agents that provide narrated elaborated feedback could enhance learning (L. Lin et al., 2013).

There are mixed results, however, from studies using animated agents for learning. While some researchers found that animated agents positively led to learning gain (Al-Kaisi et al., 2020; Carlotto & Jaques, 2016; D'Mello & Graesser, 2013; Lippert et al., 2019; Schroeder et al., 2013), others found no difference between the presence of the agent or its absence (L. Lin et al., 2013; N. Wang & Johnson, 2008). If the agent produces high levels of interactivity, then it may shift attention and generate cognitive overload (Carlotto & Jaques, 2016; Sweller & Chandler, 1994). On the other hand, Craig et al. (2002) found no split attention when using an animated pedagogical agent but instead found that it helped improve performance. Also, L. Lin et al. (2013) found no difference in the cognitive load when using the agent or not.

2.4.4.2 Animated Agents and Emotions

Animated agents that understand the learner's emotions can effectively help in teaching (Elliott et al., 1997) because they increase positive emotions and learners' self-perceptions (Lane, 2016). Animated agents that provide positive feedback increase the learner's interest in learning and their self-efficacy (Kim et al., 2007; Romero-Hall, 2016). Coping messages that provide social-emotional support through animated agents reduced math anxiety, (X. Huang & Mayer, 2019; Im, 2012), which lowered the cognitive load (X. Huang & Mayer, 2016). Similarly, simulating a caring persona can improve physiological, cognitive, and psychological states (Bickmore & Picard, 2004; Romero-Hall, 2016), and encourage learning (Elliott et al., 1997). Verbal signals from animated agents can help convey emotions (Lane, 2016). Social agency theory suggests using social cues to encourage learners to interact with the system (Lane, 2016).

Adaptive emotional agents that communicate with the learner using voice and an animated character influence the learner's emotional state (Faivre et al., 2002). Also, emotive animated agents could induce enthusiasm to learn (Beege & Schneider, 2023; Hubal, 2008; W. L. Johnson et al., 2000; Romero-Hall, 2016). Animated agents that express emotions can encourage and motivate learners and create an enjoyable learning experience (W. L. Johnson et al., 2000; Romero-Hall, 2016). Expressive animated agents that promote engagement, encourage motivation, and attract the learner's attention can increase learning gain (Romero-Hall, 2016; Veletsianos, 2009). Animated pedagogical agents can also enhance students' self-efficacy and reduce anxiety (Arroyo et al., 2014; Beege & Schneider, 2023; Lester et al., 1997; Romero-Hall, 2016; Van der Meij et al., 2015).

Within a foreign language learning environment, using animated agents reduces language barriers and improves communication skills, while having no animated agents increases shyness and worries(Al-Kaisi et al., 2020). In a study that taught Arabic as a foreign language, a pedagogical agent increased motivation regardless of whether they provided polite or direct feedback (N. Wang & Johnson, 2008). An example of polite feedback is "It's usually hard to get answers to this question right, but that means 'This is a sergeant.' How about we try it again?" An example of direct feedback is, "No, that means 'This is a sergeant.' Try again" (N. Wang & Johnson, 2008). Also, a conversational agent can lower anxiety and enhance self-confidence, which increases willingness to communicate in a foreign language (Ayedoun et al., 2015, 2019).

Even though there are many positive effects of using animated agents to reduce negative emotions and increase learning, the research needs to be more conclusive about the long-term effects because most previous studies measured emotions within a short-term controlled experimental setting. Researchers suggest using the animated agent for a more extended period to expand the positive effect than using it for a short-period (X. Huang & Mayer, 2019; Lester et al., 1997).

2.4.5 Emotional Support

Emotional support involves providing sympathy, encouragement, empathy, and reassurance to the learner (Ayedoun et al., 2019; Deloatch et al., 2017; Mohanan et al., 2017). Within classrooms and e-learning systems, researchers have tried to offer emotional support to enhance learners' performance (Deloatch et al., 2017) and reduce negative emotions (Im, 2012; Joseph et al., 2016). Using a pedagogical agent with coping motivational support effectively reduces math anxiety (Im, 2012). However, some researchers recommend providing emotional support only when needed (D'Mello & Graesser, 2013).

Providing understanding and motivational support to learners improves the effectiveness of a learning environment (Bigdeli, 2010; Chaffar & Frasson, 2010; Y. Liu, 2022; Marlow, 2021; Mohanan et al., 2017) because it reduces anxiety (Deloatch et al., 2017; Hayasaki & Ryan, 2022; Heilmann et al., 2016; Jin & Dewaele, 2018). Adaptive emotional support helps to alleviate negative emotions when learning (Chaffar & Frasson, 2010). Adequate emotional support can produce positive effects that last for a prolonged time, while moderate support can generate a beneficial effect for short periods, and the greater the emotional support, the fewer people think about the stressor (Joseph et al., 2016). However, short-term emotional support is also acknowledged to reduce anxiety (Heilmann et al., 2016). Teacher support can increase student enjoyment, while a teacher with a negative attitude may increase anxiety (De Ruiter et al., 2019). In particular, a supportive conversation can help avoid FLA (Dewaele et al., 2008; Horwitz, 2010).

A conversational agent that provides empathetic support by encouraging, congratulating, and reassuring the learner could alleviate anxiety and increase confidence (Ayedoun et al., 2019). Similarly, empathetic messages can increase confidence, learning interest, and self-persistence (Karumbaiah et al., 2017). Lack of supportive, motivational, and encouraging feedback can increase FLA (Al Mamun, 2021; Rafada & Madini, 2017; Shao et al., 2013). Some researchers suggest using constructive motivational feedback to improve speaking English as a second language (Sallang & Ling, 2019). More supportive feedback can be needed to produce competent communicators (Ayedoun et al., 2019).

Even though motivational feedback has various advantages, some researchers used direct feedback, including corrective feedback and an explanation. They found no difference between using polite or direct feedback (N. Wang & Johnson, 2008); however, the latter tends to decrease achievements and produce confusion (Karumbaiah et al., 2017). At the same time, some high achievers experience high anxiety levels (Gkonou et al., 2017), so adaptive support can also help them. There are gender differences in accepting and getting the benefits of the affective animated agent. For example, male-gendered high achievers got better scores without the presence of motivational support from the animated agent, while female-gendered learners acquired more confidence with its presence (Arroyo et al., 2011; Burleson & Picard, 2007).

Given these mixed findings, researchers investigated different types of feedback to produce the best positive foreign language learning environment. They found that providing positive support is an effective way to moderate FLA and increase self-esteem (Rafada, Madini, et al., 2017). Using indirect correctness and positive feedback could reduce FLA (Al Mamun, 2021; Ansari, 2015; Marlow, 2021; Rafada, Madini, et al., 2017). Other researchers found that motivational assistance encouraging the learner achieved a similar result while increasing self-confidence (Shao et al., 2013). Teaching stress management, and providing empathy improves learners' emotional competencies, which in turn reduces FLA (Al Mamun, 2021; Gkonou et al., 2017; Pishghadam, 2009). Other successful techniques are encouraging self-confidence, praising learners' efforts, and enhancing their self-confidence in class (Ansari, 2015; H.-j. Liu, 2013; M. Liu & Huang, 2011; M. Liu & Jackson, 2008; Salehi & Marefat, 2014).

2.4.6 Shifting Emotional Attention

Shifting emotional attention is used to help learners cope with their negative emotions. According to inattentional blindness theory, when the mind focuses on an emotion or specific goal, it may not capture prominent events or things in the environment beyond what is occupying it (J. Johnson, 2020). It often occurs in the classroom when students focus too much on their anxiety and overlook the lecture. Therefore, researchers used mindfulness and shifting attention to switch the focus from anxiety to the present moment (Mortimore et al., 2017; Wehrenberg, 2018). Others directed attention to relaxing positions (Han et al., 2014; D. R. Johnson, 2009; Wehrenberg, 2018). Specifically for overcoming FLA, Onwuegbuzie et al. (1999) suggested shifting learners' attention from self-worry to the learning material. Some researchers found that as long as the eyes are open, any technique could help change the attention from anxiety and direct it to a calm situation (Wehrenberg, 2018). Using emotional intelligence techniques could reduce anxiety (Brackett et al., 2004), and the more frequently people apply such mechanisms, the calmer they become (Wehrenberg, 2018).

To shift learners' attention, psychologists studied mindset theories such as fixed and growth mindsets. People with a fixed mindset believe that personality and intellectual ability are immutable, while people with a growth mindset believe these skills can be improved and developed (Y. Liu, 2022; Yeager & Dweck, 2020). For example, students with a growth mindset attempt challenging exercises to enhance their learning, while learners with a fixed mindset avoid challenging activities to avert failures (Lou & Noels, 2020; Marlow, 2021). In return, a growth mindset can reduce negative emotions such as anxiety and depression (Marlow, 2021; Schleider & Weisz, 2016).

Within foreign language learning, researchers found that a fixed mindset positively correlated with learning avoidance and negative emotions (Ciaccio, 2019; Lou & Noels, 2020; Marlow, 2021). A growth mindset is helpful for learners' communication, reduces their fear of negative evaluations, and minimizes their maladaptive outcomes (Y. Liu, 2022; Lou & Noels, 2020). Moreover, a growth mindset increases learners' motivation to learn and interact with their peers (Lou & Noels, 2020) because people with a growth mindset see their mistakes as a learning opportunity rather than an obstacle to learning (Lou & Noels, 2020; Marlow, 2021). In particular, to reduce FLA, researchers suggest using a growth mindset (Lou & Noels, 2020; Marlow, 2021), while a fixed mindset could increase FLA and reduce performance (Y. Liu, 2022; Marlow, 2021).

It is beneficial to shift learners' mindset from fixed to growth to reduce anxiety and improve learning achievement (Lou & Noels, 2020; Marlow, 2021). One way to build a growth mindset is to motivate the learners and assure them that mistakes help them learn (Lou & Noels, 2020; Marlow, 2021). Also, encouraging the learners and emphasizing the correct answer rather than the learner's performance can help to improve the growth mindset (Lou & Noels, 2020; Marlow, 2021).

2.5 Summary

The literature reviews about emotions and learning, especially foreign language anxiety implications, detection, and reduction, are summarized:

- Emotion affects daily life experiences, and it is affected by it. Specifically, emotions and cognition have an intertwined relationship, which affects learning (C.-M. Chen & Wang, 2011; Lopatovska & Arapakis, 2011; Trigwell et al., 2012). Negative emotions such as anxiety obstruct learning acquisition (Bigdeli, 2010; C.-M. Chen & Wang, 2011; Levitt, 2015; Tyng et al., 2017).

- Foreign language learners face emotional and pedagogical challenges. One of the main impediments is foreign language anxiety because it has a long-term effect on willingness to communicate (Ayedoun et al., 2019; M. Liu, 2006; M. Liu & Jackson, 2008). It inhibits language acquisition by increasing learners' reluctance to practice (Ismail & Hastings, 2019, 2020; M. Liu, 2006; M. Liu & Huang, 2011). Moreover, it hinders performance (M. Liu, 2006; M. Liu & Huang, 2011) and achievements (Farid, 2021).

- To detect emotions, physical measures, self-reporting, expert observers, facial expressions, and human behaviors were used. Each of these methods has its pros and cons. Researchers chose the approach that suits their study objectives (Dzedzickis et al., 2020; Henderson et al., 2020; Ismail & Hastings, 2019; Kazdin, 2000; Lopatovska & Arapakis, 2011).

- To reduce foreign language anxiety, researchers used ITSs, games, robots, animated agents, emotional support, shifting emotional attention, and adaptive systems (Alemi et al., 2014; Alhabbash et al., 2016; C.-M. Chen & Lee, 2011; Deloatch et al., 2017; Hayasaki & Ryan, 2022; Heilmann et al., 2016; Jin & Dewaele, 2018; H.-C. K. Lin et al., 2015; Vallejo Balduque, 2018).

2.5.1 Implications

As mentioned above, the relationship between emotions and learning is a complicated one (C.-M. Chen & Wang, 2011; Lopatovska & Arapakis, 2011; Trigwell et al., 2012). Especially, learning a foreign language is accompanied by complex emotions (H. Jeong et al., 2015). In this research, I focused on foreign language anxiety (FLA) as a special case of anxiety accompanying learning a foreign language.

Using physical measures, expert observers, facial expressions, and self-reports is intrusive, expensive, and still unreliable (Imani & Montazer, 2019; Lopatovska & Arapakis, 2011; Picard, 2008). Using sensor-free human behavioral methods is practical, discreet, and cost-effective (Dzedzickis et al., 2020; Lan et al., 2020). For my research, I studied the effectiveness of sensor-free human behavioral metrics in detecting FLA.

To reduce FLA, researchers used games, robots, or intelligent tutoring systems. However, these methods had limitations, such as addiction, inaccessibility, and a temporary effect on reducing anxiety (Lai & Wen, 2012; H.-C. K. Lin et al., 2015; Randall, 2019). Using affective user models can facilitate and enhance learners' affective states (Elliott et al., 1999; Hudlicka, 2020; Martinho et al., 1999). Using animated agents can reduce the language barrier and improve willingness to communicate in a foreign language, which can lower anxiety (Al-Kaisi et al., 2020; Ayedoun et al., 2015, 2019). Providing empathy and motivational support can reduce anxiety (Ayedoun et al., 2019). Shifting the learners' attention away from the anxious state to the learning material or a calming situation can lower their anxiety (Onwuegbuzie et al., 1999; Wehrenberg, 2018). Directing the learners to use a growth mindset can also reduce their anxiety and depression (Marlow, 2021; Schleider & Weisz, 2016). Using an adaptive system improves learners' affective states (Arroyo et al., 2014; Elliott et al., 1999; Hudlicka, 2020; Martinho et al., 1999). For my research, I studied the effectiveness of adaptive, motivationally supportive animated agents to reduce FLA. I designed the feedback to focus on the growth mindset and shift learners' attention from their performance to a motivational encouraging situation.

2.5.2 Conclusion

Emotions and learning are interrelated; therefore, ensuring a positive learning environment could improve performance and learning acquisition (Shute et al., 2015). Negative emotions hinder learning (Bigdeli, 2010; C.-M. Chen & Wang, 2011; Levitt, 2015; Tyng et al., 2017) and affect learners' well-being (Bigdeli, 2010; Kazdin, 2000). Researchers investigated emotions accompanying learning, like motivation, confusion, frustration, and boredom, to improve education (D'Mello & Graesser, 2013; Tettegah & Gartmeier, 2016). Others studied emotions that occur in specific situations, such as foreign language anxiety because it disturbs learning (Castillejo, 2018), diminishes confidence (Lai & Wen, 2012; Lu et al., 2007), and impairs performance (Bigdeli, 2010; H. T. D. Huang, 2018; M. Liu, 2006; M. Liu & Huang, 2011; Salehi & Marefat, 2014; Sparks et al., 2018). Therefore, by reducing foreign language anxiety, we can reasonably predict there will be a positive learning environment, which enhances motivation to learn (Lai & Wen, 2012; Onwuegbuzie et al., 1999) and increases the learner's performance (C.-M. Chen & Lee, 2011; X. Huang & Mayer, 2016).

Detecting FLA is the first step to reducing and eventually defeating it. Researchers used physical metrics, self-reports, expert observers, and human behavioral measures to recognize FLA and other emotions. Each of these metrics has pros and cons that must be addressed to choose the tool that suits a study. While for detecting FLA in particular, researchers mainly used self-reports. Ultimately, I investigated sensor-free human behavior detectors, as researchers in this era recommend, because it is the least intrusive to the learning process (Baker et al., 2015; Imani & Montazer, 2019).

To reduce FLA, researchers suggest using ITS (H.-C. K. Lin et al., 2015), conversational agents (Ayedoun et al., 2015, 2019), or emotional support (Jin & Dewaele, 2018). After evaluating the benefits and disadvantages of these methods, for my study, I investigated the efficacy of an emotionally adaptive intelligent tutoring system that provides an animated agent equipped with motivational supportive feedback.

Chapter 3

Detecting FLA

Research Question 1 focuses on whether detecting FLA using sensor-free human behavioral metrics is effective [1].

RQ1: Can FLA be detected using sensor-free human behavioral metrics in an e-learning context?

To summarize the main relevant points from Chapter 2, it is essential to understand learners' emotional state to provide a beneficial learning environment (C.-M. Chen & Lee, 2011). Recognizing FLA is important because anxiety impedes learning and blocks the cognitive process (C.-M. Chen & Lee, 2011; Horwitz et al., 1986; X. Huang & Mayer, 2016; Onwuegbuzie et al., 1999; Shao et al., 2013). Detecting anxiety is the first step to reducing it and overcoming it in the future (Farid, 2021; Horwitz et al., 1986; Ismail & Hastings, 2019). It is essential to measure anxiety efficiently so that help can

[1] Portions of the content of this chapter have been published in (Ismail & Hastings, 2019, 2020, 2022).

be provided when needed (Onwuegbuzie et al., 1999). Identifying FLA using sensor-free behavioral measures would grant maximum utility of emotion detection (Baker et al., 2012).

The previous research presented in Section 2.3 discussed the pros and cons of existing emotion detectors. To detect FLA, previous research used self-reporting, physical measures, and facial expressions, which proved to be suboptimal. On the other hand, sensor-free human behavioral metrics can provide accurate predictions and enhance learning (Arevalillo-Herráez et al., 2017; T.-Y. Yang et al., 2019). Researchers have used sensor-free metrics to detect emotions such as confusion, frustration, boredom, or motivation (Baker et al., 2012), but not FLA. These sensor-free metrics recognize learners' emotions in their environments without disturbing the learning processes and provide maximum utility (Baker et al., 2012; Dzedzickis et al., 2020; Lan et al., 2020). In general, the use of sensor-free human behavioral metrics is a relatively new area of research, so there is a need for more research about the applicability and effectiveness of these metrics.

It is unknown to science the best way to detect foreign language anxiety, especially within an e-learning system when there is no interaction with a human tutor. Also, existing approaches to detecting foreign language anxiety showed some limitations that prevented researchers from detecting foreign language anxiety effectively. To address them and Research Question 1, I did exploratory research to identify which physical and sensor-free metrics allow us to determine when the learner feels anxious. Because it is exploratory, I am testing two sets of metrics to see which are predictive. Two different versions of e-learning systems were developed and tested. The versions were related, but each version used somewhat different pedagogical content, metrics, and evaluations.

Experiment 1 used a non-adaptive e-learning system and tested using physical metrics and self-reports in a lab-based setting. Section 3.2 describes the Experiment 1 e-learning system, design, and method.

Experiment 2 converted the approach to an online system for the purpose of identifying FLA with human behavioral metrics. It included more challenging questions as well as videos and a wider range of question types. Section 3.5 describes the Experiment 2 e-learning system, design, and machine learning method.

3.1 Hypotheses for Research Question 1

To find the best method for detecting FLA without using any sensors, I addressed the following sub-questions:

3.1.1 Usefulness of Classroom Anxiety Metrics

RQ 1.1: Do metrics for classroom FLA help predict FLA in an online system?

As mentioned in Section 2.2, when learners are anxious in one situation, they would likely be anxious in a similar context. Understanding the interaction between different anxiety-producing situations could help to overcome anxiety (H. T. D. Huang, 2018; MacIntyre & Gardner, 1994).

Hypothesis 1.1: I hypothesized that learners who are anxious in a foreign language classroom would also experience anxiety while using an e-learning system.

3.1.2 Exercise Difficulty

RQ 1.2: What is the relationship between FLA and the difficulty of the exercise?

As cited in Section 2.2.2, there is conflicting evidence about the relationship between FLA and language difficulty. Some research found a positive correlation between language complexity and anxiety (Robinson, 2007). However, other researchers found no significant interaction between task complexity and language anxiety because of the repeated practice. They hypothesized that the learners' familiarity with the exercises reduced their anxiety and led to a lack of a significant interaction between task complexity and anxiety (Kim & Tracy-Ventura, 2011).

Hypothesis 1.2: I hypothesized that more difficult exercises would increase FLA.

3.1.3 Effectiveness of Behavioral Metrics

RQ 1.3: Can FLA be identified by the learner's interaction with the system?

The goal of answering RQ 1 is to investigate different FLA-measuring techniques that can effectively identify FLA with minimal user interruptions. As mentioned in Section 2.3.5, ideal detectors should be convenient for the learner. Students should be able to access the system in their comfortable environments instead of artificial lab settings (Imani & Montazer, 2019). Previous researchers have found that measuring emotions using sensor-free metrics can be beneficial because there is no interruption to the learning process (Baker et al., 2015). Also, they are scalable, interpretable, and non-invasive (Lan et al., 2020).

Hypothesis 1.3: I hypothesized that sensor-free human behavioral metrics could effectively detect FLA within an e-learning system.

To test these hypotheses, I developed two somewhat different e-learning systems. The first e-learning system had listening, speaking, vocabulary, grammar, and conversation exercises. The description of this system is described in Section 3.2.1. The second e-learning system, described in Section 3.5.1, addressed some limitations of the first system, such as evaluating all exercises without needing a human grader.

3.2 Method for Experiment 1

To answer Research Question 1 about detecting FLA, I first conducted an observational study in the lab. Below is a description of Experiment 1's e-learning system, design, and measures, along with the data analyses.

3.2.1 E-Learning System 1

I built an e-learning system that teaches English as a foreign language. It was implemented as a browser-based application using HTML, PHP, and JavaScript and included animated agents from Media Semantics. I used the following principles from the Cognitive Theory of Multimedia Learning (CTML, Clark & Mayer, 2016; Mayer, 2005) to provide an effective e-learning system:

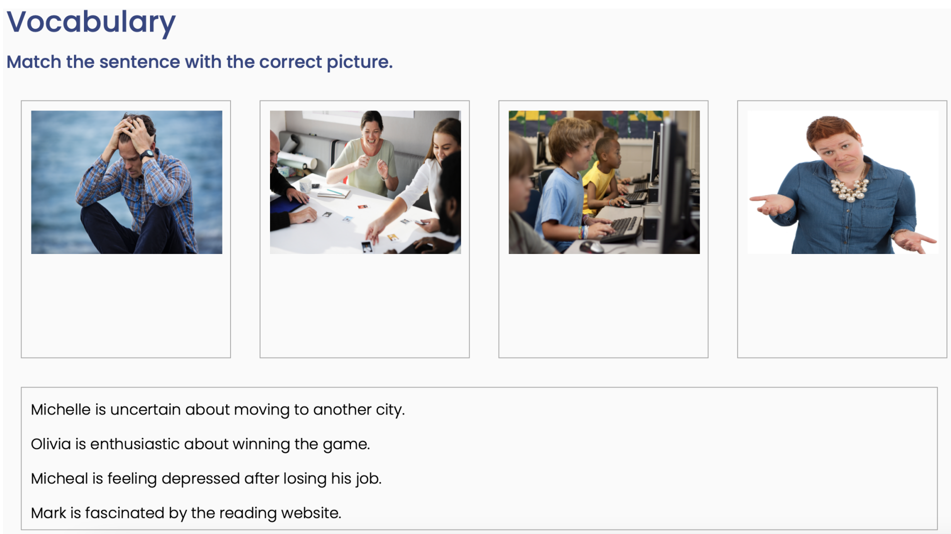


Figure 3.1: Multimedia in e-learning system 1.

Multimedia: The multimedia principle states that using visual illustrations to explain and elucidate the learning material. I applied multimedia by illustrating the vocabulary exercise instances for example pictures related to the text, as shown in Figure 3.1.

Redundancy: The redundancy principle states that on-screen text which mirrors spoken text will interfere with learning, *except* in certain circumstances including when the learner is learning a new language (Clark &

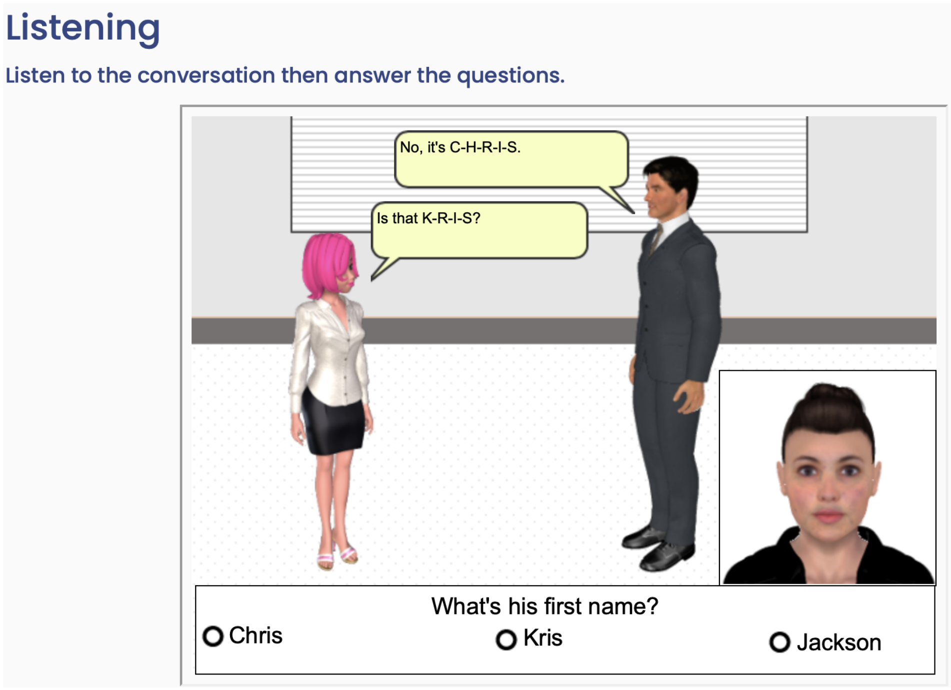


Figure 3.2: Redundancy in e-learning system 1.

Mayer, 2016). I added speech bubbles for the listening exercises that included spoken words. (See Figure 3.2.)

Coherence: The coherence principle states that eliminating non-essential sounds and graphics that do not add helpful information. I applied the coherence principle by only using graphics and sound that help to convey the learning material. For example, there are no extraneous graphics. The graphics are used only to illustrate the vocabulary items. There is no background music.

Segmentation: The segmentation principle states that dividing the lesson into multiple small chunks so the learners can access it at their own pace. I applied the segmentation principle by dividing each lesson into multiple exercises.

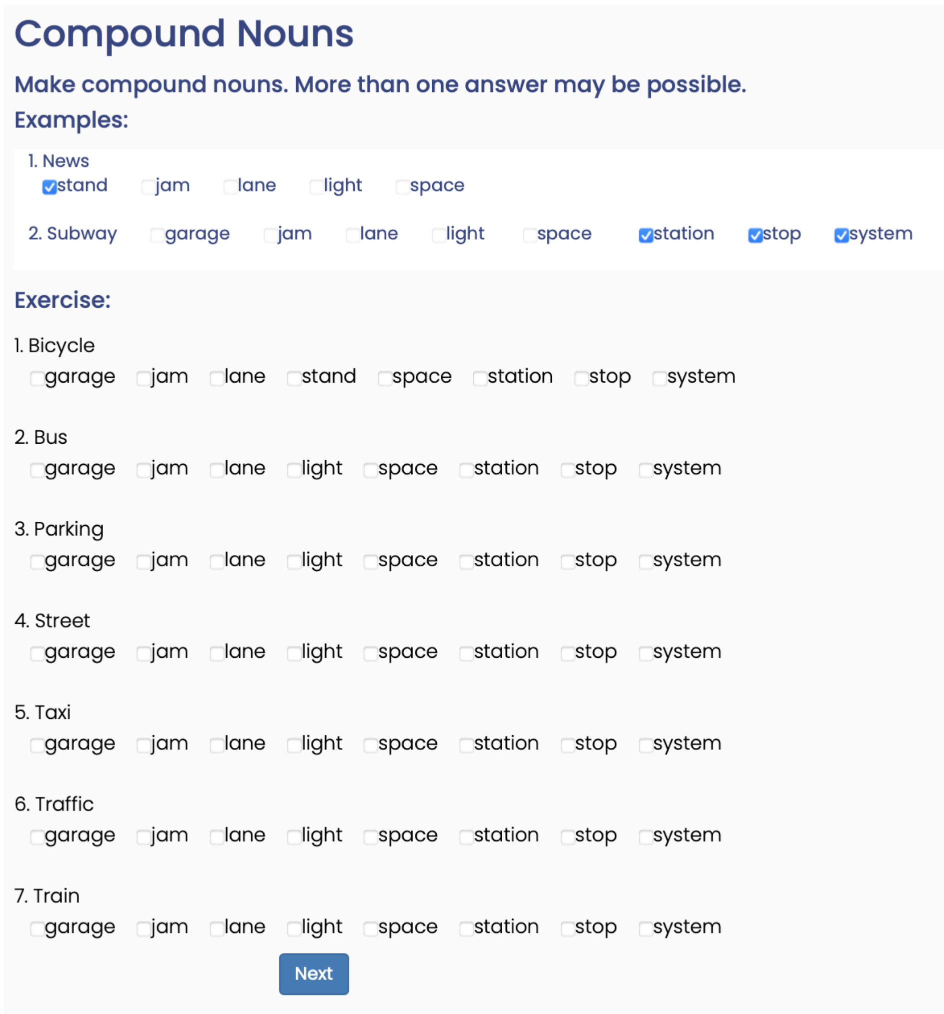


Figure 3.3: Leveraging examples in e-learning system 1.

Examples: The Leveraging of Examples Principle suggests adding examples to explain the learning material. I applied this principle by providing examples of answers similar to the exercises as shown in Figure 3.3.

The content of the e-learning system consisted of 27 exercises focused on greeting, transportation, and emotions (see Appendix F.) These topics were presented within the following tasks:

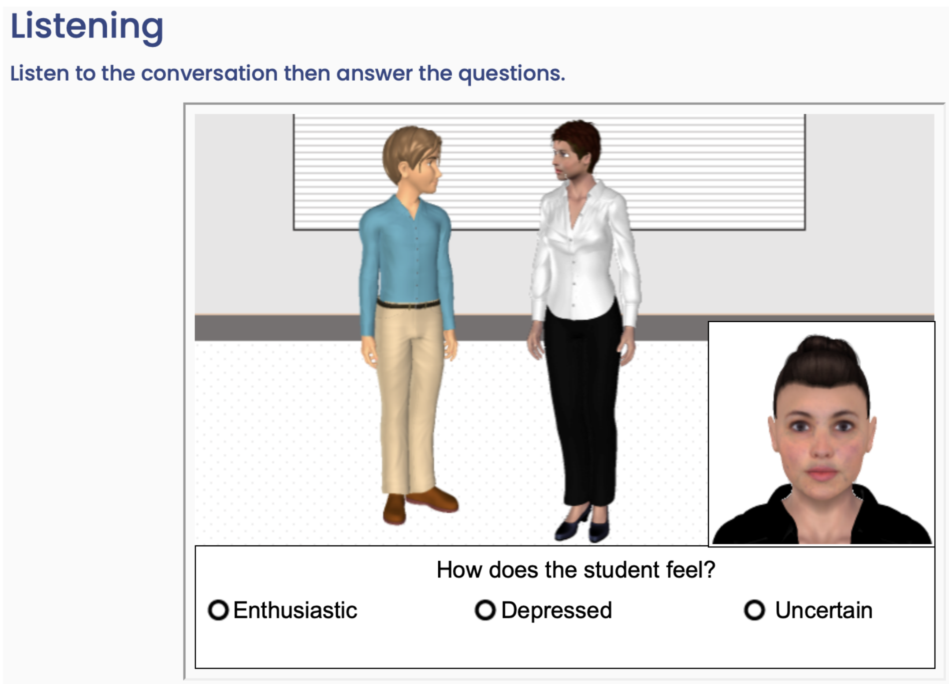


Figure 3.4: Listening in e-learning system 1.

- **Listening:** There were conversations between two people, and the agent asked the learner questions about them. (See Figure 3.4.)
- **Speaking:** The learner read a conversation written on the screen and then recorded it, as shown in Figure 3.5.
- **Vocabulary:** The learner matched the sentence with the appropriate picture. (See Figure 3.6.)

Reduced Forms

Click "start recording", then read the conversation in the reduced form, when you finish click "stop recording".

Example:

To say "Olivia: What did you do last night?" we should say, "Olivia: Whadja do last night?"

Exercise:

Say:

Sarah: Excuse me, Are you Chris Carson?

Chris: Yes, I'm.

Sarah: Hi, I'm Sarah Smith. I'm in your science class.

Chris: Oh, yes I remember you.

Sarah: Tomorrow we are going to the museum of science and industry do want to join us?

Chris: Sure, I will love too.

Sarah: See you tomorrow.

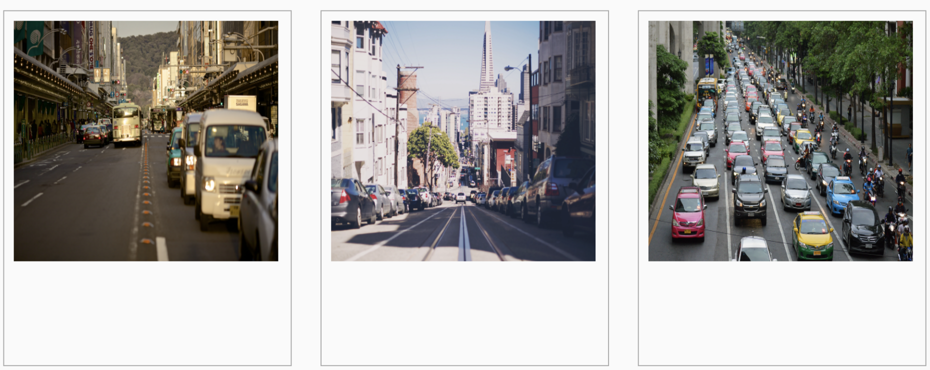
Chris: See you tomorrow.

start recording | stop recording

Figure 3.5: Speaking in e-learning system 1.

Vocabulary

Match the sentence with the correct picture.



I think there are too many cars on the road. All the cars, taxis, and buses make it really dangerous for bicycles. There is too much traffic!.

What about the buses? They are old, slow, and cause too much pollution. I think there should be less pollution in the city.

There should be fewer cars, but I think that the biggest problem is parking. There just isn't enough parking.

Figure 3.6: Vocabulary in e-learning system 1.

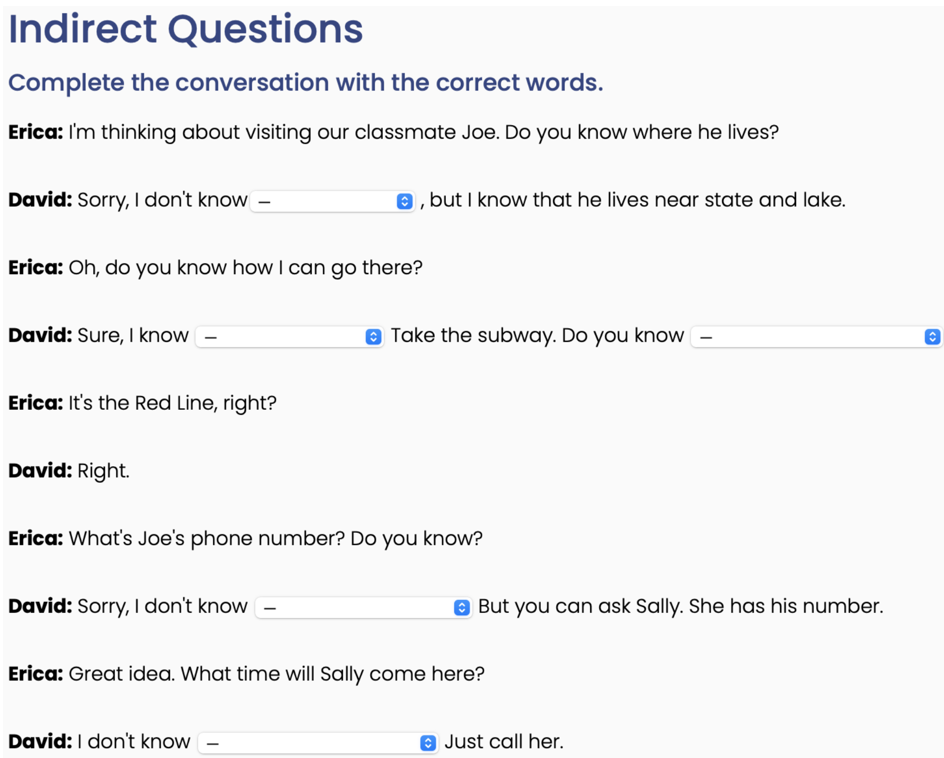


Figure 3.7: Grammar in e-learning system 1.

- **Grammar:** The learner should choose the correct answer from multiple choice options to complete the sentence in the proper grammatical form as shown in Figure 3.7.

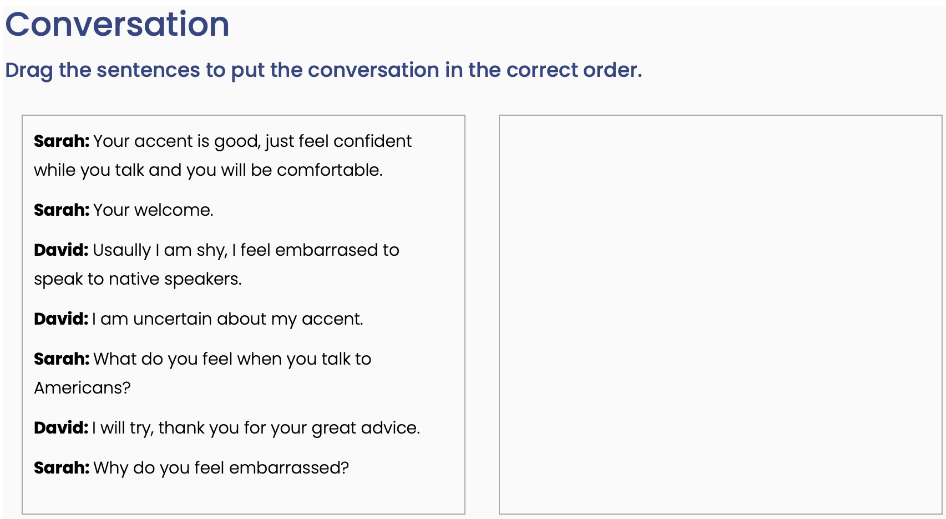


Figure 3.8: Conversation in e-learning system 1.

- **Conversation:** The learner rearranged sentences to produce the correct conversation order (see Figure 3.8).

3.2.2 Design

Three rounds of pilot tests were performed to validate the system's usability, self-reports, and physical measures. Each pilot test round consisted of 2 participants.

An observational study was performed in the lab. All the sessions were audio/video recorded. A log sheet documented any unusual occurrences. The participants took an average of 43 minutes to complete the self-reports and exercises. Each participant received a $20 Amazon gift card.

3.2.3 Participants

Thirty adult non-native English speakers were recruited. Ages were between 18 and 54 years old; 77% (N=23) female and 23% (N=7) male. There were 40% (N=12) native Arabic speakers, 37% (N=11) native Chinese speakers, 13% (N=4) native Spanish speakers, and 10% (N=3) native Thai speakers. The education level was 7% (N=2) high school, 80% (N=24) bachelor's degree, and 13% (N=4) master's degree. Their English level was 17% (N=5) beginner, 53% (N=16) intermediate, and 30% (N=9) advanced.

3.2.4 Measures

Before the study, the participants answered the FLCAS, which assesses their anxiety level in the context of an English as a second language class. (See Section 2.3.2.) The FLCAS score classified the participants into anxious (score 90 or above) or non-anxious (score below 90) (Al Mamun, 2021; Guo et al., 2018). Participants' FLCAS answers were divided into its main components: communication apprehension, fear of negative evaluation, and test anxiety (Horwitz et al., 1986). The responses within each component were averaged and then used as predictors for FLA.

During the study, the anxiety was measured using self-report, heart rate, blood pressure, and eye fixation. To avoid misunderstandings, the self-report was translated into the learner's native language (Arabic, Chinese, Japanese, Korean, Spanish, and Thai). It included three components: language difficulty, system difficulty, and current level of anxiety see Figure 3.9.

The language difficulty and system difficulty metrics came from the participants' Likert scale responses. The level of anxiety self-report was coded from the participants' continuous-valued slider response as a value from 0 to 100. The participants answered the self-report after each exercise to measure their anxiety level.

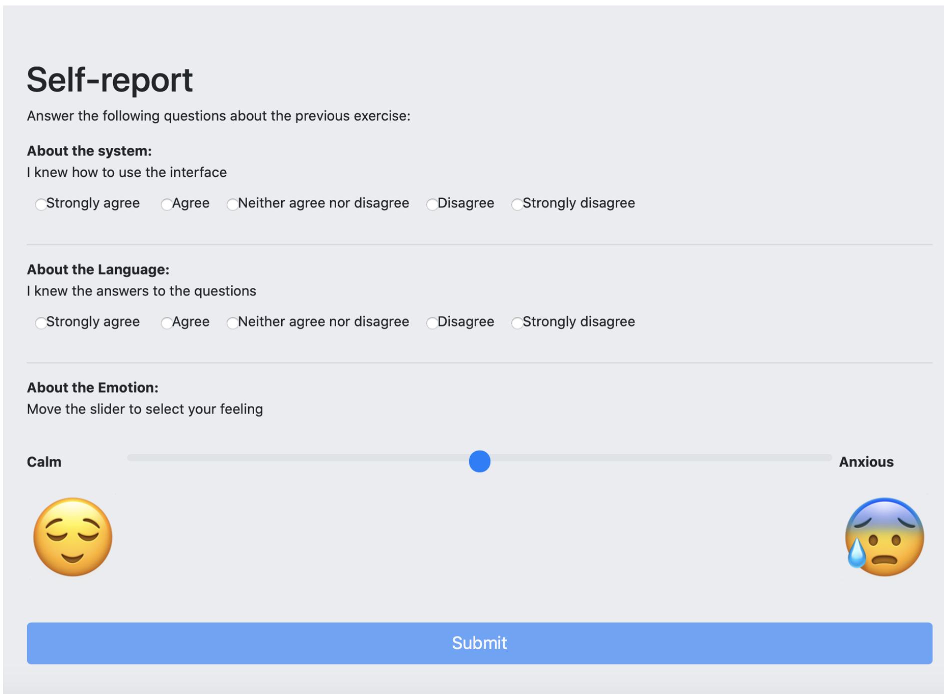


Figure 3.9: Self-report.

As mentioned in Section 2.3.1, blood pressure is positively correlated with anxiety, so I measured the learner's blood pressure to determine its usefulness for detecting FLA. Blood pressure was measured while the participant answered the FLCAS to get a baseline, then again during each exercise. However, the varying amount of time spent on each exercise affected the frequency of readings. In some activities, there were three readings, while there were none in others that were completed faster. To calculate the blood pressure during the exercise, I compared the change in systolic and diastolic pressure readings with the baseline blood pressure, providing a more robust metric than the absolute blood pressure values.

Some researchers found a relationship between anxiety and heart rate variability (see Section 2.3.1). For my study, I measured the learner's heart rate to evaluate its usefulness for detecting FLA. The participants wore a fitness tracker on the left wrist to measure heart rate. The fitness tracker provided continuous reading for the whole session. This information was exported from the fitness tracker to a log file. Based on the timestamp, heart rate was paired with the exercise. The difference between the maximum and minimum heart rate per activity was measured to capture changes that might occur during the exercise because different people have different base rates. I also explored the use of average, maximum, and minimum heart rates, but they did not provide an accurate reading of change in anxiety; the difference did.

Eye fixation can help to detect anxiety (see Section 2.3.1). In this study, I used a Tobii eye tracker, which was connected to the screen's bottom frame. This eye tracker provided the number of fixations, as well as the time on task and the number of mouse clicks.

Each participant's score for each exercise was calculated as the percentage of correct answers for that exercise. Also, I calculated the percentage of the correct answers across all participants to measure the aggregate exercise difficulty. Then, I classified the exercises into three levels (easy, medium, and hard).

3.3 Data Analysis and Results for Experiment 1

3.3.1 RQ 1.1: Relationship Between In-Class and Online FLA

RQ 1.1 asked whether metrics for in-class FLA help predict FLA in an e-learning system. More specifically, I used a Mann-Whitney U-Test, a nonparametric statistical analysis for comparing two independent samples (Corder, 2014), to determine whether classroom FLA (as determined by the FLCAS) was significantly related to metrics collected during Experiment 1. The FLCAS was used as described above to classify the participants as anxious or non-anxious in classroom settings. The online anxiety was measured while using e-learning system 1 using the following measures: level of anxiety self-report, language difficulty self-report, the change rate of systolic (SYS) and diastolic (DIA) blood pressure, exercise score, number of fixations, the change in heart rate, system difficulty self-report, time on task, and the number of mouse clicks.

There was a significant difference between the two groups (anxious and non-anxious) in the level of anxiety self-report, language difficulty self-report, the change rate of systolic (SYS), and diastolic (DIA) blood pressure measurement. On the other hand, there was no significant difference between the two groups in the exercise score, number of fixations, difference in heart rate, system difficulty self-report, time on task, or the number of mouse clicks as shown in Table 3.1.

Table 3.1: Differences between anxious and non-anxious learners.

Variable	Anxious Median	Non-anxious Median	Mann-Whitney U	p value
Level of anxiety self-report	14	2	57404.5	$<$0.001
Language difficulty self-report	2	1	67585.0	$<$0.001
Change rate of SYS	-5	-8	49766.5	$<$0.001
Change rate of DIA	-2.667	-5.2	51734.0	$<$0.001
Difference in heart rate	10	10	74523.0	0.067
System difficulty self-report	1	1	76941.0	0.193
Exercise score	100	95	43037.5	0.554
Time on task	62.61	61.17	78668.5	0.641
Number of mouse clicks	9	9	78570.5	0.679
Fixations	164	161	80458.5	0.977

3.3.2 RQ 1.2: Relationship Between FLA and Exercise Difficulty

To answer RQ 1.2 about the relationship between FLA and the difficulty of the exercise, I performed a Spearman correlation. The FLA was measured based on the level of anxiety self-report. The exercise difficulty was measured in two distinct ways: the learner's self-report of language difficulty and aggregate exercise difficulty. The latter was calculated based on all participants' scores as described in Section 3.2.4.

The results showed a significant, moderate positive correlation between the level of anxiety self-report and language difficulty self-report $r = 0.582, p < 0.001$.

There was a significant, weak positive correlation between the aggregate exercise difficulty and the level of anxiety self-report $r = 0.086, p = 0.036$. It is worth mentioning that there was a significant weak positive correlation between the language difficulty self-report and aggregate exercise difficulty $r = 0.144, p < .001$.

3.3.3 RQ 1.3: Identifying FLA Using Learner Interaction

A Pearson correlation was done to understand the relationship between FLA as measured by the level of anxiety self-report and the physical measurements. The results showed a weak but significant positive correlation between the level of anxiety self-report and the number of fixations $r = 0.171, p < 0.001$, heart rate $r = 0.166, p < 0.001$, the change rate of SYS $r = 0.174, p < 0.001$ and DIA $r = 0.149, p < 0.001$.

For the following analyses, the ground truth for FLA is the self-reported anxiety level after each exercise. The goal is to accurately predict FLA based on the learner's interaction with the e-learning system. Multiple regression analysis was conducted to predict FLA using language difficulty self-report, system difficulty self-report, score, aggregate exercise difficulty, time on task, and the number of mouse clicks as independent variables. The dependent variable was the level of anxiety self-report. The model's overall prediction was not improving with the addition of more predictors. All possible models were compared to find the best fit based on the R^2, adjusted R^2, and predicted R^2.

To answer RQ 1.3 on identifying FLA based on the learner's interaction with the system, I did a multiple regression to examine how the metrics collected while using the system could predict FLA. The best predictors for FLA were language difficulty self-report, system difficulty self-report, and exercise scores. The other variables did not improve the accuracy of prediction. The combination of the three predictors accounted for about 30% of the variation in FLA, $R^2 = 30.79\%$, $R^2(adj) = 30.45\%$, and $R^2(pred) = 29.10\%$. The regression equation indicated that the model was a significant predictor of anxiety $(F3, 599) = 88.40, p < 0.001$ see Table 3.2. As mentioned earlier, I did regression to predict FLA, not to describe or fit data. Thus, to evaluate if the model is overfitting and the generalizability to new data, I did a 10-fold cross-validation. The three predictors accounted for about 30% of the variation in FLA, $R^2 = 29.5\%$.

Table 3.2: Multiple regression coefficients.

Term	Coef	SE Coef	t-value	p-value
Constant	15.305	0.663	23.07	$<$0.001
Language difficulty self-report	9.659	0.781	12.37	$<$0.001
System difficulty self-report	1.772	0.769	2.30	0.022
Exercise Score	-0.580	0.683	-0.85	0.396

To predict FLA based on the exercise type (listening, grammar, speaking, or vocabulary), multiple regression analysis was performed. For each regression, the self-reported level of anxiety was the dependent variable, and the relevant component of the FLCAS score, as described in Section 3.2.4, was the independent variable.

For listening exercises, the independent variable was average communication apprehension from the FLCAS, and the dependent variable was the level of anxiety self-report. The predictors accounted for 13% of the variation in anxiety, $R^2 = 12.6\%$, and $R^2(adj) = 12.1\%$. The regression equation indicated that the model significantly predicted anxiety, $F(1, 179) = 25.647, p < 0.001$. I did a 10-fold cross-validation to evaluate how well this prediction would generalize to new data. The average communication apprehension from the FLCAS accounted for 5% of the variation in FLA, $R^2 = 5.2\%$.

For grammar exercises, the independent variable was average test anxiety scores from the FLCAS, and the dependent variable was the level of anxiety self-report. The predictors accounted for 18% of the variation in anxiety, $R^2 = 17.9\%$, and $R^2(adj) = 17.3\%$. The regression equation indicated that the model significantly predicted anxiety, $F(1, 149) = 32.278, p < 0.001$. Then, I did a 10-fold cross-validation to evaluate the generalization of this prediction. The average test anxiety scores from the FLCAS accounted for 2% of the variation in FLA, $R^2 = 1.8\%$.

For speaking exercises, the independent variables were the average fear of negative evaluation, and the average communication apprehensions, and the dependent variable was the level of anxiety self-report. The predictors accounted for 21% of the variation in anxiety, $R^2 = 21.1\%$, and $R^2(adj) = 20.3\%$. The regression equation indicated that the model significantly predicted anxiety, $F(2, 209) = 27.682, p < 0.001$. After doing a 10-fold cross-validation, I found the two predictors accounted for about 11% of the variation in FLA, $R^2 = 11\%$.

For vocabulary exercises, the independent variables were average test anxiety and average fear of negative evaluation, and the dependent variable was the level of anxiety self-report. The predictors accounted for 25% of the variation in anxiety, $R^2 = 25.2\%$, and $R^2(adj) = 22.6\%$. The regression equation indicated that the model was a significant predictor of anxiety, $F(2, 59) = 9.595, p < 0.001$. Then I did a 10-fold cross-validation to check and evaluate the generalization of this prediction. The two predictors accounted for about 7% of the variation in FLA, $R^2 = 7.3\%$.

To predict FLA using sensor-free measures regardless of the type of exercise, I used each of the FLCAS components mentioned above as independent variables. The dependent variable was the level of anxiety self-report. These predictors accounted for about 18% of the variation in anxiety, $R^2 = 18.1\%$, and $R^2(adj) = 17.9\%$. The regression equation indicated that the model was a significant predictor of anxiety, $F(2, 807) = 88.99, p < 0.001$. Then I did a 10-fold cross-validation to check and evaluate the generalization of this prediction. The predictors accounted for about 15% of the variation in FLA, $R^2 = 15\%$.

The prediction of FLA can be improved by combining the FLCAS component scores with sensor-lite metrics. In particular, as Table 3.3 shows, I used the independent variables of language difficulty self-report, system difficulty self-report, and exercise score along with the FLCAS component scores to predict the dependent variable of the level of anxiety self-report. These predictors accounted for about 43% of the variation in anxiety, $R^2 = 42.7\%$, and $R^2(adj) = 42.2\%$. The regression equation indicated that the model was a significant predictor of anxiety $F(5, 599) = 88.404, p < 0.001$. Average test anxiety, the third component of FLCAS, was dropped from the analysis because the tolerance was zero; the variance in the predictive level of test anxiety for anxiety self-report was redundant with the other predictors. To evaluate the generalization of this prediction, I did a 10-fold cross-validation. The model achieved an estimated of 40% of the variation in FLA, $R^2 = 40.4\%$.

Table 3.3: Predicting FLA using sensor-lite metrics.

Term	Coef	SE Coef	t-value	p-value
Constant	-30.746	3.476	-8.844	$<$0.001
Fear of negative evaluation	7.853	1.102	7.125	$<$0.001
Communication apprehension	0.899	1.43	0.629	0.53
Language difficulty self-report	11.331	1.01	11.223	$<$0.001
System difficulty self-report	3.959	1.168	3.388	$<$0.001
Exercise Score	-0.453	0.232	-1.956	0.051

3.4 Discussion of Results for Experiment 1

3.4.1 RQ 1.1: Relationship Between In-Class and Online FLA

RQ 1.1 asked whether metrics for classroom FLA help in predicting FLA when using an online system. When looking at metrics collected using the system to see if they significantly differentiated the groups (anxious versus non-anxious), there was a significant difference in the anxiety self-report, language difficulty self-report, and average diastolic (DIA) and systolic (SYS) blood pressure level. My hypothesis was supported because students who suffer from FLA in a classroom situation were also anxious while using an e-learning system as measured by these metrics.

Importantly, as I expected, students who were more anxious in the classroom, as determined by the FLCAS, reported more anxiety while they were using the system. This finding replicates MacIntyre and Gardner (1994), who emphasized that when learners are anxious in a situation, they are likely to be anxious in a similar context. Also, it would indicate that the level of anxiety self-report is a valid tool to measure language anxiety. Moreover, the median and average of the level of anxiety self-report were both higher for the anxious group. This result means that the level of anxiety self-report provided accurate information about the current learner's emotional status.

The median value of the language difficulty self-report item ("I knew the answers to the questions.") for anxious learners was 2 "Agree" on the 5-

point Likert scale. For the non-anxious learners, the median corresponded to "Strongly Agree." This finding means the anxious learners felt the questions were more challenging than the non-anxious learners. The anxious learners believed the exercises were slightly more difficult than the non-anxious learners.

Average diastolic (DIA) and systolic (SYS) blood pressure was higher for anxious than non-anxious learners, replicating previous research (Mucci et al., 2016; Z. Zhang et al., 2011). Although both median and average readings for both groups were in the normal DIA and SYS according to (Whelton et al., 2018), there was a slight increase in the average and median readings for anxious learners.

I expected to get a significant difference in the exercise score between the two groups. The results showed no significant difference, similar to Tanielian and English (2014). It could be because I did not show the exercise score to the participants after the activities, so there was no significant impact of the score on anxiety.

I assumed there would be a difference between anxious and non-anxious learners in the time spent on task and the number of mouse clicks because FLA affects self-confidence and self-esteem (M. Wang, 2014); however, there was no difference. Anxious learners spent slightly more time on the exercises apparently because the exercises were not challenging. The number of mouse clicks was the same for both groups, which reflects clicking the target button only once when needed.

3.4.2 RQ 1.2: Relationship Between FLA and Exercise Difficulty

RQ 1.2 asked whether there is a relationship between FLA and the difficulty of the exercise. I measured the difficulty of the language using self-report and based on all the participants' scores. The language difficulty self-report represents the user's impression of the exercise. In contrast, the exercise difficulty describes the overall difficulty; in some situations, exercises were easy for some participants while hard for others. I found that both measurements for the difficulty of the language are positively correlated with the level of anxiety self-report. This finding allows us to accept the hypothesis that language difficulty affects FLA. I assumed that the learners become more anxious when the exercise is challenging. Similar to Robinson (2007), I found evidence that the difficulty of the exercise affects the learners' anxiety level. When the learners face an easy exercise, they become calm; when they face a challenging exercise, they become anxious. This result reinforced I.-J. Chen and Chang (2009) who also found that when the difficulty increases, the anxiety rises too.

3.4.3 RQ 1.3: Identifying FLA Using Learner Interaction

To be able to predict FLA, I measured FLA using physical metrics and self-reports. Some physical measurements had a low correlation, while others did not correlate with the level of anxiety self-report. My results confirmed Kazdin (2000) with a low correlation between self-reporting and physical tools. My findings showed that anxious learners had more eye fixations than calm learners. This result means anxious foreign language learners tend to have more eye fixation (Runswick et al., 2017).

The main reason for finding the correlation between the level of anxiety self-report and the difference in heart rate was because the difference gave me the amount of change in heart rate. The average heart rate did not provide an accurate indication. The results showed that increasing the anxiety level would increase the difference between the highest and lowest heart rate per exercise. If the learners were calm before the exercise, their heart rates would be relatively low. Then, through the exercise, if the learners become anxious, their heart rate increases. Based on the level of anxiety, the change in heart rate occurs (Gotardi et al., 2018; Kantor et al., 2001; Z. Zhang et al., 2011).

Similar to (Mucci et al., 2016; Z. Zhang et al., 2011), the results showed a significant positive correlation between the level of anxiety self-report and blood pressure. However, the correlation was weak. One possible explanation for the weak correlation was that the exercises were too easy to provoke high anxiety. Based on the FLCAS, 87% of the participants have mentioned that fear of the consequences of failure is the biggest anxiety producer. Study participation was voluntary and did not affect the participants' grades, which means a cause of anxiety was absent. This result suggests that there could be better tools to identify FLA within an e-learning system than physical measurements.

RQ 1.3 asked whether we can identify FLA from user interaction with the system. The factors that were the most effective predictors for FLA were language difficulty, system difficulty, and exercise scores. Students consistently reported their feelings; they felt anxious when they believed they did not know how to answer the question and vice versa. There is a relationship between the complexity of the task and anxiety (Robinson, 2007). This relationship led to having a language difficulty self-report as the most precise FLA predictor.

The second predictor was the self-report system difficulty. I assumed this predictor would affect language anxiety because the lack of technical knowledge would confuse the learner, which could lead to frustration and anxiety. The inability to solve the activity due to the system difficulty enhanced the language anxiety. The system difficulty would reduce self-efficacy, which induces anxiety (Saadé & Kira, 2009). These two predictors replicate using the self-report by Wixon et al. (2014) as a sensor-free emotion detector.

The third predictor was the learner's exercise score because FLA affects students' language achievement (MacIntyre & Gardner, 1994). The score represents how well the student did in the exercise. Although the score was not shown to the students in the e-learning system, it affected their anxiety levels.

The other predictors were less significant than expected. One of the predictors used by Wixon et al. (2014) was time on task. I assumed that anxiety would affect the time spent on a task. For example, if the learners were anxious, they would tend to take a longer time to answer a question. However, taking the time on task into account when detecting FLA plays did not help the model. The power of the prediction was not highly affected by the time on task.

I assumed using aggregated language difficulties would add power to the anxiety predictor. Based on Robinson (2007), task difficulty is affected by anxiety, but task complexity is another dimension affected by individual differences. What could be easy for one learner could be challenging for another one. Adding the aggregated exercise difficulty would not improve the power of prediction.

I predicted anxious learners would click the mouse more than non-anxious learners, based on the assumption that anxious learners would not be sure about their answers, so they would change their answers. However, this assumption was wrong. The number of mouse clicks is not an efficient predictor for language anxiety.

To identify FLA, I studied the relationship between anxiety and exercise types. I used the FLCAS as the primary medium for predicting the learner's anxiety level. The FLCAS is a reliable measure for foreign language in the *classroom* (Horwitz et al., 1986). The current study is designed to demonstrate that it can also predict anxiety in an e-learning context. The e-learning system I used in the study involved listening, grammar, vocabulary, and speaking exercises.

For the listening exercises, previous research indicated that listening is a factor of communication apprehension (Atasheneh & Izadi, 2012; Horwitz et al., 1986); thus, I assumed that the communication apprehension questions of the FLCAS would predict the learner's anxiety level. Regardless of the medium for learning — in a classroom or through an e-learning system — anxiety production would be the same. People are less apprehensive when communicating in an interpersonal situation and become more anxious in public (Bodie & Villaume, 2003). The listening exercise is within an e-learning system, so the learner interacts with a computer without contact with people. The effect of communication apprehension is based on the habituation of previous listening exercises in class. That explains the weak prediction, which accounted for about 5% of the variation in FLA.

Using grammar in a foreign language is a complex task, which frequently causes frustration for the learner in a foreign language classroom (Mufidah, 2016). Research has identified grammar as the most challenging aspect of the English proficiency test (Mufidah, 2016). I hypothesized that average test anxiety from the FLCAS would predict the anxiety level in a grammar exercise. The average test anxiety accounted for about 18% of the variation in FLA. However, after doing cross-validation, the accuracy dropped to 2%. I used only one predictor, whereas more features may be required to increase the prediction. The questions in the FLCAS test anxiety section focused on worrying about the consequences of failure, forgetting known material, and getting more confused with studying. These items do not apply to the grammar exercises within the e-learning system because the study does not affect failure in any test, class, or social setting. There are two directions to predict the FLA within a grammar exercise: get more data, then check the prediction, or add more predictors.

Foreign language speaking anxiety is produced by communication apprehension and fear of negative evaluation (Rafada & Madini, 2017). The primary source of FLA is the need for automaticity, which requires the learners to remember the word and use it in speaking instantly (Balemir, 2009). Other aspects that affect speaking anxiety are communication and sociolinguistic competence (Balemir, 2009). Negative feedback from the teacher or the peer induces anxiety and prevents the learner from speaking in class (Rafada & Madini, 2017). I hypothesized that fear of negative evaluation and communication apprehension could predict foreign language speaking anxiety in the context of an e-learning system. Feeling worried about negative feedback would produce an unwillingness to communicate (Rafada & Madini, 2017), which could prevent the learner from engaging in social activities. Even though the prediction after doing cross-validation was only around 11% of the variation in FLA, it aligned with Balemir (2009), Horwitz et al. (1986), and Rafada and Madini (2017) about the relationship among foreign language speaking anxiety, fear of negative evaluation, and communication apprehension.

To measure the anxiety level within a vocabulary exercise, I hypothesized that average test anxiety and fear of negative evaluation would be effective predictors. Vocabulary anxiety correlates significantly with test anxiety and fear of negative evaluation (X. Chen, 2015). The accuracy after cross-validating the dataset dropped from 18% to 15% of the variation in FLA. This result may be due to the small size of the dataset. There are only two vocabulary exercises and 30 participants, so the total size of the dataset may need to increase to get an accurate prediction. This analysis needs further investigation to determine if the amount of data is the problem or if the predictors are ineffective.

To predict FLA regardless of the type of exercise, I used a combination of FLCAS and self-report. Specifically, I hypothesized that a combination of average fear of negative evaluation, average communication apprehension, language difficulty self-report, system difficulty self-report, and exercise score would predict FLA. FLCAS average test anxiety was excluded because the tolerance was 0, which means that the variance in predictor level of anxiety self-report was already contained in, or redundant with, the other predictors. As mentioned before, when participants are anxious in one situation, they are likely to be anxious in a similar context (MacIntyre & Gardner, 1994). Language difficulty self-report, system difficulty self-report, and exercise score effectively measured anxiety in an e-learning system (Ismail & Hastings, 2019).

The e-learning system 1, which I used in this analysis, had some limitations, such as the small range of difficulties of the exercises. Also, I could not evaluate the speaking exercises due to technical issues, which reduced the number of available exercise scores and kept me from using the previous exercise score as a predictor for FLA. Using regression and the suggested predictors did not provide a high prediction. I only got moderate predictiveness when including self-reports. To address these limitations from Experiment 1, I developed and evaluated e-learning system 2 of the system, which included more challenging materials and a complete set of exercises that could be evaluated online.

3.5 Method for Machine Learning

Based on the results of Section 3.3.3, the predictions of FLA were up to 40%, which is not very high. Also, to reach my optimum goal of this research, which is identifying and overcoming FLA using an emotionally adaptive intelligent tutoring system, I decided to build a machine learning model to predict FLA. Machine learning could allow us to predict FLA accurately and provide personalized interventions to reduce FLA.

I built a machine learning model using the data from Experiment 1 and compared it with the data from Experiment 2 to examine its reliability. Below is a description of Experiment 2 e-learning system, design, and measures along with the extracted features and machine learning methods for both experiments.

3.5.1 E-Learning System 2

I developed the second e-learning system to overcome the limitations of the first e-learning system and to study identifying and reducing FLA. In e-learning system 2, the difficulty of the language was increased to be in line with the TOEFL and IELTS English language standardized tests. The system could also evaluate all the exercises without requiring a human grader. Moreover, a feedback about the learner's answers was provided to give the learner an indication of the correct answer.

I implemented the e-learning system 2 using MYSQL, PHP, HTML, and JavaScript. The animated agent was created using Media Semantics. In this version of the system, the application of these CTML principles (Clark & Mayer, 2016; Mayer, 2005) described in Section 3.2.1 was modified or extended as described below:

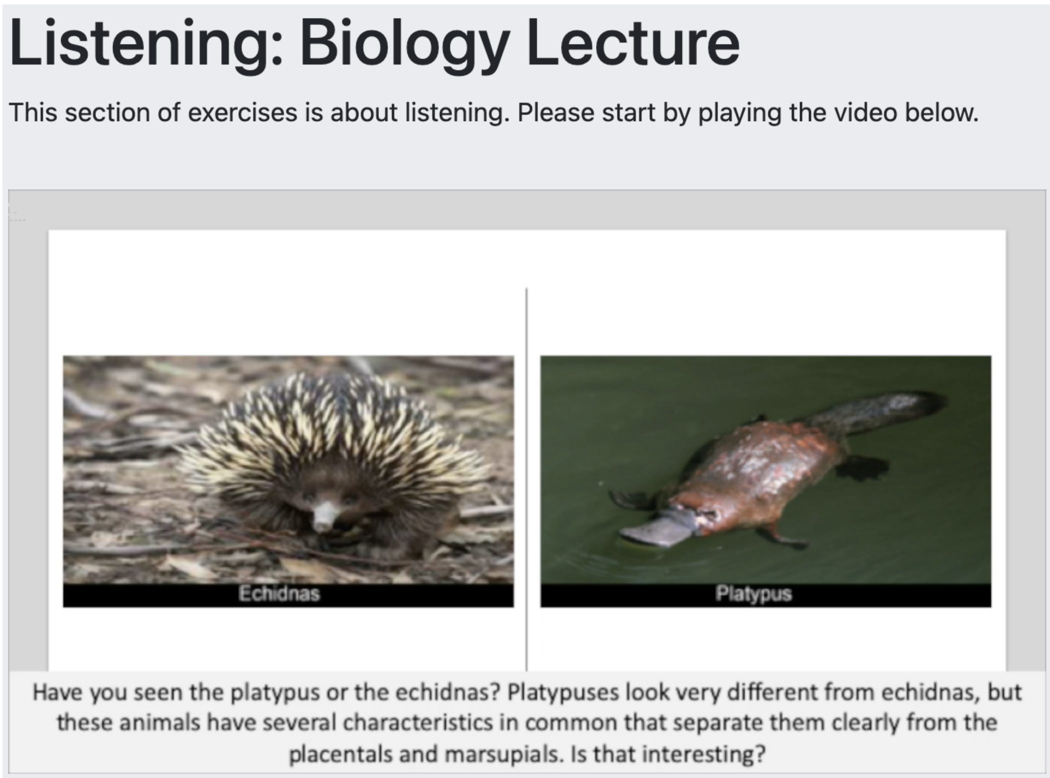


Figure 3.10: Multimedia in e-learning system 2.

Multimedia: I applied the multimedia principle by making a video for each lesson. The video included pictures and narration to explain the material. Also, the reading material included graphics with the text to help the learner visualize and understand the article. (See Figure 3.10.)

Redundancy: In the listening exercises, I added audio captions. Also, for the vocabulary, grammar, and writing exercises, I added audio narration plus text to explain the learning material as shown in Figure 3.11.

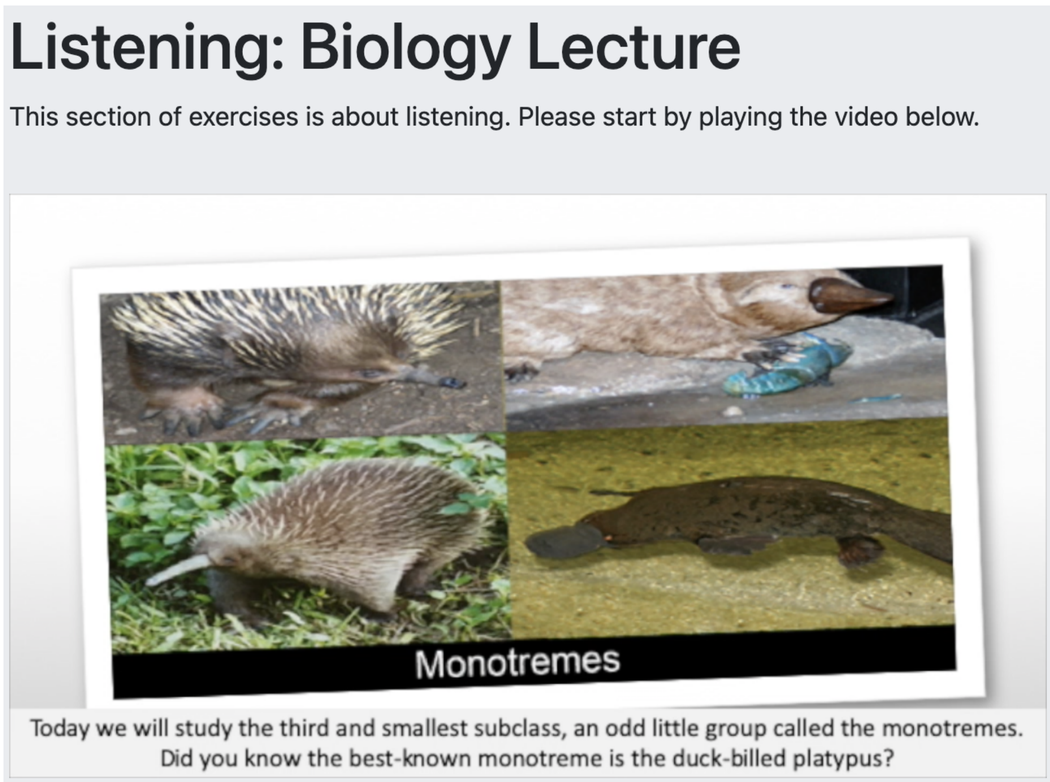


Figure 3.11: Redundancy in e-learning system 2.

Coherence: I applied the coherence principle by adding graphics and sound that helped to convey the material.

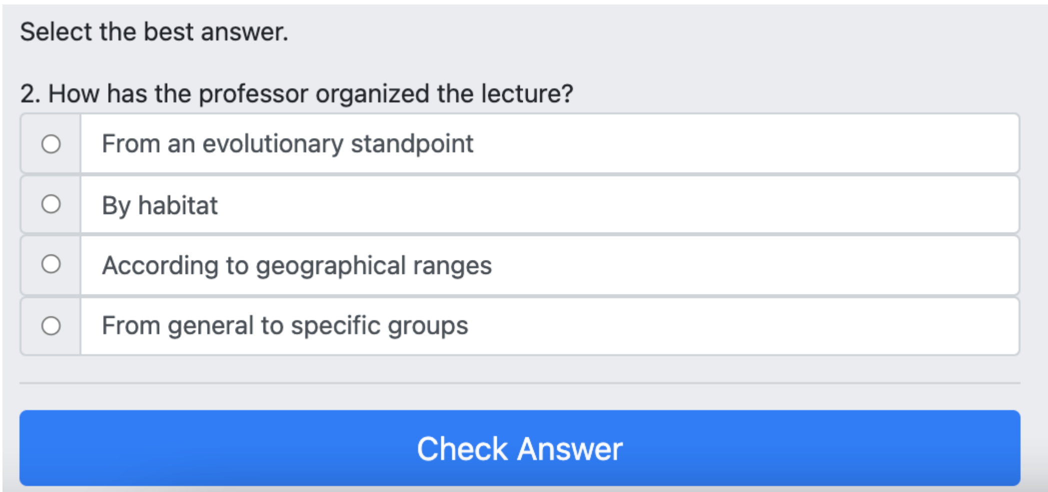


Figure 3.12: Segmentation in e-learning system 2.

Segmentation: I applied the segmentation principle by placing one exercise per page. (See Figure 3.12.)

Leveraging examples: I applied this principle by adding examples to explain the vocabulary, grammar rules, and writing principles as shown in Figure 3.13.

These CTML principles (Clark & Mayer, 2016; Mayer, 2005), which were not applied in e-learning system 1, were also included:

Modality: The Modality Principle states that using audio narration instead of text to deliver the learning material. I used videos that included audio, text, and graphics to explain the lessons.

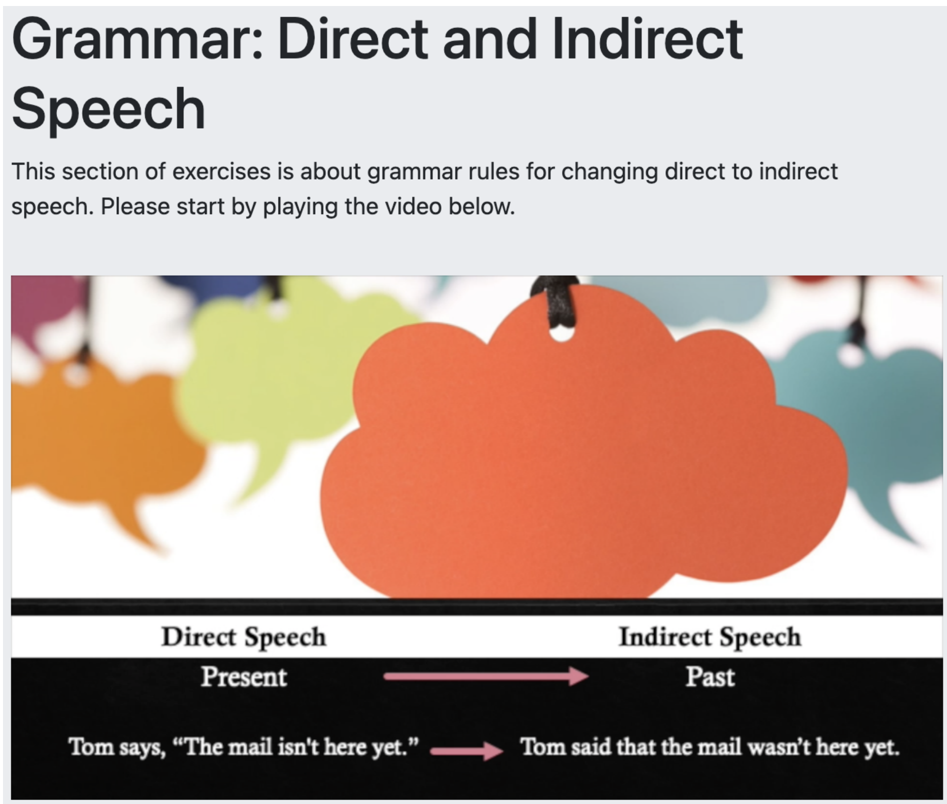


Figure 3.13: Leveraging examples in e-learning system 2.

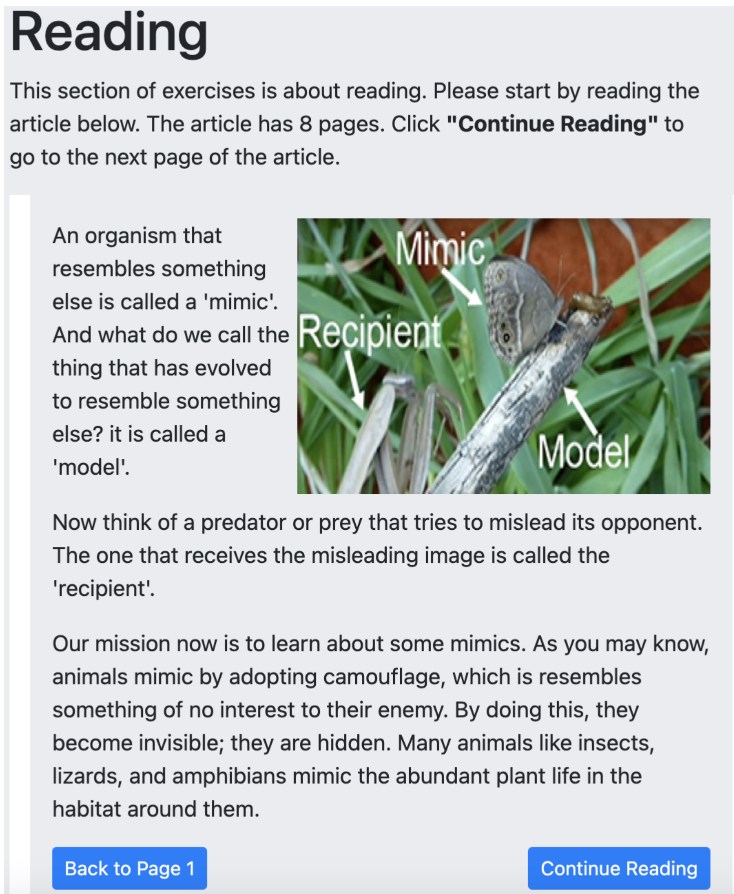


Figure 3.14: Contiguity in e-learning system 2.

Contiguity: The contiguity principle states that graphics and their associated text should be placed next to each other with no scrolling required. I applied this principle in the video tutorials and the reading material. As seen in Figure 3.14, the picture is placed next to the related text.

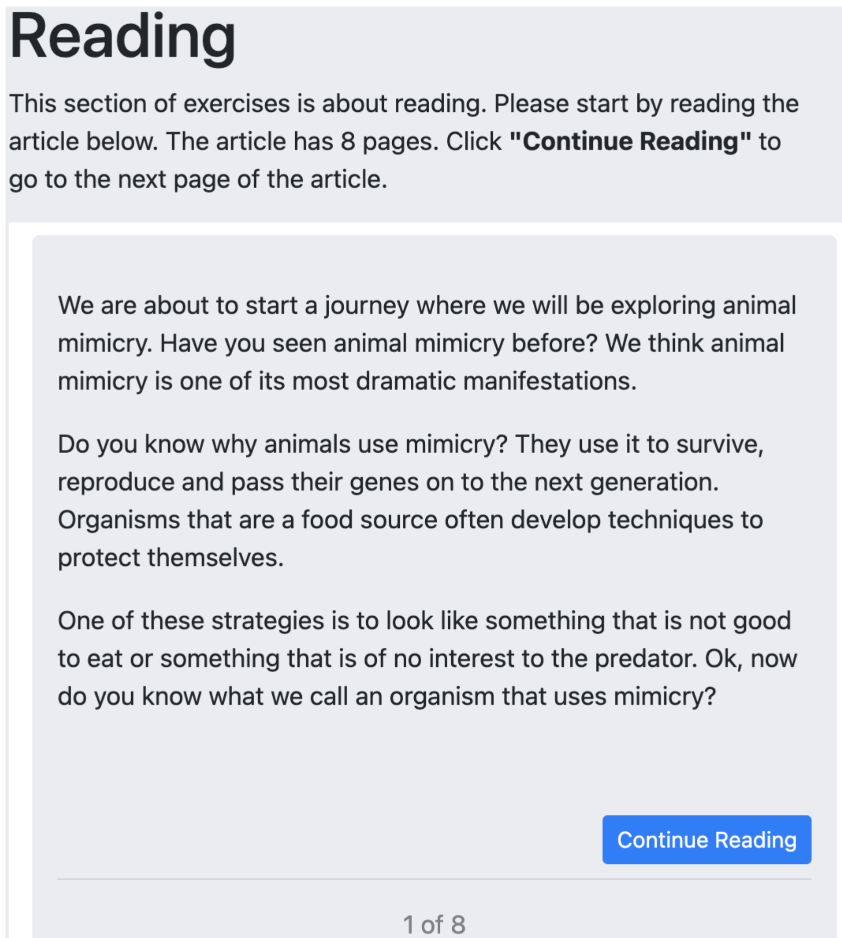


Figure 3.15: Personalization in e-learning system 2.

Personalization: The personalization principle states that learning is improved when the text uses a conversational style rather than a formal style. All the video narration and reading material in e-learning system 2 used conversational style. (See Figure 3.15.)

The system had 26 exercises and was built to match TOEFL and IELTS English language standardized tests by including challenging material like the vocabulary word, "Pathogen" (see Appendix G.) It focuses on the following topics:

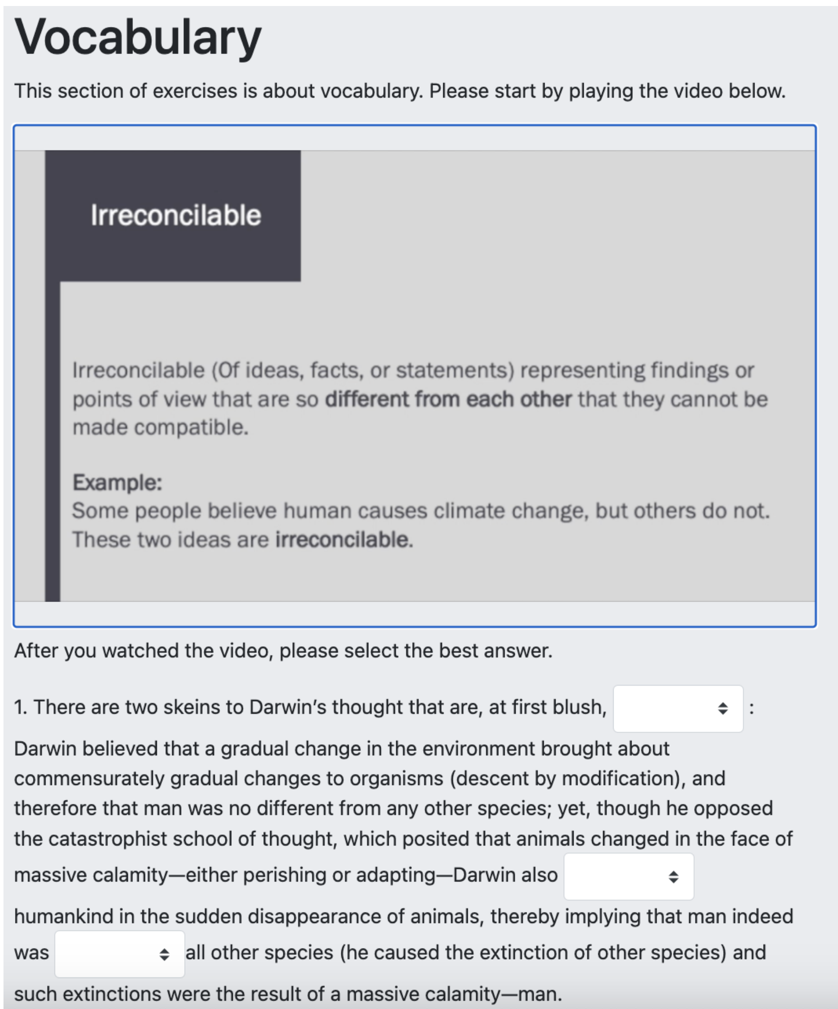


Figure 3.16: Vocabulary in e-learning system 2.

- **Vocabulary:** Each vocabulary exercise included a video and several multiple choice questions about words in the video. Then, the learner answered various questions with multiple choices as shown in Figure 3.16.

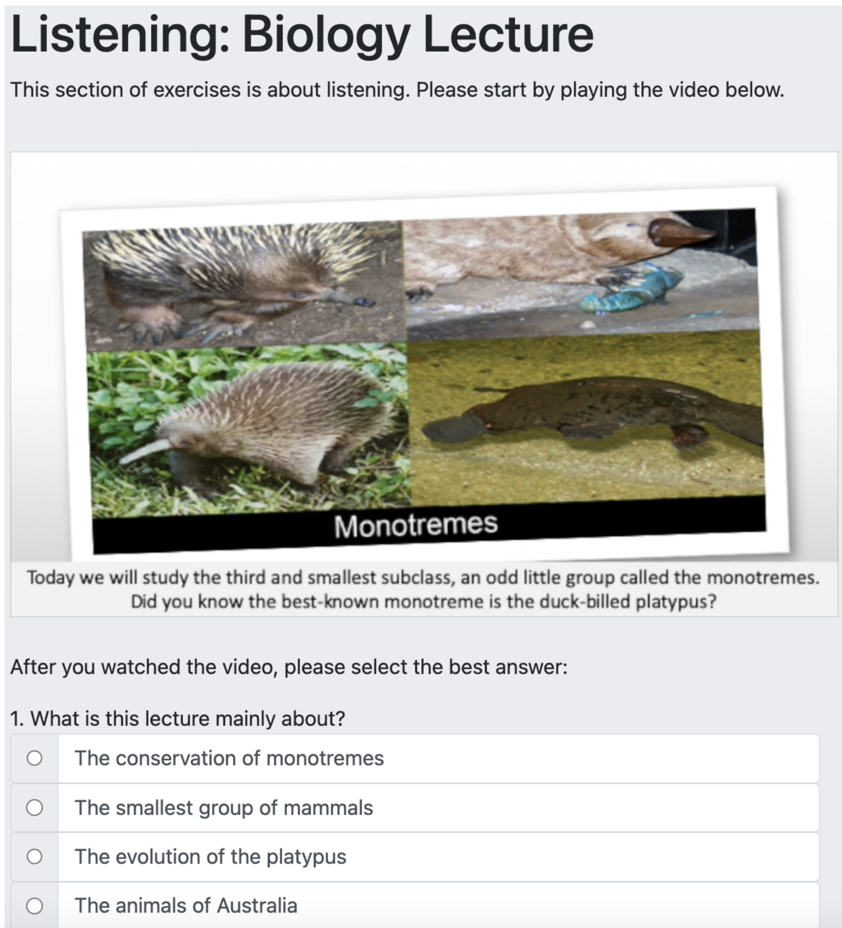


Figure 3.17: Listening in e-learning system 2.

- **Listening:** Each exercise included a descriptive video. Then, the learner answered a question about the topic. Six questions about the same topic were separated into multiple pages. (See Figure 3.17.)

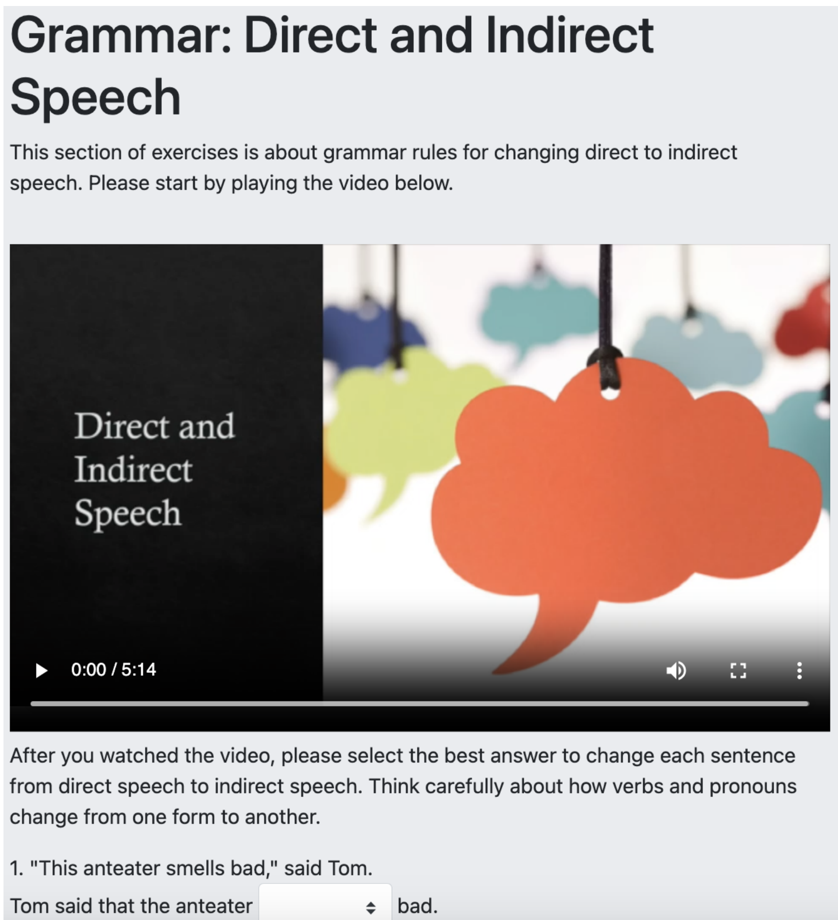


Figure 3.18: Grammar in e-learning system 2.

- **Grammar:** A video explained how to convert direct to indirect speech. Then, the learner answered multiple choice questions about converting direct to indirect speech using the correct grammar tense as shown in Figure 3.18.

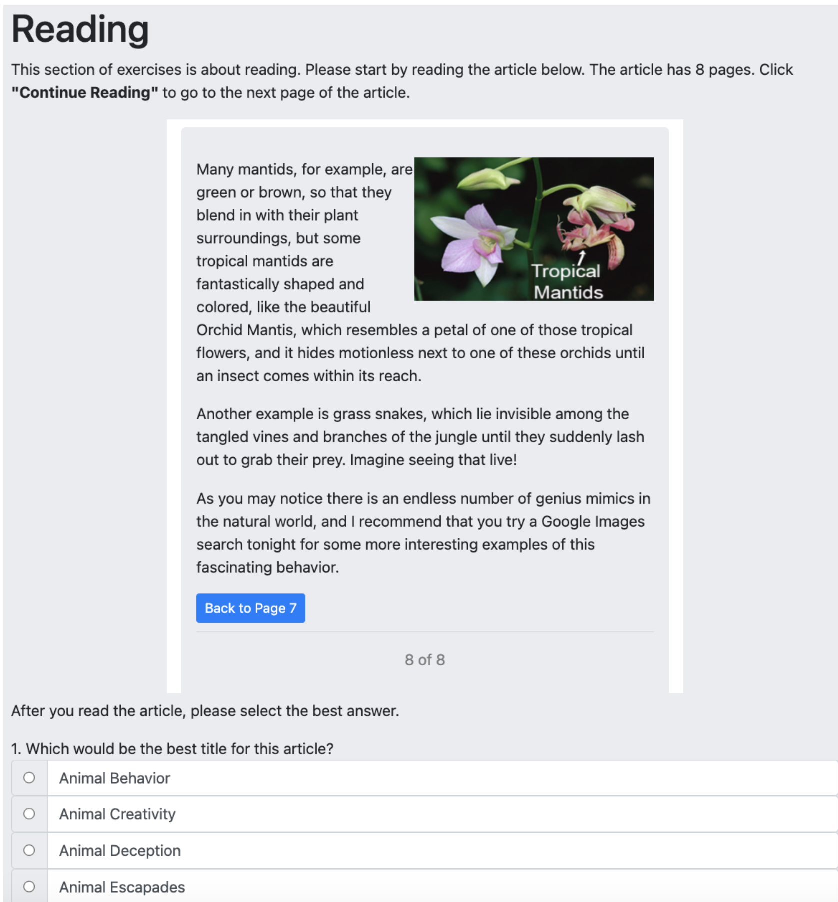


Figure 3.19: Reading in e-learning system 2.

- **Reading:** The students read an eight-page article about mimicry and answered questions about it. Each question was designed to be on a separate page. (See Figure 3.19.)

Figure 3.20: Writing in e-learning system 2.

- **Writing:** There was a video describing using punctuation. Then, the learner had to put the correct punctuation in the plain text. (See Figure 3.20.)

3.5.2 Design

Three rounds of pilot tests were performed to validate the system. Each round consisted of two participants.

In the online experiment, the participants spent around 30 minutes within the e-learning system, watching video tutorials, completing the exercises, and self-reports. After each exercise, they received feedback that explained the correct answer (Ismail & Hastings, 2021). Participants received a $15 Amazon gift card.

3.5.3 Participants

Twenty-nine adult non-native English speakers were recruited. The average age was 28 years old; 59% (N= 17) female and 41% (N= 12) male. There were various native languages, 3.45% (N=1) Polish, 13.79% (N=4) Spanish, 48.28% (N=14) Chinese, 13.79% (N=2) Japanese, 6.90% (N=2) Korean, 3.45% (N=1) Russian, 3.45% (N=1) French, 3.45% (N=1) Mongolian and, 3.45% (N=1) Turkish. The education level was 11% (N= 3) Less than a high school diploma, 3% (N= 1) high school degree or equivalent, 59% (N= 17) associate degree, 24% (N= 7) bachelor's degree, and 3% (N= 1) master's degree. Their English level was 4% (N= 1) foundations, 31% (N= 9) intermediate, 17%

(N= 5) high intermediate, 41% (N= 12) advanced, and 7% (N= 2) university bridge.

3.5.4 Measures

Before the experiment, the participants reported their demographic information (age, gender, English level, educational level, and the number of years studying English). Also, they completed the FLCAS. (See Section 2.3.2.) After each exercise the participants completed a self-report, evaluating the language/system difficulty and their level of anxiety (see Figure 3.9). The self-report level of anxiety after each exercise was counted as the ground truth FLA.

3.5.5 Feature Extraction and Selection

As mentioned in Section 3.3.3, using regression to identify FLA reached up to 40% when using self-report with FLCAS components and exercise score. This prediction is not high, interrupting the learning process with self-report. In this section, I describe how I extracted and selected features for predicting FLA using machine learning methods. To guarantee the reliability of the machine learning models, I built two models using two distinct data from the two experiments and compared their performance and accuracy. When a model performs the same or better on a second dataset than on the one it was developed, that provides evidence of its reliability. I built a machine learning model using the data from Experiment 1 (see Section 3.2.4), then compared it with another machine learning model using the data from Experiment 2 (see Section 3.5.4) which used the same features and procedure.

To build the machine learning model, I extracted 16 features from Experiment 1 using user pre-defined data and system interaction based on Ismail and Hastings (2020) and Onwuegbuzie et al. (1999). Then I did the same procedure with data from Experiment 2. Both studies started with demographic information and the Foreign Language Classroom Anxiety Scale (FLCAS). I separated FLCAS for each participant into its three main components: fear of negative evaluations, communication apprehension, and test anxiety, then used the average of these three components as features (Ismail & Hastings, 2020). Also, from the pre-defined data, I extracted the following features: overall FLCAS score and participant's age, gender, education level, and English level. I extracted these features from the current exercise interaction: exercise score, duration, and topic. These additional features were related to previous exercises: score on the preceding exercise, percentage of previous incorrect scores, percentage of previous correct scores, the average percentage of all previous exercises, and average duration of exercises of the same topic (e.g., vocabulary, grammar).

I did a correlation analysis and set an absolute threshold value of 0.5 to eliminate multicollinearity (Tsagris & Pandis, 2021) and exclude highly correlated features. Then, I used the Gini importance feature selection algorithm (Nembrini et al., 2018) to distill the features that could cause overfitting and added features that improve the model's goodness[2]. I selected the features

[2]Initially, I used forward feature selection to select the features that improved the regression model, but I found that Linear Regression had lower performance than ensemble

sequentially by adding them to support the model until no more features improved its goodness. Nine features emerged that provided an acceptable accuracy with negligible bias.

3.5.6 Model Selection and Evaluation

To predict FLA using sensor-free human behavioral metrics, I built a machine-learning model instead of multiple regression because machine learning helps solve complex logic in addition to scalability, personalization, and responsiveness. Moreover, it helps to get better predictions.

I evaluated the ability of six different regression methods to predict participants' anxiety levels from these nine sensor-free human behavioral metrics. I performed regression instead of classification because I used continuous-valued self-report to measure anxiety, because it can measure moment-to-moment emotion fluctuation (Lottridge et al., 2011) and provide more accurate high-resolution measurements than the Likert classification scale. Also, regression prediction would allow me to provide interventions to reduce anxiety adaptively because regression gives exact measurements, which would allow me to provide accurate intervention. The methods I evaluated were Random Forests, XGBoost, Gradient Boosting Regressor, Linear Regression, Bayesian Ridge Regression, and Support Vector Regression (SVR). These six methods had previously been used successfully to detect emotions, including FLA as discussed in Section 2.3.5.2. I implemented these machine learning models in the scikit-learn library in Python (Pedregosa et al., 2011).

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algorithms. Thus, I used the Gini importance algorithm to find the features that best improved the ensemble methods.

I evaluated each detector using 10-fold cross-validation, using 90% of the data as training and the other tenth as the test set. The models' goodness of fit was selected as the optimal model based on R^2 value, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE).

3.6 Data Analysis and Results for Machine Learning

3.6.1 Features for Detecting FLA

First, I looked for features that best detect FLA without interrupting the learner. To address this, I used the multicollinearity analysis mentioned above to filter out features that did not help predict FLA. I found that the FLCAS score was highly correlated with FLCAS components: fear of negative evaluation $r = 0.83, p < .001$, communication apprehension $r = 0.92, p < .001$, and test anxiety $r = 0.83, p < .001$. Also, I found that the average percentage of all previous exercises is highly correlated with the percentage of previous correct scores $r = 0.98, p < .001$, and the score on the preceding exercise $r = 0.57, p < .001$. Therefore, to avoid overfitting, I excluded these five features. I used Gini importance feature selection and found that the least important features were educational level (Importance: 0.01) and gender (Importance: 0.02). These did not improve model performance, so I removed them.

The selected features for detecting FLA were exercise score, percentage of all previous exercise scores, percentage of previous incorrect scores, exercise duration, relevant exercise duration (the time spent on exercises with the same topic), FLCAS score, English level, exercise topic, and age. Within the data from Experiment 1, these features accounted for up to 47% of variance in FLA. When I repeated the analysis with the data from Experiment 2, which included more difficult material, the prediction was increased to 66%. The predictors that accounted for the highest Gini importance were the FLCAS score, followed by the average percentage of all previous exercises. Table 3.4 shows the Gini feature importance.

Table 3.4: Gini importance.

Variable	Data from Experiment 1	Data from Experiment 2
FLCAS	0.4	0.23
All Pre-score	0.13	0.13
Exercise Score	0.07	0.13
English Level	0.02	0.11
Duration	0.11	0.11
Pre-incorrect	0.1	0.1
Relevant Exercise Duration	0.08	0.07
Age	0.05	0.06
Exercise type	0.04	0.06

3.6.2 Machine Learning Methods

To find out which machine learning method could best detect FLA, I compared the performance of six machine learning models: Random Forest, XGBoost, Gradient Boosting Regressor, Linear Regression, Bayesian Ridge, and SVR based on R^2 value, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) on the two datasets, as shown in Table 3.5. The results for data from Experiment 1 show that Random Forest outperformed all models. XGboost performed a comparable performance to Random Forest. The Gradient Boosting Regressor performed slightly lower than Random Forest and XGboost. In comparison, Linear Regression, Bayesian Ridge Regression, and SVR provided much worse predictions of FLA.

I compared the performance of the features and models on data from two Experiments that used somewhat different systems, namely Experiment 1 and Experiment 2. I found that the performance of the model trained on data from Experiment 2 was better overall than the performance of the model trained on data from Experiment 1. Random Forest and XGBoost produced similar accuracy concerning R^2 and almost identical MAE and RMSE. For Gradient Boosting Regressor, Linear Regression, Bayesian Ridge, and SVR, the models perform analogously to data from Experiment 1.

Table 3.5: Predictive performance of the six machine learning models.

Model	Context	MAE	RMSE	R^2
Random Forest	Dataset 1	**10.281**	**15.433**	**0.47**
	Dataset 2	**12.14**	**17.564**	**0.66**
XGBoost	Dataset 1	10.604	15.732	0.45
	Dataset 2	**11.999**	**17.370**	**0.66**
Gradient Boosting Regressor	Dataset 1	11.187	15.887	0.41
	Dataset 2	14.515	19.371	0.53
Linear Regression	Dataset 1	14.947	19.080	0.19
	Dataset 2	21.173	26.694	0.21
Bayesian Ridge	Dataset 1	15.094	19.176	0.19
	Dataset 2	21.378	26.753	0.21
Support Vector Regressor	Dataset 1	14.638	21.349	0.004
	Dataset 2	24.784	29.195	0.06

3.7 Discussion for Machine Learning

RQ 1.3 was whether FLA could be detected in an English for Speakers of Other Languages (ESOL) system without interrupting the learner. To answer this question, I searched for the best features to detect FLA and the most effective machine learning methods to use them. I compared 16 features to predict FLA using sensor-free human behavioral metrics within an ESOL learning system. Prior research used FLCAS components and exercise scores as sensor-free metrics to predict FLA (Ismail & Hastings, 2020). I extended this finding by uncovering features that produce better predictions using machine learning without interrupting the learning process.

Concerning the validity of our features for predicting FLA, the most important feature is the FLCAS score, a well-validated measure for anxiety within a classroom environment (Horwitz et al., 1986; Shao et al., 2013). Having the FLCAS score as a significant predictor supports the validity of our model. The second significant predictor is the average percentage of all previous exercises, which measures student achievement. This finding is consistent with previous research showing a correlation between student achievement and FLA (Shao et al., 2013). The data from experiment 1 and experiment 2 had equal highest feature importance. This result implies that the features could be generalized to any e-learning system that teaches English as a foreign language, primarily because these features can be extracted from any e-learning system (Ismail & Hastings, 2022).

Other features that contribute to predicting FLA were the current exercise score and percentage of previous incorrect scores, which are also linked to student achievement and task fulfillment, which have also been linked with FLA in previous research (Horwitz et al., 1986; Onwuegbuzie et al., 1999; Shao et al., 2013). Other important features are the duration spent on the exercise and the average duration of exercises in the same section. Previous research showed that anxious learners spend more time on a task due to interference with the cognitive processes (Shao et al., 2013). Also, I found that age, English level, and the exercise topic are important features for predicting FLA. This finding is consistent with the prior research, which found that multiple learner and situational variables affect learners' vulnerability to anxiety, such as age, experience with the foreign language, and the subject (Gkonou et al., 2017; Hashemi, 2011; Ismail & Hastings, 2022; Onwuegbuzie et al., 1999). This evidence supports the validity of our features for measuring FLA.

These sensor-free human behavioral metrics capture up to 66% of the variability in anxiety, which is imperfect yet satisfactory since affect detection is challenging because it is not directly accessible (Baker et al., 2012). Detecting emotions using human behaviors is usually less than 50% accurate because it is much harder to predict than physical measurements (Qorbani et al., 2020; Westfall & Arias, 2020). Based on our results, using these features to predict FLA within data from Experiment 2 provided better performance than data from Experiment 1. The reasons for this finding may include: e-learning system 2 (see Section 3.5.1), which was used in Experiment 2, had exercises similar to the English language standardized test, which induced comparable anxiety levels. Furthermore, e-learning system 2 provided explanatory feedback about the answers, which gave the learners indications about the correctness of their work, which could also affect their anxiety levels. Moreover, the participants were in their environment, not at the lab, producing anxiety similar to real situations. Replicating the same features to predict FLA using two distinct datasets and getting better predictions suggests reliable progress toward FLA detection.

I found earlier that using sensor-free metrics to predict FLA accounted for an 18% variation in anxiety when using Linear Regression. In contrast, machine learning models achieved better prediction than Linear Regression. Ensemble learning models (Random Forest, XGBoost, Gradient Boosting Regressor) outperform Linear models (Linear Regression, Bayesian Ridge) and SVR. The high performance of the ensemble learning models is not surprising given the robustness, reliability, and stability of the models (Hueniken et al., 2021). Also, the ensemble learning models achieved consistently higher accuracy than Linear models and SVR. The relatively high performance and accuracy of the ensemble learning models prove their validity and effectiveness in predicting FLA using sensor-free human behavioral metrics, which can allow a system to adaptively intervene when learners are anxious. (See Ismail and Hastings (2022) and Chapter 5).

My ensemble learning models achieved a good prediction, especially given the difficulty of predicting emotion. When the performance of a model on a second dataset is the same or better than on the one for which it was developed, that provides evidence for the model's reliability (Bosnić & Kononenko, 2009; Ismail & Hastings, 2022). This study demonstrates that machine learning methods can provide reliable and valid predictions of FLA from sensor-free behavioral metrics. Furthermore, my approach can be generalized to any ESOL system because I used features that can be extracted from any system.

3.8 Research Question 1: Summary

This section discussed ways to identify FLA using physical measures, self-report, and sensor-free metrics. Specifically, I addressed the first research question with two ESOL systems, one using physical metrics and the other using human behavioral metrics. Here I summarize the important conclusions about the RQs from these studies:

- The metrics used to measure FLA within a classroom helped to predict FLA when using an online system. Notably, the self-report, used to detect FLA within an online system, proved to be a valid measure of FLA. Learners who are anxious in class reported high levels of anxiety when using the online system. The level of anxiety self-report can be an effective measure of anxiety when using an online system.

- The difficulty of the exercise affects FLA. Learners who knew how to answer the questions felt less anxious than learners who felt the exercises were challenging and vice versa.

- FLA can be identified from the learner's interaction with the system. Specifically, FLA can be detected using sensor-free human behavioral metrics and machine learning. Using the FLCAS score, all pre-exercise scores, the current exercise score, pre-incorrect answer, exercise duration, relevant exercise duration, exercise type, age, and English level as features in the machine learning model can predict FLA. The model I built reached up to 66% accuracy in predicting FLA, which is considered good for predicting emotions.

As mentioned in Chapter 2, detecting FLA is the first step to reduce it. This chapter discussed answering Research Question 1 about detecting FLA using sensor-free human behavioral metrics. In Chapter 4, I will discuss ways to reduce FLA.

Chapter 4

Reducing FLA

Research Question 2 centered on finding ways to alleviate FLA in the context of an e-learning system [1].

RQ2: Can FLA be effectively reduced by different types of feedback, different modalities of feedback presentation, or a combination of the two?

As discussed in Chapter 2, reducing FLA can improve learning and increase positive emotions (X. Huang & Mayer, 2016; Küçük et al., 2014). Two important dimensions of emotionally effective feedback are motivational supportive feedback and the medium for delivering it (Van der Meij et al., 2015). As mentioned in Section 2.4, previous research has used various methods for reducing anxiety, like ITSs, animated agents, emotional support, and shifting attention from negative to positive emotions. This has been applied in various domains, such as science and linguistics. The impact of motivational support on decreasing FLA is still unknown. Also, no research has yet addressed using

[1] Portions of the content of this chapter have been published in (Ismail & Hastings, 2021).

an animated agent that provides emotionally supportive feedback to reduce FLA. Therefore, through this study, I investigated this methodology.

4.1 Hypotheses for Research Question 2

To find the best methods for reducing FLA in the context of an ESOL system, I focused on both the type of feedback and method of its delivery. I generated the following sub-questions:

4.1.1 Effectiveness of Feedback Type on FLA Based on Learner's Performance

RQ 2.1: Does the correctness of the learner's answer impact the effectiveness of motivational, supportive feedback?

High-knowledge learners prefer direct feedback and do not need emotional support, while low-knowledge learners benefit from supportive feedback when they receive it as needed (D'Mello & Graesser, 2013). Also, providing motivational support judiciously is beneficial because it can reduce anxiety when the learner gives an incorrect answer, but it increases anxiety when the learner answers correctly, perhaps by implying that they're not doing as well as they thought (Ismail & Hastings, 2021).

Hypothesis 2.1: I hypothesized that motivational supportive feedback is only effective when the learner answers incorrectly.

4.1.2 Effectiveness of Feedback Type and Modality on FLA

RQ 2.2: Are there interactions between feedback type and modality when reducing FLA?

As cited in Section 2.4, the ideal interventions should shift the learner's attention from negative to positive emotion while studying foreign language (Onwuegbuzie et al., 1999). Researchers proved that providing emotionally supportive feedback by an animated agent effectively reduces math anxiety (X. Huang & Mayer, 2019; Im, 2012), and empathetic agents that encourage and reassure the learners have proven to reduce FLA (Ayedoun et al., 2019).

Hypothesis 2.2: I hypothesized that motivational supportive animated agents could help reduce FLA.

4.1.3 Effectiveness of Feedback Type and Modality on FLA by Gender

RQ 2.3: Are there interactions between gender, feedback type, and modality when reducing FLA?

As mentioned in Section 2.2.2, there are inconsistent results about foreign language anxiety levels between genders. Gender is one of the learner variables that affect FLA. Also, there are interactions between situational and learner variables (Williams & Andrade, 2008).

Hypothesis 2.3: I hypothesized that each gender would benefit from different combinations of feedback types and modalities.

4.1.4 Effectiveness of Feedback Type on FLA by Gender and Performance

RQ 2.4: Are there interactions between gender, performance, feedback type, and modality for reducing FLA?

As discussed in Section 2.2.2, different learner's and situational variables affect FLA. In addition to gender differences, learners' performance also affects FLA (I.-J. Chen & Chang, 2009; Fariadian et al., 2014; Ismail & Hastings, 2019).

Hypothesis 2.4: I hypothesized that based on gender and performance, different combinations of feedback type and modality would decrease FLA.

Previous research showed that interventions within experimental settings may not eliminate the bad effect completely. They could reduce negative emotions and increase learning for the short-term but not long-term (X. Huang & Mayer, 2019; Lester et al., 1997). For example, when using a treatment in an experiment, it could produce a temporally good effect, but it will not fully treat it. Therefore, my interventions could reduce FLA in the short term within the experiment.

4.2 Method for Reducing FLA

To answer Research Question 2 about reducing FLA, I conducted an experimental study online. The e-learning system that I used for this experiment is a mod to e-learning system 2 (see Section 3.5.1). Below is a description of the design, interventions, and measures, along with the data analyses.

4.2.1 Design

A 2x3 factorial experimental compared FLA when receiving various interventions (feedback type X feedback modality) as will be described in Section 4.2.2. The experiment was a between-subject. The Institutional Review Board of DePaul University approved the study (see Appendix A), and all participants agreed to the informed consent (see Appendix C).

4.2.2 Interventions

A factorial design was used. One factor was **feedback type** with two levels: *Explanatory* (see Figure 4.1) vs. *Motivational Supportive* (see Figure 4.2). The other was **feedback modality** with three levels: *Text only* (see Figure 4.3), *Voice and Text*, and *Animated Agent with Voice and Text* (see Figure 4.4). Based on previous research, female agents help reduce frustration; thus, I used a female agent to present the feedback (Hone, 2006). Additionally, a human voice was used for the agent to provide a realistic and acceptable feel because a synthetic voice reduces acceptance (Clark & Mayer, 2016; Law et al., 2020).

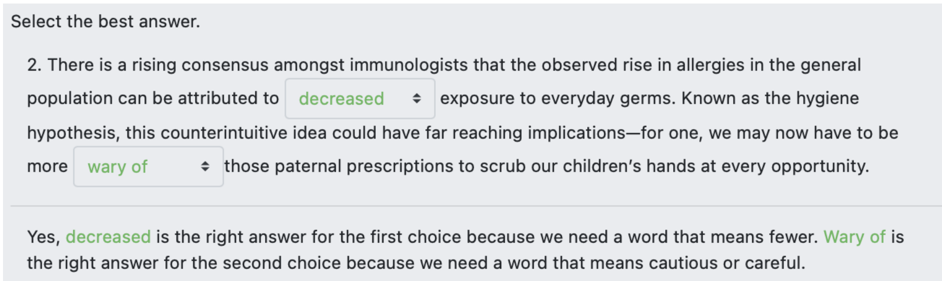


Figure 4.1: Explanatory feedback.

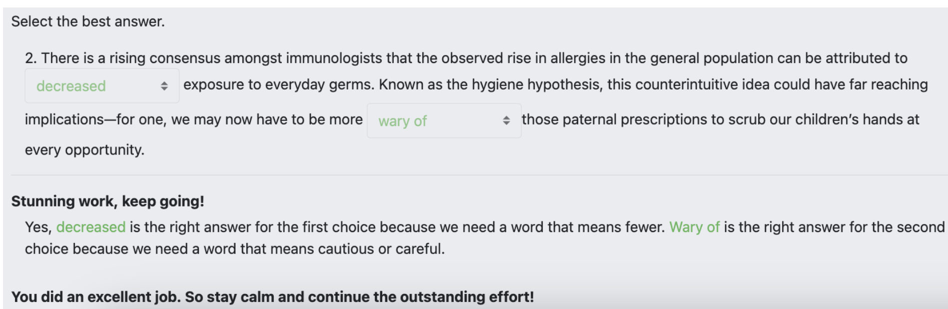


Figure 4.2: Motivational supportive feedback.

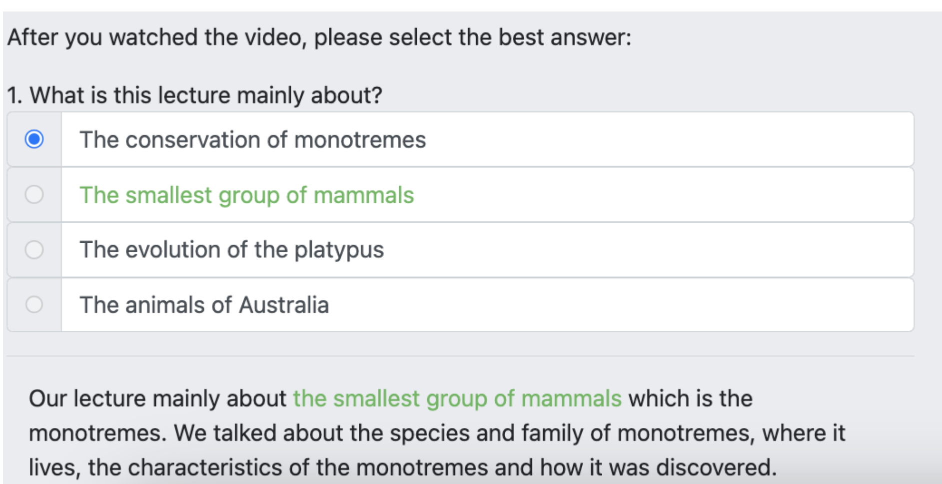


Figure 4.3: Text feedback.

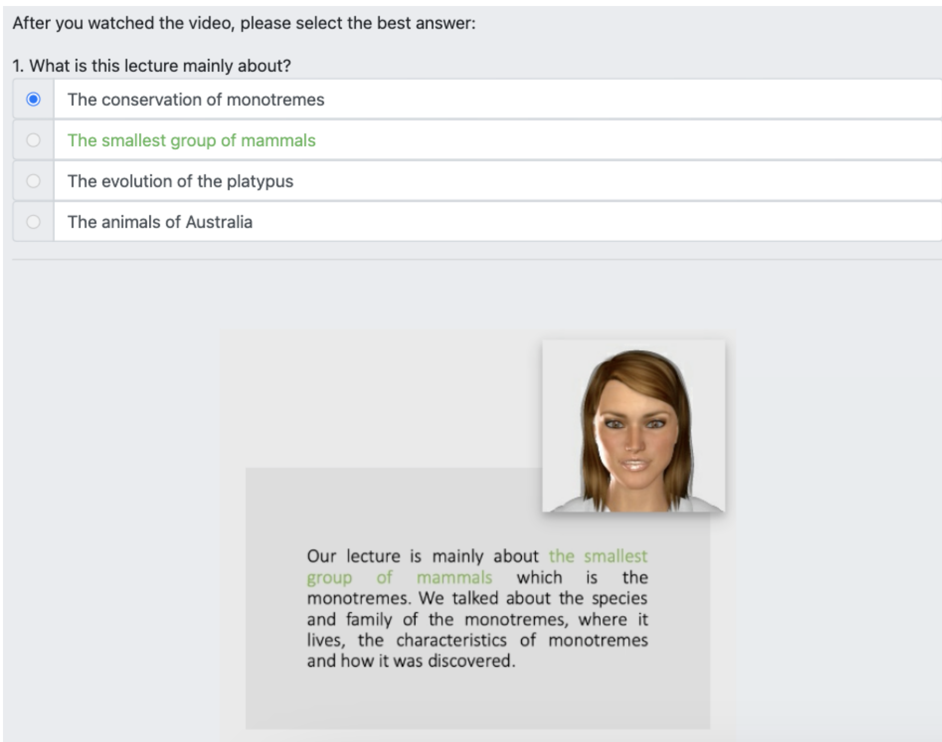


Figure 4.4: Text and animated agent feedback.

In all conditions, textual feedback was shown on the screen. In the voice modality condition, the text is accompanied by narration. Both voice and agent conditions use recordings provided by a female actor, not synthesized speech. The speech aligns with the text provided on the screen. After the learners answer a question, the system evaluates their answer, highlighting it green if correct and gray otherwise. Then, the system provided its feedback depending on the condition. In every case, an explanation like this one will be given:

> "Decreased is the right answer for the first choice because we need a word that means fewer. Wary of is the right answer for the second choice because we need a word that means cautious or careful."

Additional feedback was given depending on the feedback type factor. In the explanatory feedback condition, if the learner's answer was correct, the feedback was **"Yes,"** followed by the explanation (see Figure 4.1). If the answer was incorrect or partially correct, only the explanation was given. The motivational supportive feedback conditions used a sandwich feedback model, which puts the explanatory feedback between two positive comments (Prochazka et al., 2020). Figure 4.5 shows how the explanation is embedded in the motivational supportive feedback, depending on evaluating the learner's answer. The first statement motivates the learner, followed by explanatory feedback; then the last comment provides support and more motivation. Each exercise has unique motivational supportive feedback to give the learners a personalization effect. Figure 4.2 shows motivational supportive feedback within the system. Appendix H includes motivational supportive feedback for each exercise.

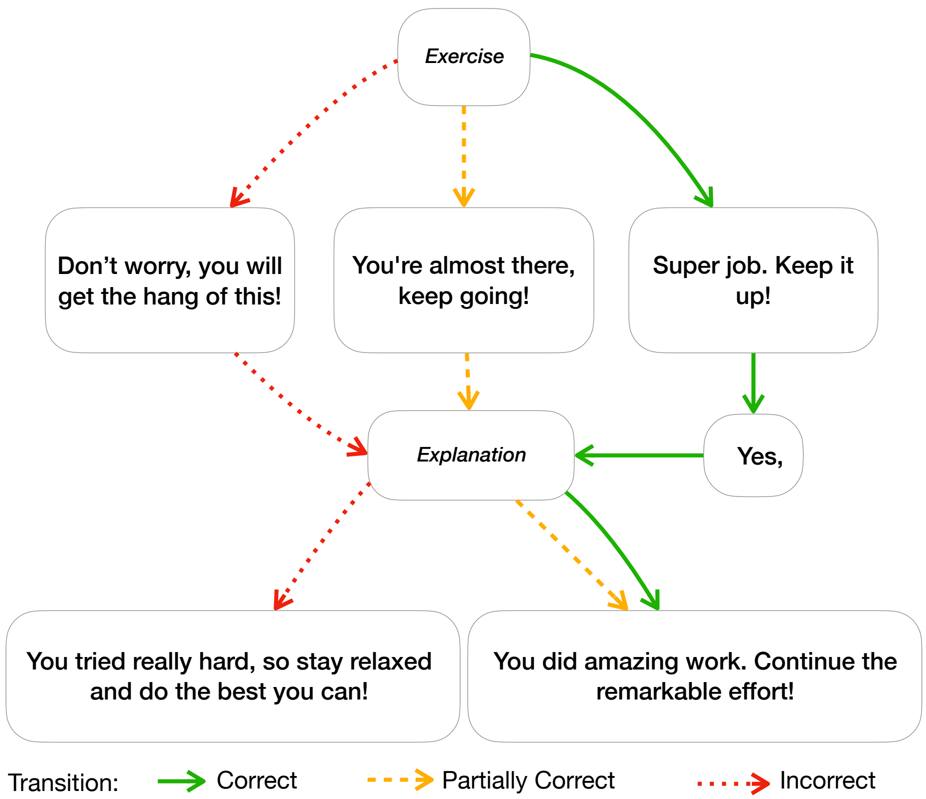


Figure 4.5: Motivational supportive feedback flow chart.

4.2.3 Participants

The participants were randomly assigned to six different groups (Text Explanatory N=25, Text Supportive N=22, Voice Explanatory N=28, Voice Supportive N=25, Agent Explanatory N=20, Agent Supportive N=27). One hundred sixty-eight participants finished all the exercises and self-reports. I excluded 21 participants because they finished both doing the exercises and reading/listening to the feedback so quickly (in less than 30 minutes) that they must have moved on to the "next" items without really reading the question and/or the feedback. The participants should spend around 30 minutes answering the demographics information, FLCAS, exercises, and self-reports. All participants who finished the study around 30 minutes in good faith received $15 Amazon gift card.

The average age was 27 years old. Gender was 61% (N= 87) female, 37% (N= 53) male, 1% (N= 1) other, and 1% (N= 1) prefer not to say. There were a variety of native languages: 3% (N= 4) Arabic, 1% (N= 1) Bengali, 45% (N= 64) Chinese, 1% (N= 1) Farsi, 2% (N= 3) French,1% (N= 1) Gujarati, 1% (N= 1) Hindi, 1% (N= 1) Indonesia, 1% (N= 1) Italian, 7% (N= 10) Japanese, 7% (N= 10) Korean, 3% (N= 4) Mongolian, 1% (N= 1) Polish, 4% (N= 5) Portuguese, 2% (N= 3) Russian, 15% (N= 21) Spanish, 1% (N= 1) Taiwanese, 1% (N= 1) Thai, 2% (N= 3) Turkish, 1% (N= 1) Venezuelan, and 4% (N= 5) Vietnamese. The education level was 12% (N= 17) less than a high school diploma, 3% (N= 4) high school degree, 3% (N= 4) some college, 39% (N= 56) associate degree, 37% (N= 52) bachelor's degree, 6% (N= 9) master's degree Their English level was 3% (N= 4) foundations, 29% (N= 41) intermediate, 18% (N= 25) high Intermediate, 47% (N= 67) advanced, and 4% (N= 5) university bridge.

4.2.4 Measures

After the learners answered the demographic information, they did FLCAS to measure their anxiety level during foreign language classes. After each exercise, the participants answered a self-report consisting of language difficulty, system difficulty, and level of anxiety. The ground truth FLA was the self-report level of anxiety after each exercise.

4.3 Data Analysis and Results for Reducing FLA

4.3.1 RQ 2.1: Effect of Learner Performance and Feedback Type on FLA

RQ 2.1 asked whether the correctness of the learner's answer impacts the effectiveness of motivational supportive feedback. To measure the learner's performance on each exercise, their score on that exercise was segmented into one of three groups: correct (completely), partially correct (10–90%), and incorrect. To answer this question, I conducted a two-way ANOVA with the performance group and type of feedback as factors. The dependent variable was FLA. The test revealed a significant effect of feedback type $F(5, 3422) = 10.445, p < .001$ as shown in Table 4.1. To further investi-

Table 4.1: Mean FLA (with SD) for learner's performance and feedback type.

	Explanatory	Supportive
Correct	19.92 (25.45)	20.73 (22.07)
Partially Correct	34.67 (29.22)	33 (27.45)
Incorrect	46.09 (30.73)	37.28 (27.93)

gate the effect of the feedback type for each performance group, I did a post-hoc test with a Bonferroni adjustment; I found only a significant difference between explanatory and supportive feedback for incorrect answers, $t(900) = 19.942, p < .001$. However, there were no significant differences for the feedback type within the correct group, $t(1971) = .573, p = .449$, or partially correct group $t(551) = 0.478, p = 0.49$.

4.3.2 RQ 2.2: Effect of Feedback Type and Modality on FLA

RQ 2.2 asked whether there are interactions between feedback type and modality when reducing FLA. I did a two-way ANOVA with feedback type (explanatory vs. motivational supportive) and feedback modality (text vs. voice vs. agent) as between-subjects factors. The results revealed no main effect of feedback modality, $F(2, 3429) = .018, p = .982$. There was, however, a main effect of feedback type, $F(1, 3429) = 13.314, p < .001$, and a crossover interaction between feedback type and modality, $F(2, 3429) = 22.78, p < .001$ see Table 4.2.

Using a post-hoc test with a Bonferroni adjustment, I found no significant difference between motivational supportive feedback present by text

Table 4.2: Mean FLA (with SD) for feedback modality and type.

	Explanatory	Supportive
Text	33.57 (31.15)	23.27 (25.04)
Voice	25.73 (31.16)	30.67 (26.23)
Agent	30.87 (26.13)	25.81 (24.96)

and by agent, $t(1151) = 2.937, p = .366$. Also, there was no significant difference between explanatory feedback presented by text or agent, $t(1070) = 1.511, p = .302$. There was no significant difference between explanatory feedback given by voice and motivational supportive feedback given by the text, $t(1140) = 2.095, p = .148$. There was no significant difference between explanatory feedback given by voice and motivational supportive feedback given by the agent, $t(1269) = .002, p = .961$. There was no significant difference between explanatory feedback given by the agent and motivational supportive feedback presented by voice, $t(1045) = .014, p = .906$.

4.3.3 RQ 2.3: Effect of Feedback Type and Modality on FLA by Gender

First, I did a one-way ANOVA to understand whether there are gender differences in FLA when using the e-learning system. The results revealed a significant effect of gender on FLA, $F(3, 3434) = 24.601, p < .001$. Males reported higher overall anxiety (M=33.07, SD=31.16) than females (M=25.164,

Table 4.3: Mean FLA (with SD) for feedback type and modality between gender.

	Male		Female	
	Explanatory	Supportive	Explanatory	Supportive
Text	44.41(37.87)	29.38 (21.76)	27.39(24.57)	21.43(25.69)
Voice	29.65 (34.71)	33.97(26.88)	20.22(24.37)	27.25(26.63)
Agent	42.69 (27.73)	24.37(23.06)	27.12(24.47)	26.67 (26.04)

SD=25.456). Only one participant chose "Other" as gender (M= 45.95, SD= 12.6), and one chose "Prefer not to specify" (M=26.96, SD=11.95) [2].

RQ 2.3 asked whether there are interactions between gender, feedback type, and modality when reducing FLA. A factorial ANOVA was done with gender, feedback type (explanatory vs. motivational supportive), and feedback modality (text vs. voice vs. agent) as the factors. Afterward, to understand the effectiveness of the interaction between feedback type and modality in each group, I split the data based on gender.

The results revealed a main effect of gender, $F(3, 3388) = 77.826, p < .001$. This finding was qualified by interactions between gender and feedback type $F(1, 3388) = 23.117, p < .001$. However, the interaction between gender and feedback modality did not reach the $\alpha < 0.05$ threshold: $F(2, 3388) = 2.753, p = .064$. The predicted interaction among gender, feedback type, and feedback modality was significant $F(2, 3388) = 4.717, p = .009$ see Table 4.3.

There was no main effect of feedback type for females $t(2088) = 0.197, p = .657$. The impact of feedback modality for females did not reach the $\alpha < 0.05$

[2] I excluded ("Others" and "Preferred not to say") from the following analysis because there was only one participant in each group.

threshold: $F(2, 2088) = 2.745, p = .064$. However, there was a significant interaction effect of feedback type and modality in females $F(2, 2088) = 10.644, p < .001$. Using a post-hoc test with a Bonferroni adjustment, I found no significant difference between supportive feedback presented by text and explanatory feedback presented by voice, $t(655) = .368, p = .545$.

There was no main effect of feedback modality in males $F(2, 1299) = 2.809, p = .061$. There was a main effect of feedback type in males $F(1, 1299) = 27.603, p < .001$. Moreover, there was a significant difference in the interaction between feedback type and modality in males $F(2, 1299) = 17.994, p < .001$. Using a post-hoc test with a Bonferroni adjustment, I found no significant difference between motivational supportive feedback presented by text and explanatory feedback presented by voice, $t(485) = .006, p = .937$. There was a significant difference between motivational supportive feedback given by text and by agent $t(358) = 3.883, p = .05$.

4.3.4 RQ 2.4: Effect of Feedback Type and Modality on FLA by Gender and Performance

RQ 2.4 asked whether there are interactions between gender, performance, feedback type, and modality. An ANOVA revealed no interaction effect among feedback type, modality, gender, and performance $F(4, 3381) = 0.981, p = 0.417$. Also, there was no interaction effect between feedback type, modality, and performance $F(4, 3381) = 0.211, p = 0.933$. However, there was an interaction between feedback type, gender, and performance $F(2, 3381) = 3.644, p = 0.026$ see Table 4.4.

Table 4.4: Mean anxiety (with SD) for learner's performance and feedback type between gender.

	Male		Female	
	Explanatory	Supportive	Explanatory	Supportive
Correct	23.93(31.17)	24.46(22.83)	17.42(20.75)	17.82(21.27)
Partially	39.28(34.28)	32.59(25.09)	31.41(24.63)	33.49(29.22)
Incorrect	54.33(34.16)	38.32(26.24)	39.06(25.51)	36.72(29.02)

Using a post-hoc test with a Bonferroni adjustment, I found no significant difference for female and performance between motivational supportive and explanatory feedback, incorrect answer $F(2, 3370) = 1.081, p = .299$, partially correct answer $F(2, 3370) = .532, p = .466$, correct answer $F(2, 3370) = .075, p = .784$. I found no significant difference in the correct answers for males between motivational supportive and explanatory feedback, $F(2, 3370) = .075, p = .784$. However, there was a significant difference in incorrect answers between motivational supportive and explanatory feedback, $F(2, 3370) = 33.616, p < .001$. Also, there was a significant difference for partially correct answers between motivational supportive and explanatory feedback, $F(2, 3370) = 3.63, p = .057$.

4.4 Research Question 2: Discussion for Reducing FLA

4.4.1 RQ 2.1: Effect of Learner Performance and Feedback Type on FLA

My second research question was how different types of feedback and methods for presenting that feedback reduce learners' anxiety levels while learning a foreign language. I used a 2x3 factorial design with two types of feedback (explanatory and motivational supportive) and three delivery modalities: text, voice, and an animated agent.

RQ 2.1 examined the relationship between the learner's performance and the effectiveness of the different types of feedback in reducing FLA. In other words, does the impact of the feedback differ based on whether the learner answers correctly or not? Following D'Mello and Graesser (2013), I hypothesized that motivational supportive feedback would only be effective when learners answered incorrectly. As shown in Table 4.1, there was a clear pattern of anxiety levels by performance, with the lowest levels of anxiety related to correct answers, the highest with incorrect answers, and the partially correct in between. That held for both types of feedback. The highest level of anxiety was reported by students giving incorrect answers and getting explanatory feedback. It should be noted, however, that the results reported by D'Mello and Graesser (2013) were based on a median split into high- and low-prior knowledge learners based on the pre-test. I analyzed the data on an exercise-by-exercise basis.

My results did show that the lowest anxiety level was reported by learners who answered correctly and received explanatory feedback; however, this was not significantly lower than the level of anxiety for correct answers when receiving motivational supportive feedback. Conversely, the highest anxiety level was reported by learners answering incorrectly and receiving explanatory feedback. This finding indicates that when the learners answered correctly, they felt less anxious when receiving explanatory feedback. However, they reacted more positively to motivational, supportive feedback when they answered incorrectly. Thus, my hypothesis was supported.

My findings align with those in D'Mello and Graesser (2013), which indicate that it is important to be supportive *only* when needed. In the study presented in this chapter, the type of feedback the participants received was based not on their knowledge level or their answers' correctness but on their assigned condition. Motivational supportive feedback that is provided adaptively — only when needed — could show a more substantial effect on reducing anxiety, which I will discuss in Chapter 5.

4.4.2 RQ 2.2: Effect of Feedback Type and Modality on FLA

RQ 2.2 asked whether there would be a difference in FLA based on feedback type and modality. I hypothesized that motivational supportive feedback provided by an animated agent would be most successful at reducing FLA. Focusing first on feedback type alone, I found a main effect across modalities. Both explanatory and motivational supportive feedback types included explanations that focused on the correct answers. Such explanations have been shown to help learners build accurate mental models that increase learning (Clark & Mayer, 2016). The motivational supportive feedback helps in lowering learners' anxiety level (Deloatch et al., 2017; Hayasaki & Ryan, 2022; Heilmann et al., 2016; Jin & Dewaele, 2018) when presented as text or agent.

It is worth mentioning that agent feedback consists of an animated agent accompanied by voice and text, which means there is an interaction between the modalities that could explain the lack of a significant difference between modalities. There may also be other factors that influence the modality results.

When I looked more closely and analyzed the interactions between the feedback type, and feedback modality, I found some significant and somewhat surprising differences. I found that the modality for providing feedback did not have an overall effect in reducing FLA. As shown in Table 4.2, anxiety levels differed across the modalities, but not uniformly.

I found a more interesting, nuanced picture of the interactions between feedback type and modality. Learners who received motivational supportive feedback presented by text reported the lowest anxiety level, followed by a motivational supportive agent and explanatory feedback presented by voice, but there was no significant difference between these three groups. Overall, motivational supportive feedback helped in lowering the anxiety level. This is consistent with Hayasaki and Ryan (2022) who urge the use of a supportive learning environment to reduce FLA. As expected, learners receiving explanatory text-only feedback reported the highest anxiety level, so my hypothesis, which was motivational supportive agent reduces FLA, was partially supported.

4.4.3 RQ 2.3: Effect of Feedback Type and Modality on FLA by Gender

RQ 2.3 asked if there were gender differences concerning anxiety when using an e-learning system for learning a foreign language. Equity, in an educational context, requires optimizing learners' outcomes regardless of gender or learning style (Hasan & Fatimah, 2014). Because prior research on gender and FLA showed conflicting results, I did not have strong expectations of how my results would turn out, only that there might be differences based on gender. My results showed that males experienced a higher level of anxiety than females. It could be, however, that different types of interactions were more effective for females than for males.

I addressed the interactions between gender and feedback type and modality. I did not find gender-based differences between different feedback modalities. However, I found gender differences based on the feedback type and the combination of feedback type and modality.

Females' anxiety levels were lowest when receiving voice-based explanatory feedback followed by motivational supportive text; however, there was no significant difference between these two treatments. This implies that females feel calmer when hearing the explanation of the correct answer. Also, they feel relaxed when reading motivational supportive feedback. Since there was no significant difference in feedback type or modality for females and no significant difference between explanatory feedback presented by text and motivational supportive feedback presented by the text, I will investigate the effectiveness of the explanatory feedback presented by voice in Chapter 5.

Males' anxiety levels were significantly lowest when receiving agent-based motivational supportive feedback. There was a significant difference for males between feedback types. Overall, males' anxiety was lower when receiving motivational supportive feedback regardless of the modality. This result aligns with Beege and Schneider (2023), who found that enthusiastic animated agents promote a positive emotion activation for males. An interaction between the feedback type and modality affects the males' anxiety levels. My hypothesis was partially supported that each gender benefits from different feedback types and modalities.

4.4.4 RQ 2.4: Effect of Feedback Type and Modality on FLA by Gender and Performance

I wanted to determine if there are interactions between gender, performance, and feedback type and modalities. My results echo previous research that males benefit from motivational support when answering incorrectly (Arroyo et al., 2011). However, it must be noted that in my study, the motivational supportive feedback was not provided adaptively; it was offered either all the time or never, depending on the condition. This could explain why the learners did not get the maximum benefits from the motivational supportive feedback. However, there is a clear pattern that supports Hypothesis 2.1;

males' anxiety level was lower when they answered incorrectly and received motivational supportive feedback. There was no clear pattern when learners' answers were correct; both males' and females' anxiety levels were insignificant across feedback types. My hypothesis was not supported; the interaction between gender, performance, and feedback type still needs further analysis, which could be done in future work.

4.5 Research Question 2: Summary

This chapter studied ways to reduce FLA using varied feedback types and modalities. I used motivational supportive feedback, and explanatory feedback presented by text, voice, and agent. The summary of the important conclusions is as follows:

- The correctness of the learner's answer impacts the effectiveness of motivational supportive feedback in reducing FLA. Particularly, when the learners answer incorrectly, their anxiety level is reduced more when receiving motivational supportive feedback.

- Feedback type affects learners' anxiety levels. Specifically, learners' anxiety was lower when receiving motivational supportive feedback from text or an agent.

- Overall, males' anxiety levels were higher than females. In particular, male anxiety was high when receiving explanatory feedback presented by text, while it was low when receiving motivational supportive feedback presented by agent. Also, males' anxiety levels were lower when they answered incorrectly and received motivational supportive feedback.

This chapter discussed answering Research Question 2 about ways to reduce FLA. I incorporated these methods within an adaptive system to detect and reduce FLA within an emotionally intelligent tutoring system. Chapter 5 will discuss answering Research Question 3 about the effectiveness of adaptive motivational feedback.

Chapter 5

Emotionally Adaptive ITS

Research Question 3 focuses on whether using an adaptive feedback approach sensitive to the learner's emotion is more effective at reducing FLA than using a fixed feedback approach[1].

RQ3: Is an adaptive motivational feedback strategy more effective than a fixed feedback strategy?

The general objectives of answering this research question are:

- To understand the effectiveness of an adaptive feedback strategy compared to a fixed feedback strategy in reducing FLA.
- To understand the effectiveness of adaptive feedback strategy compared to fixed feedback strategy in increasing learning gain.

As detailed in Chapter 2, prior research on this has been equivocal. An emotionally adaptive system measures the learners' emotional state and

[1] Portions of the content of this chapter have been published in (Ismail & Hastings, 2023).

bases feedback on that state. The goal of assessing when to provide emotional support when teaching English as a second language is to improve positive emotions, reduce negative emotions, and enhance achievements. An adaptive system that determines the type of feedback based on the learner's emotional state can benefit learning (Harley et al., 2016). However, the literature does not offer us a clear assessment of the overall effectiveness of an emotionally adaptive system for detecting and reducing FLA. Through my study, I assessed its effectiveness within a foreign language system. I compared adaptive feedback with fixed feedback to enhance learning and reduce FLA.

5.1 Hypotheses for Research Question 3

To answer Research Question 3 about the effectiveness of an emotionally adaptive system in reducing foreign language anxiety, I created the following sub-questions:

5.1.1 Effectiveness of Adaptive Feedback for Reducing FLA

RQ 3.1: How effective is an adaptive feedback approach relative to a fixed feedback approach for reducing FLA?

Previous research has shown that emotionally intelligent tutoring systems in different domains can improve learners' emotional states, for example, (Arroyo et al., 2014; Mohanan et al., 2017). Specifically, adaptive system can reduce anxiety and increase confidence when learning math (Hwang et al., 2020; Jebur et al., 2022; Yu et al., 2023). This led me to hypothesize:

Hypothesis 3.1: Providing emotionally adaptive feedback would reduce FLA.

5.1.2 Effectiveness of Adaptive Feedback to Increase Learning Gain

RQ 3.2: How effective is an adaptive feedback approach relative to a fixed feedback approach for increasing learning?

Adaptive learning system helped to increase learning gain (S. Wang et al., 2023). Specifically, using an adaptive tutor within a math e-learning system improves the learners' performance (Arroyo et al., 2014; Hwang et al., 2020; S. Wang et al., 2023; Yu et al., 2023). Other researchers found that both adaptive and fixed feedback could help increase learning gain, but the adaptive feedback helped the learners to get superior learning gain than the fixed feedback (Bimba et al., 2021).

Hypothesis 3.2: I hypothesized that using an adaptive feedback strategy is an effective method to increase foreign language learning.

5.1.3 Effectiveness of Interventions Based on Prior Knowledge

RQ 3.3: Is there a difference between the effectiveness of adaptive emotionally supportive feedback on low vs. high knowledge learners?

An adaptive affective e-learning system helped high achievers to maintain high knowledge acquisition and at the same time helped low achievers to improve their performance (Hwang et al., 2020). It is worth mentioning that high prior knowledge learners could feel less anxious than low prior knowledge learners (J. C. Yang & Quadir, 2018), which affects their benefits from the emotional support. Adaptive motivational supportive feedback helps low prior knowledge learners to achieve high learning gain (D'Mello & Graesser, 2013), which indicates that low prior knowledge learners can benefit more from the adaptive feedback.

Hypothesis 3.3: I hypothesized that learners with low prior knowledge would feel calmed down more easily by the adaptive emotionally supportive system.

5.1.4 Effectiveness of Adaptive Feedback on Anxious/Non-anxious Learners

RQ 3.4: Is there a difference between the effectiveness of adaptive emotionally supportive feedback on anxious vs. non-anxious learners?

Anxious and non-anxious learners react differently in the language learning environment. Anxious learners get disturbed by their errors, while non-anxious learners are not bothered (Gregersen & Horwitz, 2002), which could affect their overall emotional state. Moreover, Guo et al. (2018) found that anxious learners are less likely to use self-regulatory strategies to cope with their anxiety; thus, they suggested using adaptive feedback to reduce FLA to help anxious learners.

Hypothesis 3.4: I hypothesized that an emotionally adaptive system would help anxious more than non-anxious learners.

5.2 Method for Emotionally Adaptive ITS

This section describes the methodology used to test these hypotheses. First, I will describe the tutoring system structure from a pedagogical and technical point of view. I will also describe the system architecture, experimental design, participants, measures, and data analysis.

5.2.1 E-Learning System 3

To create an emotionally intelligent tutoring system, I modified the e-learning system 2 to measure anxiety levels in real time with a machine learning model, and to provide intervention adaptively. I also added a pre-test (see Appendix E) and post-test (see Appendix I) to measure the learning gain.

The new e-learning system was constructed using Python, MYSQL, PHP, HTML, and JavaScript. The animated agent was created using Media Semantics. The system architecture has two aspects: pedagogical and machine learning. The pedagogical aspect is similar to that used in e-learning system 2 (see Section 3.5.1), adding the pre- and post-tests to measure learning. The machine learning aspect was designed to detect FLA using sensor-free human behavioral metrics and provide the appropriate intervention.

Before designing the pre-post tests, I created learning objectives. These objectives followed Bloom's Revised Taxonomy (Krathwohl, 2002). This Taxonomy has two dimensions: The Cognitive Process dimension (CPD) and the Knowledge dimension (KD). Each of these categories has subcategories. The Cognitive Process dimension includes: Remember, Understand, Apply, Analyze, Evaluate, and Create. The Knowledge dimension includes: Factual, Conceptual, Procedural, and Metacognitive knowledge.

Following is a description of the learning objectives and their connection with Bloom's Revised Taxonomy:

1. **Select the appropriate vocabularies:**
   The first learning objective is categorized as **4. Analyze** for the Cognitive Process, specifically **4.1 Differentiating** because the learner needs to analyze the sentences and select the vocabulary that suits the context. The learners must detect the sentences' meaning to choose the correct vocabulary. They should build an interrelationship between the sentence fragments to generate the proper structure. Therefore, it is under the umbrella of **Bc. Knowledge of theories, models, and structures** a subcategory of **B. Conceptual Knowledge**.

2. **Recognize the key facts of the listening material:**
   This learning objective is classified as **1. Remember**, specifically **1.1 Recognizing** for the Cognitive Process because it focuses on remembering the main idea and recognizing the key facts. Overall, the learners will make logical connections and conclusions between different parts. By performing the listening exercise, they should make a conceptual

generalization under the **B. Conceptual Knowledge** specifically **Bb. Knowledge of principles and generalizations**.

3. **Apply the correct grammar rule**

   This learning objective is categorized as **3. Apply** for the Cognitive Process, precisely **3.1 Execute** because the learners should perform a familiar task. They must convert direct to indirect speech, allowing them to apply the same concepts in real-life situations by restating what someone said. Learners should execute the same concepts in a similar procedure, which is **C. Procedural Knowledge**, explicitly **Cc. Knowledge of criteria for determining when to use appropriate procedures**.

4. **Understand the content and be able to summarize it:**

   This learning objective is classified into **2. Understand**, clearly **2.4 Summarizing** for Cognitive Process because the learners must read, understand, and summarize the passage. They should know how to retrieve information about a specific topic, teaching them to focus, pay attention to specific details, and summarize what they learned. These learning objectives fall under **A. Factual Knowledge** because the learner should pay attention to specific elements which consider **Ab. Knowledge of specific details and elements**.

5. **Apply the correct punctuation:**

   This learning objective is categorized as **3. Apply**, exactly **3.2: Implementing** for the Cognitive Process because the learners should implement techniques learned before in a new situation. They must put

Table 5.1: Bloom's revised classification of learning outcomes.

	Cognitive Process Dimension			
Knowledge Dimension	Remember	Understand	Apply	Analyze
Factual Knowledge		LO 4: Summarize content		
Conceptual Knowledge	LO 2: Recognize key facts		LO 5: Apply punctuation	LO 1: Select appropriate vocabularies
Procedural Knowledge			LO 3: Apply grammar rules	

punctuation on any piece of text. By doing so, they should make interrelationships among the text elements that enable them to produce a correct structure, requiring the use of **B. Conceptual Knowledge**. They should place the appropriate punctuation in the contextual text, considered as **Ba. Knowledge of classifications and categories**.

Table 5.1 shows Bloom's Revised Classification matrix of learning outcomes.

5.2.2 Design

I did pilot testing with six participants to verify the system's effectiveness in providing adaptive feedback and ensuring that the system works on all standardized browsers and devices. I modified the system based on the participants' feedback and interaction to ensure no interruption. I also calculated the average time spent on the system. Importantly, I compared the pre-test and the post-test to ensure the reliability and validity of the measurements. The pre-test and post-test were equivalent but not identical to avoid bias and confounding effects. To ensure no difference between the two tests, I did a parallel forms reliability evaluation, assessing that the two tests are equivalent. Using the pilot test data, I did a correlation analysis between the pre-test and post-test. I found a significant positive strong correlation between pre-test and post-test $r = 0.504, p = 0.01$.

5.2.3 Conditions

A four-group design was used: In the adaptive condition, the participants received adaptive feedback, either explanatory or motivational supportive feedback presented in text, voice, or animated agent as decided by the machine learning algorithm. In the explanatory-text condition, the participants always received static explanatory feedback in text and voice. In the motivational supportive agent condition, the participants always received motivational supportive feedback from an agent. In the explanatory-voice condition, the participants always received text-only explanatory feedback.

I used 3 fixed instead of six because, based on the results presented in Chapter 4, there was no significant difference between some groups. The adaptive feedback provided explanatory or motivational supportive feedback presented by the text, voice with text, or agent with voice and text. The machine learning model decided which intervention would better reduce the learner's anxiety.

As discussed in Chapter 4 and based on Ismail and Hastings (2021), I knew that motivational supportive feedback presented by the agent could reduce FLA the most, followed by explanatory text feedback. Thus, I used a motivational supportive agent and explanatory text as a fixed strategy condition. Following research supporting the use of recorded voice along with text for foreign language learners (Clark & Mayer, 2016), the voice explanatory condition added recorded voice to the feedback in the text explanatory condition.

I detected FLA using machine learning to build an emotionally intelligent tutoring system. Based on the results of Research Question 1.3 (see Section 3.6), I implemented a Random Forest Chain Regressor model in scikit-learn Python machine learning library (Pedregosa et al., 2011) to predict FLA, change in FLA, and intervention. The predicted FLA measures the learner's current anxiety level. The change in FLA measures the difference between the current FLA and the anxiety level after receiving the intervention (Ismail & Hastings, 2023).

5.2.4 Participants

One hundred and eight participants did the study (Adaptive N=26, Voice Explanatory N=21, Agent Supportive N=30, Text Explanatory N=31). All participants who finished the study in good faith received $15 Amazon gift card. I discarded the data from participants who spent less than 30 minutes doing the exercises because, based on the pilot testing, the exercises should take at least 30 minutes to do in good faith, as opposed to just clicking without reading.

5.2.5 Model for Selecting Intervention

First, I divided the data, which was extracted from the study that was described in Section 4.2, into six groups based on the type and modality used. I applied a Random Forest Chain Regressor algorithm for each group to calculate FLA and change in FLA after using the intervention. I used 10-fold cross-validation and 100 random generations for each model for the chain order. There were nine independent features: FLCAS score, all pre-exercise scores, the current exercise score, pre-incorrect answer, exercise duration, relevant exercise duration, exercise type, age, and English level (see Section 3.5.5) and two dependent variables (FLA and change in FLA)[2]. To provide adaptive intervention, I predicted the intervention based on the Random Forest algorithm, which chose the intervention that caused the maximum reduction in FLA.

5.2.6 Measures

First, the participants provided demographic information (age, gender, English level, educational degree, native language, marital status, employment status, and number of years studying English). After that, they completed the FLCAS questionnaire to measure their anxiety during English class. Then

[2] I used Joblib library for the pipeline jobs.

they answered the pre-test, which consists of five sections (vocabulary, listening, grammar, reading, and writing) described in Section 5.2.1. After that, they did 26 exercises, the same exercises used in e-learning system 2. (See Section 3.5.1.) After each exercise, the machine learning algorithm calculated the anxiety level reduction and gave feedback according to the assigned condition. If the participant was in the adaptive condition, they received feedback based on their anxiety level. After each exercise, the participants gave a self-report about their current anxiety level, which consists of a slider from calm (0) to anxious (100). (See Figure 5.1.) After completing all the exercises, the participants answered post-test questions similar to the pre-test but not identical to avoid the confounding effect as described in Section 5.2.1.

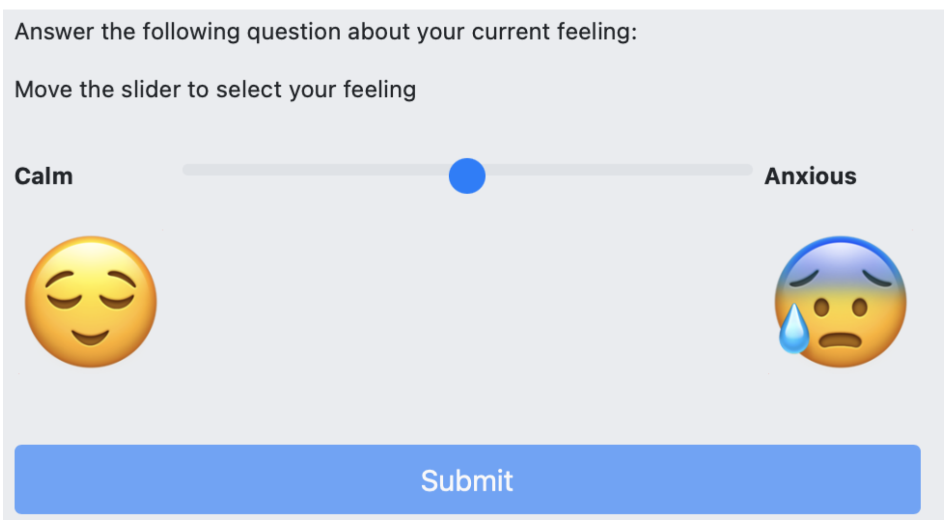


Figure 5.1: Level of anxiety self-report.

5.3 Data Analysis and Results for Emotionally Adaptive ITS

5.3.1 Comparing Machine Learning Models

The original machine learning model used in this study was built based on all the data from Section 4.2.3 before removing data from participants who rushed through the study. To demonstrate that the machine learning model used in the study was still valid, I built a new model after removing data from the rushing participants and compared the two models.

I did a paired samples t-test analysis to compare the intervention used in the adaptive system with the intervention predicted from the new model. I found no significant difference between the intervention suggested by the original and modified model for the feedback type $x^2 = .13, df = 1, p = .719$. Table 5.2 shows the number and percentages of the different types of feedback that the two models suggested for most effectively reducing FLA for the 5982 instances of feedback from the system.

Table 5.2: Occurrences and percentages of feedback type.

	Original Model	Modified Model
Explanatory	2566 (43%)	1994 (34%)
Supportive	3416 (57%)	3988 (66%)

For feedback modality, however, there was a significant difference $x^2 = 10.107, df = 4, p = .039$. Table 5.3 shows the number and percentages of different modalities of feedback that the two models suggested for most effectively reducing FLA.

Table 5.3: Occurrences and percentages of feedback modalities.

	Original Model	Modified Model
Text	386 (6%)	3330 (56%)
Voice	2073 (35%)	1104 (18%)
Agent	3523 (59%)	1548 (26%)

5.3.2 RQ 3.1: Effect of Adaptive Feedback to Reduce FLA

RQ 3.1 asked about the effectiveness of adaptive feedback for reducing FLA. To address this, I did an ANOVA to compare the reduction of learners' FLA when using adaptive feedback vs. fixed feedback. The reduction of FLA is calculated as the level of anxiety before and after receiving the intervention, I used the following formula:

$$Change\ in\ FLA = Predicted\ FLA - Self\text{-}reported\ FLA \tag{5.1}$$

The independent variable was the difference between predicted anxiety and self-reported anxiety. I found a significant reduction in anxiety in the adaptive condition $F(3, 2792) = 13.542, p < .001$. Table 5.4 and Figure 5.2

Table 5.4: Change in FLA between groups.

	Mean	SD	SE
Adaptive	7.56	31.42	1.21
Voice explanatory	3.33	30.35	1.3
Agent supportive	6.18	31.44	1.13
Text explanatory	-1.64	28.62	1.01

present the mean and standard deviation for the change in FLA after receiving the feedback.

To investigate this more thoroughly, I did separate t-tests comparing adaptive with other conditions; there was a significant difference between the adaptive and explanatory text, $t(1469) = 5.871, p < 0.001$. Also, there was a significant difference between the adaptive and voice explanatory, $t(1214) = 2.371, p = .018$. But there was no significant difference between the adaptive and motivational supportive agents, $t(1448) = .834, p = .404$.

5.3.3 RQ 3.2: Effect of Adaptive Feedback for Increasing Learning Gain

RQ 3.2 was about empowering learning with fixed or adaptive feedback. First, to ensure no difference in the prior knowledge between the four groups, I did an ANOVA with a pre-test as an independent variable. I found no significant difference $F(3, 539) = 1.181, p = .316$.

To answer the second sub-question about the effectiveness of adaptive feedback in increasing learning gain, I compared the pre-test and post-test

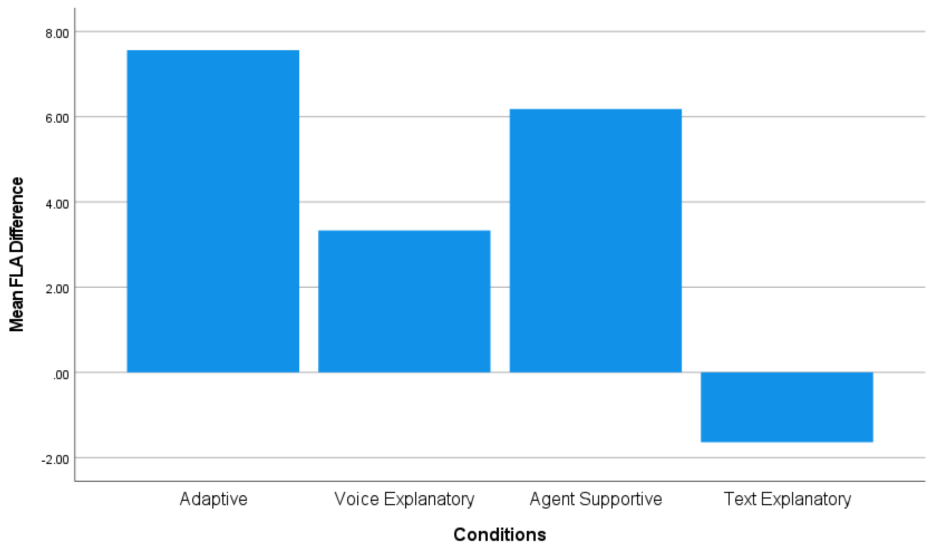


Figure 5.2: Change in FLA between groups.

results using paired samples t-test analysis. Overall, I found a significant difference between pre-test and post-test scores, $t(539) = -8.152, p < .001$ with a higher score for post-test (M = 57.32, SD=34.25) than pre-test (M = 44.59, SD=29.18).

Then, I did paired samples t-tests for each condition. For the adaptive condition, I found that post-test scores were significantly higher (M = 61.12, SD = 34.8), than pre-test scores (M = 47.55, SD=30.25), $t(129) = -4.274, p < .001$. The effect size for this learning gains ($d = .4$) is considered moderate. Also, I found that post-test scores were significantly higher than the pre-test for the fixed groups: motivational supportive emotional feedback presented by agent $t(149) = -3.695, p < .001$, explanatory text feedback $t(154) = -3.099, p < .001$, but the effect size was small (d= .33, and respectively d= .39). The post test scores were also significantly higher for

Table 5.5: Mean score (with SD) for pre-test and post-test.

	Pre-test	Post-test	Effect size
Adaptive	47.55 (30.25)	61.12 (34.8)	.4
Voice explanatory	45.08 (29.86)	60.43 (32.59)	.49
Agent supportive	45.19 (28.69)	53.52 (33.94)	.33
Text explanatory	41.18 (28.22)	53.52 (33.94)	.39

explanatory voice feedback $t(104) = -4.288, p < .001$, however, the effect size was moderate (d= .49) as shown in Table 5.5.

To find the difference between conditions, I calculated the normalized change score using the following formulas (Marx & Cummings, 2007):

$$c = \begin{cases} \frac{post-pre}{100-pre} & post > pre \\ drop & post = pre = 100 \; or \; 0 \\ 0 & post = pre \\ \frac{post-pre}{pre} & post < pre \end{cases} \tag{5.2}$$

Then, I did an ANOVA using the normalized change as the dependent variable and the four conditions themselves as the independent variable[3]. As shown in Figure 5.3, overall, I found no significant difference between the conditions $F(3, 508) = .222, p = .881$. Then I did separate t-tests comparing adaptive with other conditions; there was no significant difference between

[3]I used the normalized change instead of the normalized gain because it eliminated the bias associated with low pre-test scores and equal pre-post-test scores.

adaptive and motivational supportive agent $t(257) = .43, p = .667$. Also, nor was a significant difference between adaptive and explanatory voice $t(216) = -.243, p = .808$. Also, there was no significant difference between adaptive and explanatory text $t(266) = .434, p = .665$.

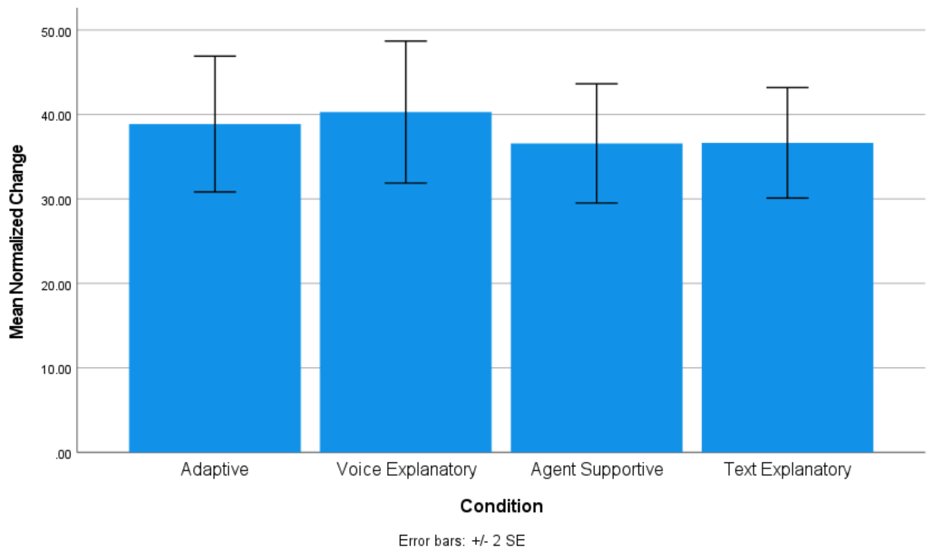
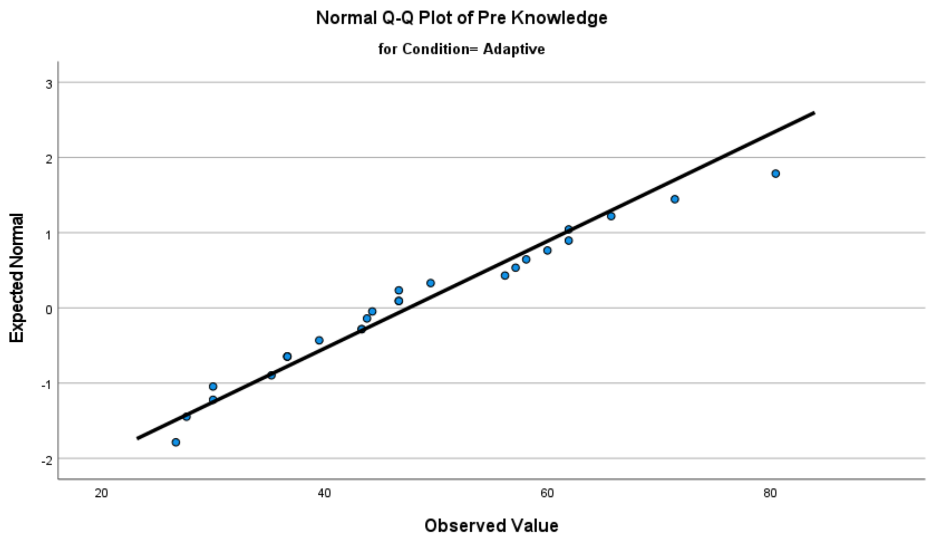


Figure 5.3: Learning gain between conditions.

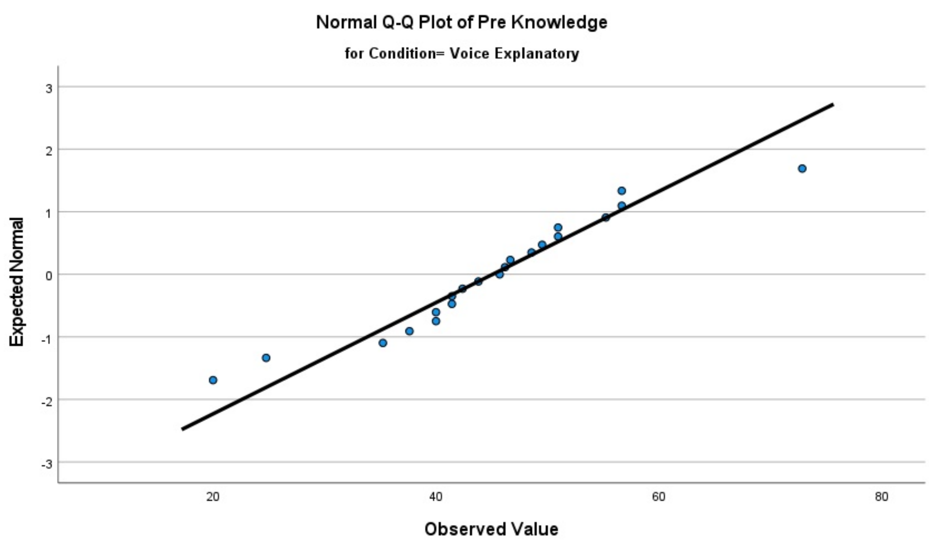
5.3.4 RQ 3.3: Effect of Interventions Based on Prior Knowledge

RQ 3.3 asked whether prior knowledge affects the effectiveness of the interventions. Before understanding the effectiveness of the interventions based on prior knowledge, a Shapiro-Wilk test was conducted for pre-test scores to understand whether they were normally distributed. I found that the pre-test scores were normally distributed among the conditions (adaptive $p = .411$, voice explanatory $p = .443$, agent supportive $p = 0.077$, text explanatory $p = 0.355$) see Figure 5.4.

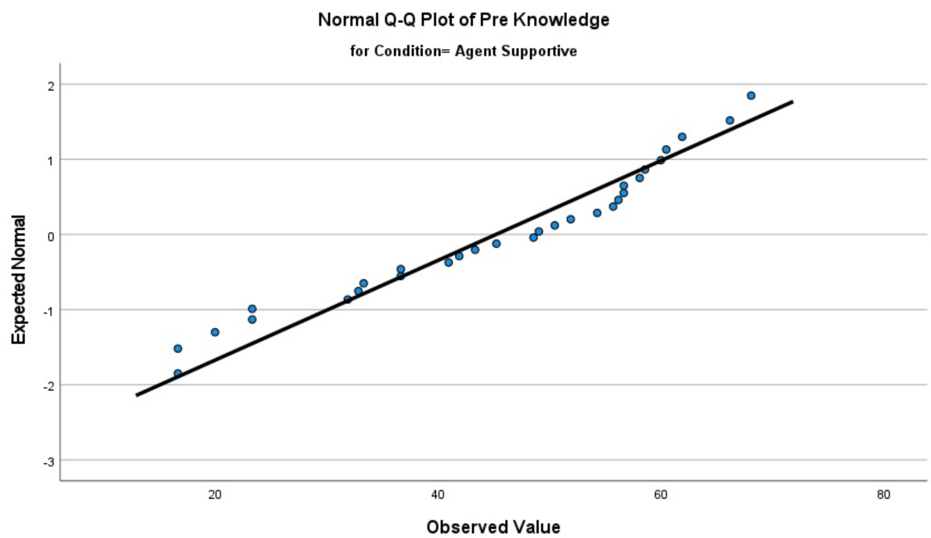
Then I did a median split for the prior knowledge to divide the participants into low (N= 54) and high (N= 54) knowledge (M= 43.81, SD= 13.9).



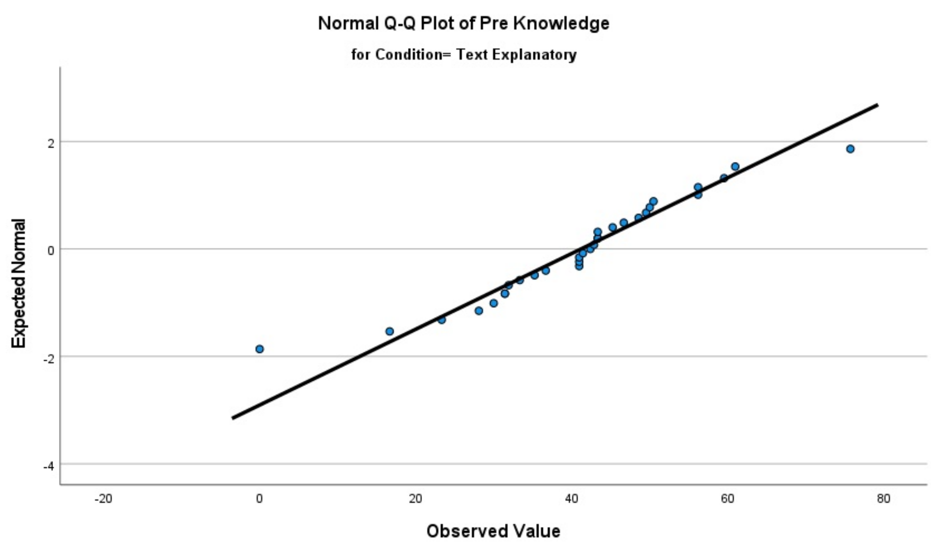
(a) Adaptive.



(b) Voice explanatory.



(c) Agent supportive.



(d) Text explanatory.

Figure 5.4: Normal Q-Q plots of prior knowledge.

Table 5.6: Mean FLA reduction (with SD) for low and high knowledge.

	Low Prior Knowledge	High Prior Knowledge
Adaptive	3.66 (33.66)	10.88 (29.02)
Voice explanatory	0.21 (32.34)	5.68 (28.58)
Agent supportive	10.39 (34.02)	2.97 (28.95)
Text explanatory	-4.32 (28.93)	3.33 (27.43)

To answer this sub-research question, I did an ANOVA to compare the reduction of learners' FLA when using adaptive feedback vs. fixed feedback based on learners' prior knowledge. As mentioned above, the reduction in FLA was calculated using the equation 5.1. I found a significant main effect of prior knowledge $F(1, 2792) = 7.524, p = .006$, and overall crossover interaction between prior knowledge and conditions $F(7, 2792) = 11.15, p < .001$. Table 5.6 shows the mean and standard deviation of the change in FLA.

5.3.5 RQ 3.4: Effect of Adaptive Feedback on Anxious/Non-anxious Learners

RQ 3.4 asked whether there is a difference in the anxiety level between anxious and non-anxious learners when receiving adaptive feedback. Anxious and non-anxious learners react differently and have distinct emotional responses (Gregersen & Horwitz, 2002). As mentioned before in Section 3.2.4, the FLCAS score classified the participants into anxious (score 90 or above) or non-anxious (score below 90). I conducted a t-test to compare the effect of adaptive feedback on anxious (N=16) and non-anxious (N=10) learners with dependent variable change in anxiety level between predicted and reported anxiety. I found no significant difference $t(670) = -.603, p = .547$. Table 5.7 show the change in FLA for anxious and non-anxious learners.

Table 5.7: Change in FLA for adaptive feedback on anxious and non-anxious.

	Mean	SD	Median
Anxious	8.14	34.36	7.45
Non-anxious	6.64	26.1	16.96

5.4 Research Question 3: Discussion

5.4.1 Comparing Machine Learning Models

To evaluate the validity of the machine learning model, I compared the original model, which I used in the study, and the model that I rebuilt using data from participants who did not rush through the study. I found no significant difference in feedback type. This result means the two models provided motivational supportive, or explanatory feedback identically or close enough. However, there was a significant difference in feedback modality, but this was expected because, based on Section 4.3.2 about the effect of feedback type and modality on FLA, there was a difference between feedback types, but there was no difference in feedback modality. Also, there was no difference in the interaction between the motivational supportive agent and the explanatory voice. There was no difference between supportive text and explanatory voice. Moreover, there was no difference between the explanatory agent and the supportive voice. This inconsistency explains the insignificance of the feedback modality between the two models. This could be checked in further research.

5.4.2 RQ 3.1: Effect of Adaptive Feedback to Reduce FLA

I wanted to determine whether adaptive feedback could reduce FLA or not. Thus, I compared adaptive feedback with different combinations of feedback types and modalities. An adaptive emotionally intelligent tutoring strategy reduced anxiety more than fixed strategies (Ismail & Hastings, 2023). This is aligned with H.-C. K. Lin et al. (2015), who found that an affective intelligent tutoring system reduced anxiety for learners of Japanese as a foreign language. However, the results did not reach the $\alpha < 0.05$ threshold between the adaptive feedback and the fixed motivational supportive agent. The presence of the emotionally supportive agent helped reduce FLA regardless of whether the system is adaptive. This partially replicates previous research, which found that emotionally supportive agents reduce FLA (Ayedoun et al., 2019; Ismail & Hastings, 2021). The adaptive feedback significantly reduced FLA compared to explanatory text and voice feedback. This supports previous research, which suggests providing adaptive feedback based on the learner's emotional state (Harley et al., 2016; Ismail & Hastings, 2023). Therefore, my hypothesis was partially supported.

5.4.3 RQ 3.2: Effect of Adaptive Feedback for Increasing Learning Gain

RQ 3.2 asked whether an adaptive feedback approach is effective for increasing learning gain. When looking at the pre-test to post-test results, there was no significant change between adaptive and fixed feedback. This may not be surprising considering that the tutoring system's content is relatively difficult, on par with TOEFL and IELTS English language standardized tests. This may limit how much the learners' anxiety levels would be reduced throughout the study and determine the extent of their learning achievement. It may take a while to pay off longer than a study, perhaps more comprehensive interaction with others. The hypothesis was not supported because there was no significant difference between the four conditions.

5.4.4 RQ 3.3: Effect of Interventions Based on Prior Knowledge

RQ 3.3 asked whether there is a difference in FLA reduction between conditions based on prior knowledge. First, it should be noted that the machine learning model did not take into account the learners' prior knowledge, which could affect its ability to appropriately adapt to high prior knowledge or low prior knowledge learners. High achievers could need motivational supportive feedback when they answer incorrectly, while they prefer explanatory feedback when they answer correctly. They might even feel irritated by motivational supportive feedback when they feel they do not need it. This finding is aligned with previous research, which found that high-domain knowledge learners appreciate support but only when they need it (D'Mello & Graesser, 2013). These results explain the insignificant difference between adaptive and motivational supportive feedback presented by the agent to reduce FLA presented in Section 5.3.2. Both interventions help different groups of people to reduce their anxiety. The adaptive feedback helped the high-knowledge learners, while the motivational supportive feedback assisted the low-knowledge learners.

It was clear that low-knowledge learners felt calmer during the study when continuously receiving motivational supportive feedback presented by the agent, which replicates previous research that found that low-domain knowledge learners benefit from supportive more than explanatory feedback (D'Mello & Graesser, 2013). The adaptive feedback made low-knowledge learners calmed down but not as much as always receiving motivational supportive feedback by the agent. Surprisingly, emotionally adaptive feedback affected high-knowledge learners more positively than low-knowledge learners because, as explained in Section 4.3, low achievers preferred to receive motivational supportive feedback. At the same time, there was inconsistency for high achievers. My hypothesis was not supported because low-knowledge learners did not benefit from the adaptive feedback.

5.4.5 RQ 3.4: Effect of Adaptive Feedback on Anxious/Non-anxious Learners

I wanted to determine if there is a difference between the effectiveness of adaptive emotionally supportive feedback on anxious/non-anxious learners in reducing FLA. There was no significant difference in FLA reduction between anxious and non-anxious learners. It is worth mentioning that given the random splitting between conditions, there were twenty-six participants in the Adaptive condition; of these, ten were classified as non-anxious learners and sixteen as anxious learners. Even though the difference in anxiety reduction between anxious and non-anxious learners did not reach a significant level, there was a trend for lower anxiety levels. Anxious learners' anxiety levels lowered more than non-anxious learners. Adaptive feedback helped both anxious and non-anxious learners, reducing their anxiety levels. This is consistent with previous research that mentioned anxious and non-anxious learners appreciate the reminder to stay calm (Gregersen & Horwitz, 2002). Thus, my hypothesis was not supported.

5.5 Research Question 3: Summary

This chapter studied the effectiveness of adaptive motivational supportive feedback. To answer this Research Question, I built an emotionally intelligent adaptive intelligent tutoring system. This system was built using a machine learning model, specifically a Random Forest Chain Regressor. It used sensor-free human behavioral metrics as features to feed the model. A combination of feedback types and modalities adaptively used to reduce FLA. A pre-post test was used to measure the learning gain. To study the model's effectiveness, I compared adaptive and fixed feedback. The essential outcomes are:

- Even though the originally used model included all previous data, I found no difference in providing explanatory and motivational supportive feedback compared to the corrected model.
- When comparing the adaptive feedback approach with explanatory text and voice, adaptive feedback significantly reduced FLA. Yet, there was no significant difference between adaptive and motivational supportive agent feedback.
- Learning gain was increased for adaptive feedback and fixed strategy. Learners' performance was improved when using the e-learning system regardless of the feedback provided.
- Adaptive motivational supportive feedback helped reduce FLA for high-prior knowledge learners, while the motivational supportive agent assisted in reducing FLA for low-knowledge learners.
- Adaptive feedback helped both anxious and non-anxious learners to reduce their anxiety levels.

This chapter discussed Research Question 3 about the effectiveness of adaptive motivational supportive feedback in reducing FLA and increasing learning gain. It was clear that adaptive feedback effectively reduced FLA more than explanatory feedback. High-knowledge learners, in particular, benefited from the adaptive feedback. Regarding learning gain, there was a small to moderate increase in all conditions. Finally, adaptive feedback helped to decrease FLA for both anxious and non-anxious learners with no significant difference.

Chapter 6

Summary and Conclusion

For an emotionally intelligent language tutoring system to effectively reduce FLA, it must be able to detect when the learner is anxious. Ideally, this would be done with sensor-free human behavioral metrics because they are scalable, practical, and not distracting. Once FLA is detected, different methods can be used to reduce FLA effectively. In particular, I focused on assessing animated agents and motivational supportive feedback, and the timing and adaptability of their intervention within the context of an e-learning system. Learning about successful methods to reduce FLA is very important because reducing FLA can increase interest in learning and motivation (M. Liu, 2006; Lu et al., 2007).

As stated before, the impact of FLA goes beyond the class. It has a long-lasting effect on emotions, health, and social activity. Moreover, FLA can split the attention between emotion and cognition. Previous research proved that while FLA reduces learners' performance and achievements, it also affects their future selection of academic majors or career paths. Therefore, decreasing FLA will improve learning achievements, and increase positive emotion, which is important for mental health (see Section 2.2.2.)

Existing methods used to recognize FLA rely on either physical measures, self-reports, or facial expressions. These methods could provide accurate results, but they could also annoy the learners, provoking more anxiety. Instead, measuring FLA using sensor-free human behavioral metrics can detect FLA with minimal user interruption and without obstructing the learning process (see Section 2.3.) In this dissertation, I have demonstrated how to detect FLA using sensor-free human behavioral metrics. Also, I have shown that using adaptive motivational supportive feedback presented by the agent can reduce FLA and increase learning gain.

6.1 Summary

Through this study, three main research questions were investigated. Research Question 1 addressed the effectiveness of human behavioral metrics to detect FLA in the context of an e-learning system. Research Question 2 discussed the effectiveness of emotionally supportive feedback provided by various modalities such as text, voice, and animated agents to reduce FLA. Finally, Research Question 3 explored the efficacy of adaptive emotional supportive feedback.

6.1.1 Detecting FLA

To answer Research Question 1, I first (Experiment 1, Section 3.2) compared FLA in the classroom and while using an e-learning system to understand the interaction between different anxiety-producing situations. The results revealed that learner anxiety levels in a classroom corresponded with those detected when using the e-learning system. I found several metrics that can be used to determine when the learners are anxious: level of anxiety self-report, language difficulty self-report, and change rate of blood pressure.

Also, through Experiment 1, I discovered that FLA can be identified by learners' interactions with the system. Language difficulty self-report, system difficulty self-report, and exercise score account for about 30% of the variance in predicting FLA, which is reasonable given that emotions (and anxiety in particular) are notoriously difficult to identify. FLCAS consists of three components that are considered dominant factors that affect FLA. During listening exercises, the average communication apprehension part of FLCAS accounted for 13% of the variance in anxiety. For speaking exercises, the average fear of negative evaluation and the average communication apprehension parts of FLCAS accounted for 21% of the variance in anxiety. For grammar exercises, test anxiety scores from the FLCAS accounted for 18% of the variance in FLA. For vocabulary exercises, test anxiety and fear of negative evaluation components of FLCAS accounted for 25% of the variance in FLA. Overall, for any exercise, all three components of the FLCAS accounted for 18% of the variance in anxiety.

I demonstrated that FLA can be detected using sensor-free human behavioral metrics in the context of an e-learning system. I discovered that FLA can be detected without a direct sensor using FLCAS score, age, English level, exercise topic, the average percentage of all previous exercises, the percentage of previous incorrect scores, the current exercise score, the duration spent on the exercise, and the average duration of exercises of the same section.

I evaluated the effectiveness of six machine learning methods. I found that Random Forest, XGboost, and Gradient Boosting Regressor models outperformed Linear Regression, Bayesian Ridge, and SVR. Random Forests captured up to 66% of the variability in anxiety. Although this variability is still imperfect, it accounts for acceptable prediction of FLA because detecting emotion is extremely difficult (Baker et al., 2012). I found that a Random Forest model using sensor-free human behavioral metrics could effectively identify FLA.

6.1.2 Reducing FLA

To reduce FLA, I examined the effectiveness of feedback type (explanatory feedback vs. motivational supportive feedback) presented by various modalities (text vs. voice and text vs. agent with voice and text). Overall, this research demonstrates that FLA can be effectively reduced by different combinations of feedback types and modalities.

I found that overall, motivational supportive feedback is effective in lowering FLA, regardless of how it is delivered. Also, motivational supportive feedback presented by text or agent reduced FLA.

I also discovered, perhaps unsurprisingly, that the correctness of the learner's answer impacts the effectiveness of the motivational supportive feedback. Learners' anxiety was lower when they received motivational supportive feedback after answering incorrectly.

The study also revealed interactions between gender, feedback type, and modality. Males' anxiety levels were higher than female anxiety levels. The interventions were more effective for males than females. Males' anxiety levels were the lowest when they received motivational supportive feedback presented by the agent. Also, there was a gender interaction with feedback type and performance, but the difference was only significant for males. Males' anxiety levels were reduced the most when they answered incorrectly and received motivational supportive feedback.

6.1.3 Emotionally Adaptive ITS

Based on the results from Experiment 1 and Experiment 2, I built an emotionally intelligent system that detected FLA and provided feedback adaptively. To answer Research Question 3, I investigated the effectiveness of the adaptive feedback strategy vs. fixed strategy for decreasing FLA and increasing learning achievement. The adaptive feedback provided either explanatory or motivational supportive feedback presented by text, voice, or agent. I compared the adaptive feedback with three fixed strategies: motivational supportive feedback presented by the agent and explanatory feedback presented by text or voice.

I found that overall, adaptive feedback was effective, but there are some factors that affect its effectiveness. For example, high-knowledge learners' anxiety levels were reduced the most when they received adaptive feedback. With respect to the learner's prior anxiety levels, the adaptive feedback supported both anxious and non-anxious learners. The learning gain was increased for all conditions. Yet, there was no significant difference in the learning gain between adaptive and fixed feedback.

6.2 Conclusions

Several conclusions can be drawn from this work that can apply to any similar emotionally intelligent language tutoring system.

- **Practical FLA detection:** The main outcome from Research Question 1 is that FLA can be detected, without any learning interruption, using sensor-free human behavioral metrics that can be extracted from any e-learning system. In particular, these metrics provide features (FLCAS score, all pre-exercise scores, the current exercise score, pre-incorrect answer, exercise duration, relevant exercise duration, exercise type, age, and English level) that can be used with a machine learning method like Random Forest Regression, to effectively detect FLA.

- **Interventions for reducing FLA:** Overall, the outcome from Research Question 2 is that motivational supportive feedback presented by an agent or text assists in reducing learners' anxiety levels. Anxiety levels for males, in particular, were lower when they received motivational supportive feedback from an agent. Females' anxiety levels were lower when receiving explanatory feedback by voice or motivational supportive feedback by text. When responding to the correctness of learners' answers, motivational supportive feedback helped reduce FLA, especially when the answers were wrong.

- **Emotionally intelligent adaptive tutoring for reducing FLA:** The outcome from Research Question 3 is that the adaptive feedback strategy supports reducing FLA more than explanatory feedback by text or voice. Yet, there was no significant difference between the motivational supportive feedback presented by an agent and the adaptive feedback strategy. The learning gain was moderate for both adaptive and fixed strategies.

6.3 Limitations

In this dissertation, I showed that FLA could be detected using sensor-free human behavioral metrics and reduced using adaptive motivational supportive feedback. However, there are limitations to the conclusions that can be drawn from this.

Most of the experimental studies in this dissertation were conducted online. This was intentional because it allows the learners to do this in their own environment, but from a scientific point of view it also can be seen as a limitation. It enabled some participants to take shortcuts in completing the tasks, presumably by paying little attention to the learning material and guessing the answers. After completing Experiment 3, I found that some of the data (around 12.5%) from Experiment 2, which were used to create the adaptive model, came from participants who had rushed through the exercises. To determine how that affected my results for Experiment 3, I rebuilt the model without the bad data and compared the results in terms of the type and modality of feedback predicted. The comparison was done with a paired statistical test, comparing what the models did for each particular instance. I found a significant difference in providing feedback modalities — the original model rarely offered text-only feedback, but the updated model suggested providing more frequent text-only feedback and about an equal amount of voice and agent feedback. However, I found no significant difference in providing feedback type, which means both models provided similar explanatory or motivational supportive feedback.

Although the noisy data from the rushing participants could implicate the scientific aspect, it might not be applicable to the voluntary online training systems because allowing participants to complete the study in their own environment could reduce anxiety. Also, when generalizing a system for people to use voluntarily to help them learn a language and become less anxious about it, the implications will be different in that situation because they are doing it voluntarily, not for money, so the issue of rushing through the exercises should not arise.

Another potential limitation is the high dropout rate by participants in the experiments, which prevented me from comparing the traditional machine learning methods with deep learning approaches to predict FLA. I did some analysis to detect FLA using Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNNs), Long-Short Term Memory (LSTMs), and Gated Recurrent Unit Networks (GRUs). Still, I did not include the comparison between deep learning and machine learning in this thesis because the dataset lacked sufficient data to generate an accurate deep learning model.

6.4 Future Work

As mentioned above, I built the model that detects FLA based on all the data from an online experiment (Experiment 2), which included data from participants who rushed through the exercises. In future work, we should evaluate how the interventions suggested by an updated model affect anxiety and learning.

In this research, I evaluated machine learning models for detecting FLA and predicting the best type and modality of feedback for reducing it, but I lacked enough data to generate an accurate deep learning model. Future research should explore incorporating deep learning models within foreign language tutoring systems to detect FLA. More data will allow researchers to compare the effectiveness of traditional machine learning methods vs. deep learning approaches. The precise prediction would help researchers to build better models and eventually overcome FLA.

To answer Research Question 2, I applied motivational supportive feedback presented by the agent. Future research could investigate the effectiveness of personalized feedback added to motivational supportive feedback. This feedback would thus be customized to each learner using the learner's demographics or behavioral patterns. For example, the motivational supportive feedback could be,

> "Super job, Jack, keep it up!
>
> Yes, Quiescent is the correct answer because we need a word that means inactive.
>
> You are on a streak by answering five correct answers; continue the remarkable effort!"

In my research, I used a low embodiment animated agent that provides feedback using a human voice with moving lips. Future research could investigate applying a high embodiment agent that uses gestures, body language, and facial expressions. More human-like agents might make be more believable to the learners and more effective for reducing FLA.

Future work could apply more user modeling features to investigate its effectiveness in detecting and reducing FLA. Customizing the system based on learners' needs and emotional states could improve learning and reduce FLA. Providing adaptive learning material based on the learners' prior knowledge and anxiety level could improve the learning environment. For example, the difficulty level of the exercises could be changed based on learners' emotional and pedagogical state. Building an ongoing relationship between learners and agents could increase the agent's effectiveness in lowering FLA.

Also, future work could investigate the long-term effect of the interventions by using emotionally intelligent tutoring over multiple sessions.

Future work could study the effect of music on expressing emotion and reducing FLA. Although, in some cases, music may cause cognitive overload and reduce learning, soothing music carries a great deal of emotions that can help people feel comfortable and relaxed. I suggest exploring the pros and cons of music for reducing FLA.

6.5 Closing Remarks

Finally, using sensor-free human behavior metrics can help prevent learners from focusing on negative emotions since they are indirect measurements and allow students to focus on learning. It is an effective approach because there is no obstruction to the learning flow. Specifically, an emotionally adaptive intelligent tutoring system employing sensor-free human behavior metrics can detect and reduce foreign language anxiety.

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Appendices

Appendix A

Appendix: IRB Approvals

DePaul University
Institutional Review Board
14 E Jackson Blvd Ste 1030
Chicago, IL 60604
(312) 362-6168

Research Involving Human Subjects

NOTICE OF INSTITUTIONAL REVIEW BOARD ACTION

To: Daneih Ismail, MA, Graduate Student, College of Computing and Digital Media

Date: January 17, 2023

Re: Research Protocol # DI112017CDM-C5
"Identifying Anxiety When Learning a Second Language Using E-Learning Systems"

Please review the following important information about your research activity.

Review Details
This submission is Continuing Review Report.

Your research project continues to meet the criteria for Expedited review under 45 CFR 46.110 under the following categories:

> *"(4) Collection of data through noninvasive procedures (not involving general anesthesia or sedation) routinely employed in clinical practice, excluding procedures involving x-rays or microwaves. Where medical devices are employed, they must be cleared/approved for marketing."*
>
> *"(6) Collection of data from voice, video, digital, or image recordings made for research purposes."*
>
> *"(7) Research on individual or group characteristics or behavior (including, but not limited to, research on perception, cognition, motivation, identity, language, communication, cultural beliefs or practices, and social behavior) or research employing survey, interview, oral history, focus group, program evaluation, human factors evaluation, or quality assurance methodologies."*

Approval Details
Your research Continuing Review Report was reviewed and approved on January 17, 2023.

Approval Period: February 7, 2023 - February 6, 2024
Please note: Under the revised regulations, some research may no longer require annual continuing review. For this protocol, the IRB determined that they would still require continuing review as it remains under the old regulations.

Approved Consent, Parent/Guardian Permission, or Assent Materials:
1) Adult Consent Form Online Version 10/14/2022 (attached)

a. waiver of documentation of consent granted under 45 CFR 46.117(c)(1) (ii)

Other approved study documents:
1) Verbal Recruitment Script Version 10/14/2022 (attached)
2) Recruit Email for forwarding by Directors Version 10/14/2022 (attached)
3) Response Email to Students Version 1-11-2021 (unchanged)
4) Recruitment Flyer, Version 10/25/2022 (attached)

Number of approved participants: 350 Total
You should not exceed this total number of subjects without prospectively submitting an amendment to the IRB requesting an increase in subject number.

Funding Source: 1) Internal CDM funds; 2) University Research Council, "Reducing language Anxiety Using E-Learning System," PI Peter Hastings, PhD .

Approved Performance sites: 1) DePaul University.

<u>Reminders</u>

- Only the most recent IRB-approved versions of consent, parent/legal guardian permission, or assent forms may be used in association with this project.
- Any changes to the funding source or funding status must be sent to the IRB as an amendment.
- Prior to implementing revisions to project materials or procedures, you must submit an amendment application detailing the changes to the IRB for review and receive notification of approval.
- You must promptly report any problems that have occurred involving research participants to the IRB in writing.
- If your project will continue beyond the approval period indicated above, you are responsible for submitting a continuing review report at least 3 weeks prior to the expiration date. The continuing review form can be downloaded from the IRB web page.
- **Once the research is completed, you must send a final closure report for the research to the IRB.**

The Board thanks you for your efforts and cooperation. If you have any questions, please contact me by email at mfox34@depaul.edu or by telephone at (312) 362-7592.

For the Board,

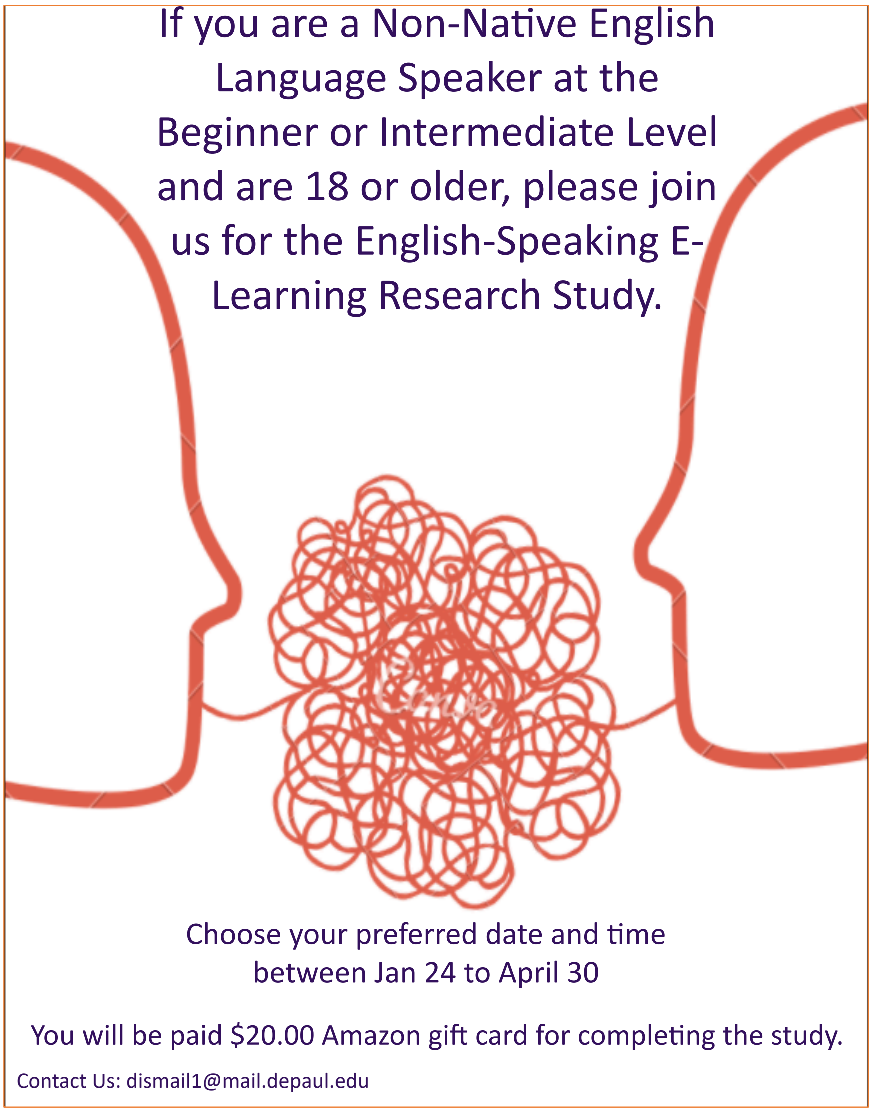
Melodie L. Fox
Research Protections Coordinator
Office of Research Services

Cc: Peter Hastings, PhD, Faculty Sponsor, College of Computing and Digital Media

Appendix B

Appendix: Flyers

B.1 Experiment 1



B.2 Experiment 3

- Are you:
  - Not a native English speaker?
  - 18 years old or older?
- If so, please join us for an English e-learning research study

You will receive a $15 Amazon gift card after completing the study

Contact us:
dismail1@depaul.edu

Scan the bar code or visit the website: flaits.org

Appendix C

Appendix: Informed Consent

DePaul IRB Approved
Protocol # DI112017CDM-C5
February 7, 2023 **Through** February 6, 2024

ADULT CONSENT TO PARTICIPATE IN RESEARCH

Identifying Anxiety When Learning a Second Language Using E-Learning System

Principal Investigator: Daneih Ismail, Graduate student
Institution: DePaul University, Chicago, Illinois, USA
Department (School, College): Computing and Digital Media.
Faculty Advisor: Peter Hastings, Associate professor, Computing and Digital Media

Key Information:

What is the purpose of this research?
We are asking you to be in a research study because we are trying to learn more about foreign language anxiety. The research aims to figure out the best intervention to reduce foreign language anxiety. This study is being conducted by Daneih Ismail, a graduate student at DePaul University as a requirement to obtain her doctoral degree. This research is being supervised by her faculty advisor, Peter Hastings. We hope to include about 350 people in the research.

Why are you being asked to be in the research?
You are invited to participate in this study because you are a student who is non-native English speaker not fluent in English. You must be age 18 or older to be in this study. This study is not approved for the enrollment of people under the age of 18. You must not have participated in this study before.

What is involved in being in the research study?
If you agree to be in this study, being in the research involves signing-up to e-learning system by filling out demographic information (email, gender, age, native language, English level, current degree, employment status, state, school name, marital status, month of birth, year of birth). After that, you will fill out a survey about your emotion when learning English as a foreign language. This survey will determine if you are doing the study in good faith or not. If you are doing the study in good faith, you will continue the study by doing a test about your English knowledge. Then you will access the e-learning system which provides video explaining the lesson and exercises meant to improve your English skills. After each exercise, you need to read/listen to the feedback. Then you will fill out a question about your current anxiety level. After you finish all exercises and self-reports, you will answer a quick test about your knowledge then we will send you Amazon gift card within 2-5 days. If you are determined to not be doing the study in good faith, giving fraudulent answers, not reading/listening to the feedback, doing the study more than once you will not be eligible to receive the gift card.

Are there any risks involved in participating in this study?
Being in this study does not involve any risks other than what you would encounter in daily life. You may feel uncomfortable or embarrassed about answering certain questions. You do not have to answer any question you do not want to. There is the possibility that others may find out what you have said, but we have put protections in place to prevent this from happening. We have created a code number for you that will be on our records, instead of using your name.

Are there any benefits to participating in this study?
You may not directly benefit from being in the research. Although the e-learning system is not a proven learning tool, it is possible that being in the research may improve your English language skills.

We hope that what we learn will help in decreasing the anxiety level of people when learning English as a foreign language.

How much time will this take?
This study will take about 75 minutes of your time. The survey, and knowledge tests will take about 15 minutes to complete. The e-learning exercise will take about 60 minutes.

Other Important Information about Research Participation

Is there any kind of payment, reimbursement or credit for being in this study?
If you are eligible to participate in the study and we found that you did the study in good faith, we will send to your email $15.00 Amazon e-gift card within 2-5 days after you finish the study otherwise you will not get paid. Please note that participants who are suspected of fraudulent behavior or falsifying information will NOT receive compensation. Multiple entries are not allowed.

Are there any costs to me for being in the research?
There is no cost to you for being in the research.

Can you decide not to participate?
Your participation is voluntary, which means you can choose not to participate. There will be no negative consequences, penalties, or loss of benefits if you decide not to participate or change your mind later and withdraw from the research after you begin participating.

If you are a student at DePaul, your decision whether or not to be in the research will not affect your grades at DePaul University. If you are an employee at DePaul, your decision whether or not to be in the research will not impact your job or relationship with DePaul.

Who will see my study information and how will the confidentiality of the information collected for the research be protected?
The research records will be kept and stored securely. Your information will be combined with information from other people taking part in the study. When we write about the study or publish a paper to share the research with other researchers, we will write about the combined information we have gathered. We will not include your name or any information that will directly identify you. We will assign you a study ID number and the recordings and study data collected from you will be identified with that number and not your name. We will make every effort to prevent anyone who is not on the research team from knowing that you gave us information, or what that information is. However, some people might review or copy our records that may identify you in order to make sure we are following the required rules, laws, and regulations. For example, the

DePaul IRB Approved
Protocol # DI112017CDM-C5
February 7, 2023 **Through** February 6, 2024

DePaul University Institutional Review Board may review your information. If they look at our records, they will keep your information confidential.

Who should be contacted for more information about the research?
Before you decide whether to accept this invitation to take part in the study, please ask any questions that might come to mind now. Later, if you have questions, suggestions, concerns, or complaints about the study or you want to get additional information or provide input about this research, you can contact the researcher, Daneih Ismail, dismail1@depaul.edu, and Peter Hastings and peterh@cdm.depaul.edu.

This research has been reviewed and approved by the DePaul Institutional Review Board (IRB). If you have questions about your rights as a research subject you may contact Jessica Bloom in the Office of Research Services at 312-362-6168 or via email at jbloom8@depaul.edu.

You may also contact DePaul's Office of Research Services if:

- Your questions, concerns, or complaints are not being answered by the research team.
- You cannot reach the research team.
- You want to talk to someone besides the research team.

Statement of Consent from the Subject:

By agree below, registering and completing the activity you are indicating your agreement to be in the research.

Do you consent to participate in the research?

Appendix D

Appendix: FLCAS

Questionnaire

Please answer the following questions about the English class

How much do you agree or disagree with the following:

1. I never feel quite sure of myself when I am speaking in my English class.

Strongly agree · Agree · Neither agree nor disagree · Disagree · Strongly disagree

2. I don't worry about making mistakes in English class.

Strongly agree · Agree · Neither agree nor disagree · Disagree · Strongly disagree

3. I tremble when I know that I'm going to be called on in English class.

Strongly agree · Agree · Neither agree nor disagree · Disagree · Strongly disagree

4.It frightens me when I don't understand what the teacher is saying in the English class.

Strongly agree · Agree · Neither agree nor disagree · Disagree · Strongly disagree

5. It wouldn't bother me at all to take more English classes.

Strongly agree · Agree · Neither agree nor disagree · Disagree · Strongly disagree

6. During English class, I find myself thinking about things that have nothing to do with the course.

Strongly agree · Agree · Neither agree nor disagree · Disagree · Strongly disagree

7. I keep thinking that the other students are better at English than I am.

Strongly agree · Agree · Neither agree nor disagree · Disagree · Strongly disagree

8. I am usually at ease during tests in my English class.

Strongly agree · Agree · Neither agree nor disagree · Disagree · Strongly disagree

9. I start to panic when I have to speak without preparation in the language class.

Strongly agree · Agree · Neither agree nor disagree · Disagree · Strongly disagree

10. I worry about consequences of failing my English class.

Strongly agree · Agree · Neither agree nor disagree · Disagree · Strongly disagree

11. I don't understand why some people get so upset over English classes.

Strongly agree · Agree · Neither agree nor disagree · Disagree · Strongly disagree

12. In language class, I can get so nervous that I forget things that I already know.
Strongly agree Agree Neither agree nor disagree Disagree Strongly disagree

13. It embarrasses me to volunteer answers in my English class.
Strongly agree Agree Neither agree nor disagree Disagree Strongly disagree

14. I would not be nervous speaking English with native speakers.
Strongly agree Agree Neither agree nor disagree Disagree Strongly disagree

15. I get upset when I don't understand what the teacher is correcting.
Strongly agree Agree Neither agree nor disagree Disagree Strongly disagree

16. Even if I am well prepared for English class, I feel anxious about it.
Strongly agree Agree Neither agree nor disagree Disagree Strongly disagree

17. I often feel like not going to my English classes.
Strongly agree Agree Neither agree nor disagree Disagree Strongly disagree

18. I feel confident when I speak in English classes.
Strongly agree Agree Neither agree nor disagree Disagree Strongly disagree

19. I am afraid that my English teacher is ready to correct every mistake I make.
Strongly agree Agree Neither agree nor disagree Disagree Strongly disagree

20. I can feel my heart pounding when I'm going to be called in the English class.
Strongly agree Agree Neither agree nor disagree Disagree Strongly disagree

21. The more I study for English test, the more confused I get.
Strongly agree Agree Neither agree nor disagree Disagree Strongly disagree

22. I don't feel pressure to prepare very well for English class.
Strongly agree Agree Neither agree nor disagree Disagree Strongly disagree

23. I always feel that the other students speak English better than I do.
Strongly agree Agree Neither agree nor disagree Disagree Strongly disagree

24. I feel very self-conscious about speaking English in front of other students.
Strongly agree Agree Neither agree nor disagree Disagree Strongly disagree

25. English class moves so quickly I worry about getting left behind.
Strongly agree Agree Neither agree nor disagree Disagree Strongly disagree

26. I feel more tense and nervous in my English class than in my other classes.
Strongly agree Agree Neither agree nor disagree Disagree Strongly disagree

27. I get nervous and confused when I am speaking in my English class.
Strongly agree Agree Neither agree nor disagree Disagree Strongly disagree

28. When I'm on my way to English class, I feel very sure and relaxed.
Strongly agree Agree Neither agree nor disagree Disagree Strongly disagree

29. I get nervous when I don't understand every word that the English teacher says.
Strongly agree Agree Neither agree nor disagree Disagree Strongly disagree

30. I feel overwhelmed by the number of rules I have to learn to speak English.
Strongly agree Agree Neither agree nor disagree Disagree Strongly disagree

31. I am afraid that the other students will laugh at me when I speak English
Strongly agree Agree Neither agree nor disagree Disagree Strongly disagree

32. I would probably feel comfortable around English native speakers.
Strongly agree Agree Neither agree nor disagree Disagree Strongly disagree

33. I get nervous when the English teacher asks questions which I haven't prepared in advance.
Strongly agree Agree Neither agree nor disagree Disagree Strongly disagree

Submit

Appendix E

Appendix: Pre-Test

Pre-Test

Vocabulary

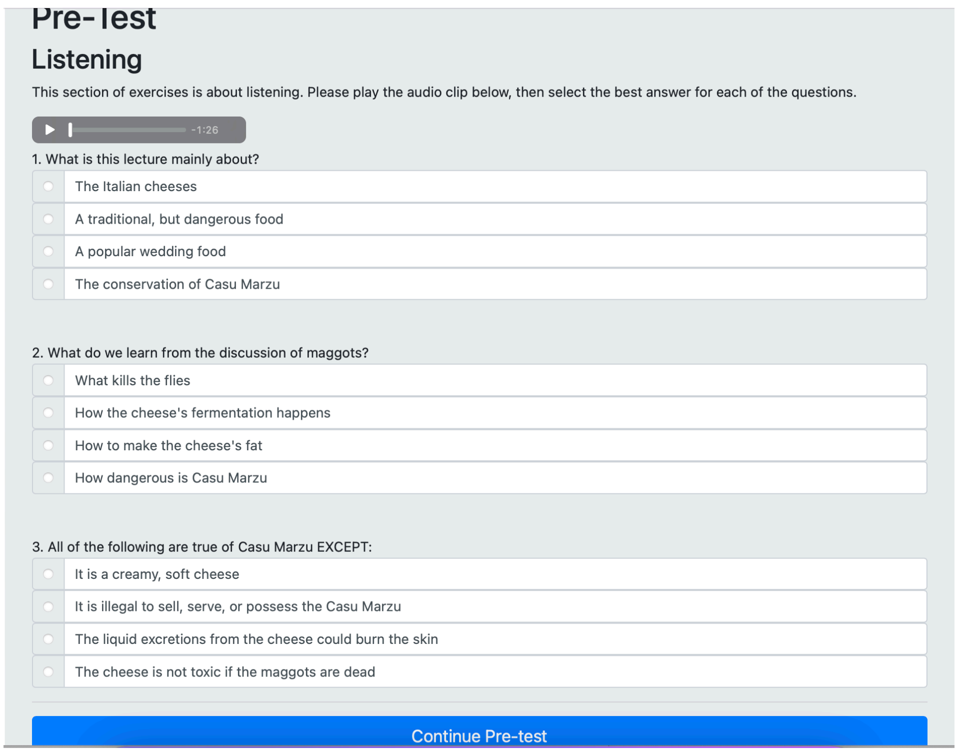
This section of exercises is about vocabulary. Please select the best answer.

1. Nutrition science has two ____ observations. One is that we can ____ how to eat healthy and maintain a healthy weight. But this conventional thinking is ____ by the ____ of cases of obesity and diabetes.

2. Insidious fungal infections by postharvest ____ remain ____ during fruit growth until, at a particular phase during fruit ripening, they kill cells and cause decay.

Continue Pre-test

14%



Pre-Test

Listening

This section of exercises is about listening. Please play the audio clip below, then select the best answer for each of the questions.

-1:26

1. What is this lecture mainly about?

- The Italian cheeses
- A traditional, but dangerous food
- A popular wedding food
- The conservation of Casu Marzu

2. What do we learn from the discussion of maggots?

- What kills the flies
- How the cheese's fermentation happens
- How to make the cheese's fat
- How dangerous is Casu Marzu

3. All of the following are true of Casu Marzu EXCEPT:

- It is a creamy, soft cheese
- It is illegal to sell, serve, or possess the Casu Marzu
- The liquid excretions from the cheese could burn the skin
- The cheese is not toxic if the maggots are dead

Continue Pre-test

Pre-Test

Grammar

This section of exercises is about grammar rules for changing direct to indirect speech. Please select the best answer.

1. "I'll lend you money for your tuition," said Tom.
Tom said he ______ me money for my tuition.

2. "I can't do the work without your help," Sara said
Sara said she ______ the work without my help.

3. "I was at the dentist all morning," Steve said
Steve said that he ______ at the dentist all morning.

Continue Pre-test

16%

Pre-Test

Reading

This section of exercises is about reading. Please start by reading the paragraph below. After you read the paragraph, please select the best answer.

Decompression sickness occurs when inert gas bubbles are formed and expelled from organic tissue during rapid ascent following an extended period of prolonged intensive atmospheric pressure. This is most commonly experienced during deepwater dives. Surface divers capable of descending to sufficient depth, or scuba divers using air tanks, supersaturate their lungs with air, which diffuses throughout the body. When pressure on the body decreases as the diver nears the surface, the diver must take care to rise gradually and expel excess gas through the mouth, nose, and ears. Without these pressure balances, the gas bubbles that form in the tissue can disrupt the joints and organs. In extreme cases, the bubbles can impede or rupture blood vessels in the brain or spine, which can lead to paralysis or even death.

1. Which would be the best title for this article?

- The predisposing factors of decompression sickness
- The causes of decompression sickness
- The symptoms of decompression sickness
- The basics of decompression sickness

2. Why does the article mention the deepwater dives?

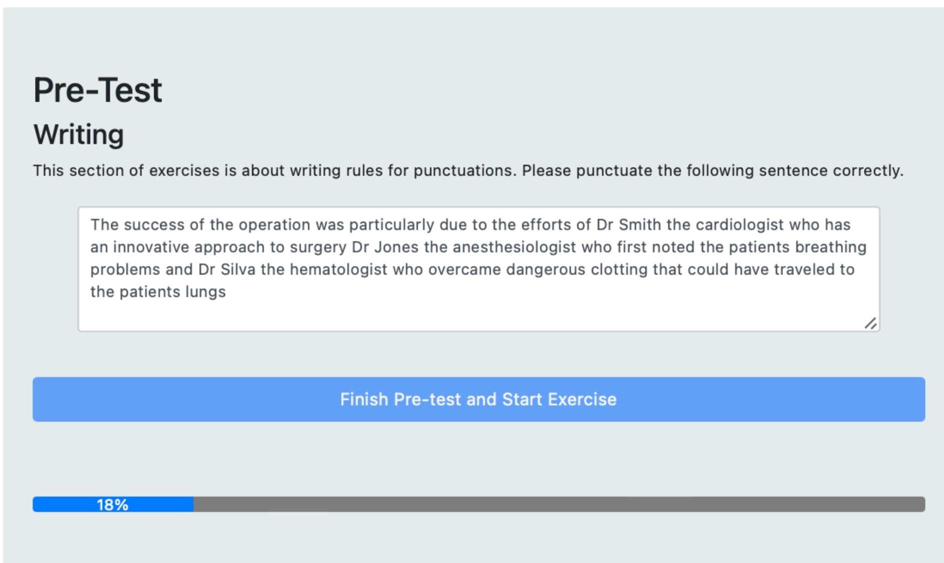
- To prognosticate decompression sickness
- To explain how decompression sickness occurs
- To show treatments of decompression sickness
- To explain the low atmospheric pressure

3. How can the diver prevent the process for decompression sickness?

- Rise gradually and expel excess gas through the mouth, nose, and ears
- Rise immediately and expel excess gas through the mouth, nose, and ears
- Balance the pressure through breathing naturally
- Maintain the gas in the organic tissue after prolonged intensive atmospheric pressure

Continue Pre-test

17%


Pre-Test
Writing
This section of exercises is about writing rules for punctuations. Please punctuate the following sentence correctly.
The success of the operation was particularly due to the efforts of Dr Smith the cardiologist who has an innovative approach to surgery Dr Jones the anesthesiologist who first noted the patients breathing problems and Dr Silva the hematologist who overcame dangerous clotting that could have traveled to the patients lungs
Finish Pre-test and Start Exercise
18%

Appendix F

Appendix: E-Learning System 1

Vocabulary

Listen to the conversation then answer the questions.

What is his first name?

- Carl
- Carson
- Kardson

Next

Conversation

Drag the sentences to the box on the right to put the conversation in the correct order:

Jennifer: It's Miller.

Jennifer: Nice to meet you, too.

Michael: Hi. my name is Michael Ota.

Michael: It's nice to meet you, Jennifer.

Jennifer: I'm Jennifer Miller.

Michael: I'm sorry. What's your last name again?

Next

Contractions

Complete the conversation with the correct words.

David: Hello, Jennifer. How — you?

Jennifer: — fine, thanks. — sorry- what's your name again?

David: — David- David Medina.

Jennifer: That's right! David, this — Sarah Conner. — in our math class.

David: Hi, Sarah. — nice to meet you.

Sarah: Hi, David. I think — in my English class, too.

David: Oh, right! I —

Next

Reduced Forms

Click "start recording", then read the conversation in the reduced form, when you finish click "stop recording".

Example:

To say "Olivia: What did you do last night?" we should say, "Olivia: Whadja do last night?"

Exercise:

Say:

Sarah: Excuse me, Are you Chris Carson?

Chris: Yes, I'm.

Sarah: Hi, I'm Sarah Smith. I'm in your science class.

Chris: Oh, yes I remember you.

Sarah: Tomorrow we are going to the museum of science and industry do want to join us?

Chris: Sure, I will love too.

Sarah: See you tomorrow.

Chris: See you tomorrow.

start recording stop recording

Next

The verb be

Complete the conversation with a form of the verb be.

Nicole: Excuse me, ________ you Steven Carson?

David: No, ________ not. My name ________ David Medina. Steven ________ over there.

Nicole: Oh, Sorry.

Nicole: ________ you Steven Carson?

Steven: Yes, I ________

Nicole: Hi, ________ Nicole Johnson.

Steven: Oh, ________ in my math class, right?

Nicole: Yes, I ________.

Steven: ________ nice to meet you.

Next

Possessive Adjectives

Drag the right answer to complate the conversation.

Carl: Hi, I'm Carl.

Carl:

Susan: Hi, My name is Susan.

Carl: It's nice to meet you.

Susan: It's nice to meet you too.

Carl:

Susan: His name is Chris.

Carl: It's nice to meet you Chris.

Chris: It's nice to meet you too.

Susan:

Carl: Her name is Sarah.

Susan: It's nice to meet you Sarah.

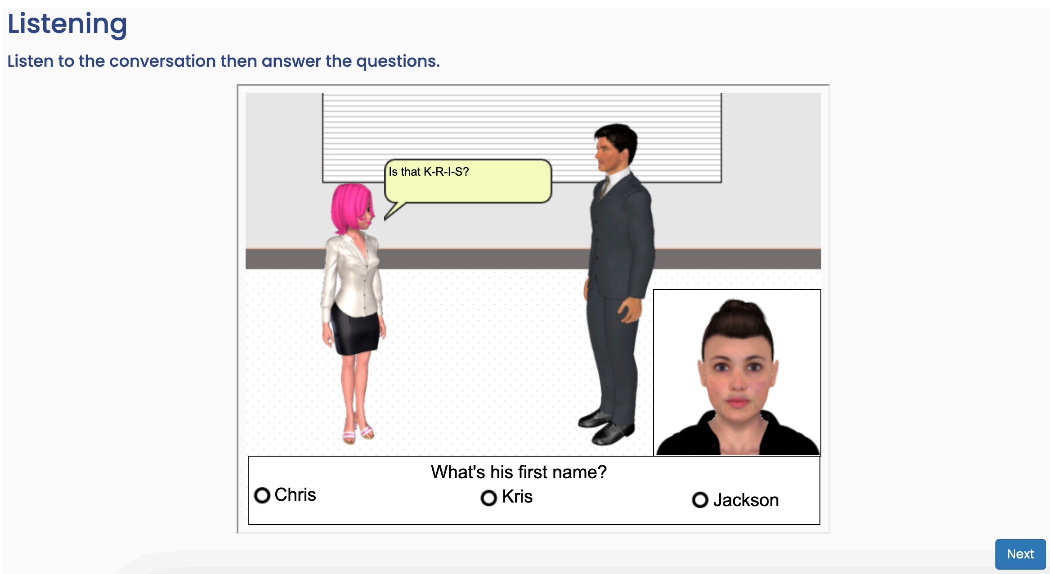
Sarah: It's nice to meet you too.

What's your name?

What's her name?

What's his name?

Next


Listening
Listen to the conversation then answer the questions.
Is that K-R-I-S?
What's his first name?
Chris
Kris
Jackson
Next

Reduced Forms

Click "start recording", then read the conversation in the reduced form, when you finish click "stop recording".

Example:

To say "Olivia: What did you do last night?" we should say, "Olivia: Whadja do last night?"

Exercise:

Say:

Olivia: Hi, I'm Olivia Jackson.

David: Hi, I'm David Santose.

Olivia: It's nice to meet you.

David: It's nice to meet you too.

Olivia: Is this your first time to visit the United States?

David: Yes, it is.

Olivia: What's your impression so far?

David: I like it.

Olivia: Good to hear that. Enjoy your stay!

David: Thank you.

start recording stop recording

Next

Possessive Adjectives

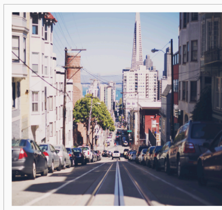
Each person on this video will introduce the people around her/him, then she/he will say their name. After all the three people finish, click "start recording" to introduce each person and then introduce yourself, when you finish click "stop recording".

start recording stop recording

Next

Vocabulary

Match the sentence with the correct picture.



I think there are too many cars on the road. All the cars, taxis, and buses make it really dangerous for bicycles. There is too much traffic!.

What about the buses? They are old, slow, and cause too much pollution. I think there should be less pollution in the city.

There should be fewer cars, but I think that the biggest problem is parking. There just isn't enough parking.

Next

Compound Nouns

Make compound nouns. More than one answer may be possible.

Examples:

1. News
☑stand ☐jam ☐lane ☐light ☐space

2. Subway ☐garage ☐jam ☐lane ☐light ☐space ☑station ☑stop ☑system

Exercise:

1. Bicycle
☐garage ☐jam ☐lane ☐stand ☐space ☐station ☐stop ☐system

2. Bus
☐garage ☐jam ☐lane ☐light ☐space ☐station ☐stop ☐system

3. Parking
☐garage ☐jam ☐lane ☐light ☐space ☐station ☐stop ☐system

4. Street
☐garage ☐jam ☐lane ☐light ☐space ☐station ☐stop ☐system

5. Taxi
☐garage ☐jam ☐lane ☐light ☐space ☐station ☐stop ☐system

6. Traffic
☐garage ☐jam ☐lane ☐light ☐space ☐station ☐stop ☐system

7. Train
☐garage ☐jam ☐lane ☐light ☐space ☐station ☐stop ☐system

Next

Adverbs of Quantity

Choose the correct word.

- In the street, we need less — .
- Where can I put my car? We don't have enough — .
- Public transportation is too crowded; we need more — .
- Factories cause too much — .
- On each subway train, I wish we had fewer — .

Next

Conversation

Drag the sentences to put the conversation in the correct order.

Jennifer: Oh, good. And can you tell me how often the buses leave for the city?

Jennifer: Excuse me. Could you tell me where the bank is?

Michael: There's one upstairs, across from the duty-free shop.

Michael: It should be open now. It opens at 8:00 A.M.

Jennifer: Do you know what time it opens?

Michael: You need to check at the transportation counter. It's right down the hall.

Jennifer: Oh. Thanks a lot.

Michael: Right behind you. Do you see where that sign is?

Jennifer: OK. And just one more thing. Do you know where the restrooms are?

Next

Indirect Questions

Complete the conversation with the correct words.

Erica: I'm thinking about visiting our classmate Joe. Do you know where he lives?

David: Sorry, I don't know [—] , but I know that he lives near state and lake.

Erica: Oh, do you know how I can go there?

David: Sure, I know [—] Take the subway. Do you know [—]

Erica: It's the Red Line, right?

David: Right.

Erica: What's Joe's phone number? Do you know?

David: Sorry, I don't know [—] But you can ask Sally. She has his number.

Erica: Great idea. What time will Sally come here?

David: I don't know [—] Just call her.

Next

Reduced Forms

Click "start recording", then read the conversation in the reduced form, when you finish click "stop recording".

Example:

To say "Olivia: What did you do last night?" we should say, "Olivia: Whadja do last night?"

Exercise:

Say:

Christopher: I am going to the downtown tomorrow because I want to visit the historical museum. Do you want to join me?

Micheal: Sure, I will love too. Do you know how to get there?

Christopher: There are lots of ways. The fastest way is to take the train to avoid the traffic.

Micheal: Sounds good, see you tomorrow.

start recording | stop recording

Next

Vocabulary

Choose the correct word.

Jennifer: How did you get to school?

Michael: I — my car.

Jennifer: Where do you — of the car?

Michael: I park the car in the garage next to the main office. What about you? Do you — the bus to school?

Jennifer: No, I usually — my bike.

Michael: Sara, Do you — a bicycle to school too?

Sarah: No. I — a bike when I was young, but now I — the bus.

Jennifer: Where do you — the bus?

Sarah: There is a bus stop near my house. I — the bus from there and — next to the library.

Next

Reduced Forms

Click "start recording", then read the conversation in the reduced form, when you finish click "stop recording".

Example:

To say "Olivia: What did you do last night?" we should say, "Olivia: Whadja do last night?"

Exercise:

Say:

Olivia: What are you going to do tonight?

Michelle: I am going to the movie theater. Could you please tell me how to drive there?

Olivia: I don't know. It is kind of hard to explain. I usually take the bus not the car. Ask Micheal I think he knows.

Michelle: Oh, I just saw Micheal, I should have asked him.

start recording | stop recording

Next

Indirect Questions

Change the following questions to indirect questions using Wh- questions.

- How much does a newspaper cost? I'm not sure —
- Where is the nearest cash machine? Do you know —
- What time do the banks open? Do you know —
- When did the flight arrive? I don't remember —
- How often does the bus come? I wonder —
- Why is the bus so crowded? Who knows —

Next

Vocabulary

Choose the positive or negative emotion that best fits the sentence.

- She wiped her eyes, — to feel the tears on her cheeks.
- I speak English well, so I am — when I talk to Americans.
- He was — about the test because his future depended on the score.
- Claudia is — with the antebellum and Civil War historic periods of the United States.
- Julia felt — when she lost her job.
- Joe is — that he will find a good job.
- She is — if she will finish her degree in two years.
- He is — about starting his degree program.

Next

Conversation

Drag the sentences to put the conversation in the correct order.

Sarah: Your accent is good, just feel confident while you talk and you will be comfortable.

Sarah: Your welcome.

David: Usaully I am shy, I feel embarrased to speak to native speakers.

David: I am uncertain about my accent.

Sarah: What do you feel when you talk to Americans?

David: I will try, thank you for your great advice.

Sarah: Why do you feel embarrassed?

Next

Reduced Forms

Click "start recording", then read the conversation in the reduced form, when you finish click "stop recording".

Example:

To say "Olivia: What did you do last night?" we should say, "Olivia: Whadja do last night?"

Exercise:

Say:

Christopher: You feel confident about the test, don't you?
Micheal: Yes, I do. How about you?
Christopher: No, I don't. I'm anxious about my results. Last week I was depressed because my grandfather passed away.
Micheal: I'm sorry to hear that. You should have told the teacher.
Christopher: I was shy to talk to her, but I will try.

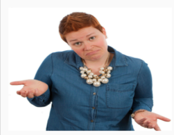
start recording stop recording

Next

Vocabulary

Match the sentence with the correct picture.



Michelle is uncertain about moving to another city.

Olivia is enthusiastic about winning the game.

Micheal is feeling depressed after losing his job.

Mark is fascinated by the reading website.

Next

Reduced Forms

Click "start recording", then read the conversation in the reduced form, when you finish click "stop recording".

Example:

To say "Olivia: What did you do last night?" we should say, "Olivia: Whadja do last night?"

Exercise:

Olivia: What do you feel about the American culture?

Michelle: I've always been fascinated by the American cultures. It's one of the most culturally diverse country in the world.

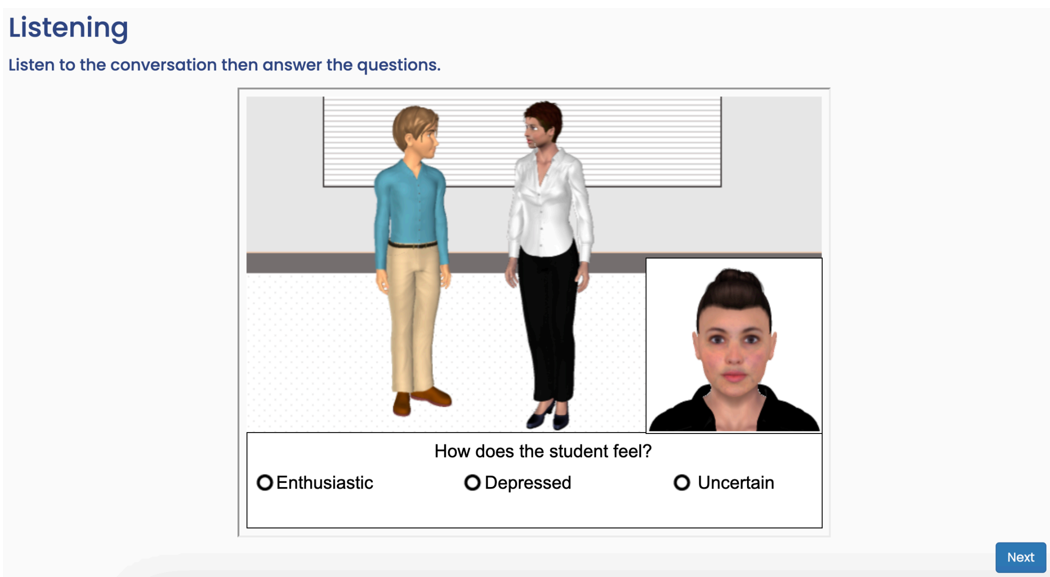
Olivia: If you are enthusiastic about learning the American culture I can give you a book that has lots of interesting facts.

Michelle: Thank you. I really appreciate it.

Olivia: Your welcome.

start recording | stop recording

Next


Listening
Listen to the conversation then answer the questions.
How does the student feel?
Enthusiastic
Depressed
Uncertain
Next

Preposition

Choose the correct preposition that best fits the sentence.

- I get embarrassed — using the wrong word.
- We are comfortable — our English classes
- She is anxious — speaking to Americans.
- We are fascinated — English slang.
- He got depressed — that movie.
- She feels confident — her English ability.
- He's uncertain — which word to use.
- We are enthusiastic — going on vacation.

Next

Inference

Listen to the conversation then answer the questions.

How does the student feel?

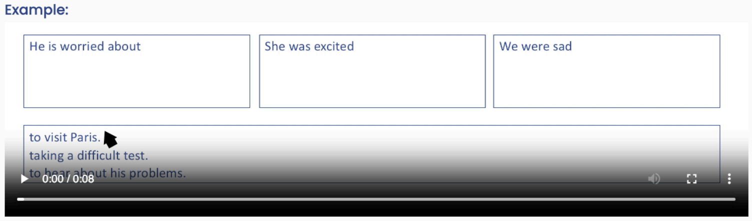
- Anxious
- Uncertain
- Comfortable

Next

Prepositions

Match each ending to the correct beginning. Watch the video below to see the example.

Example:



Exercise:

She is confident about	He was depressed	We are anxious about	He was embarrassed
They were enthusiastic about	We were uncertain about		

to wear those funny clothes.
visiting Europe.
going to the scary movie.
taking the wrong bus.
to hear about the death of the president.
speaking to Americans.

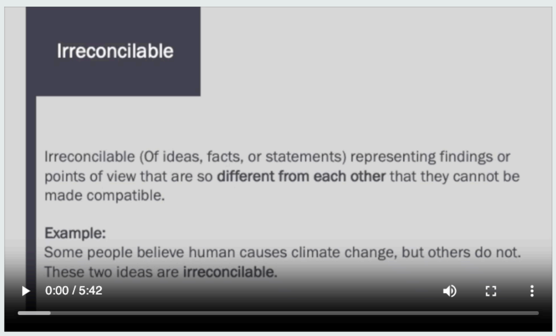
Next

Appendix G

Appendix: E-learning System 2

Vocabulary

This section of exercises is about vocabulary. Please start by playing the video below.



After you watched the video, please select the best answer.

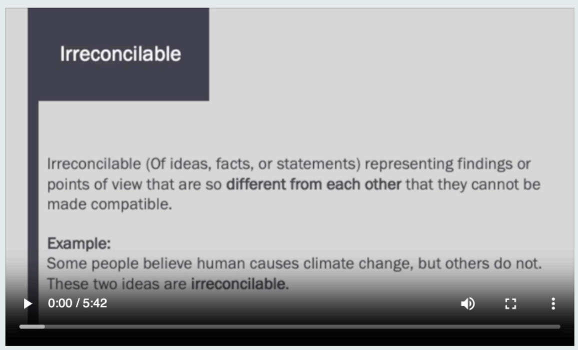
1. There are two skeins to Darwin's thought that are, at first blush, : Darwin believed that a gradual change in the environment brought about commensurately gradual changes toorganisms (descent by modification), and therefore that man was no different from any other species; yet, though he opposed the catastrophist school of thought, which posited that animals changed in the face of massive calamityeither perishing or adapting—Darwin also humankind in the sudden disappearance of animals, thereby implying that man indeed was all other species (he caused the extinction of other species) and such extinctions were the result of a massive calamity—man.

Check Answer

19%

Vocabulary

If you need a refresher on the vocabulary, you can watch the video again. Otherwise, please answer the question below.



Select the best answer.

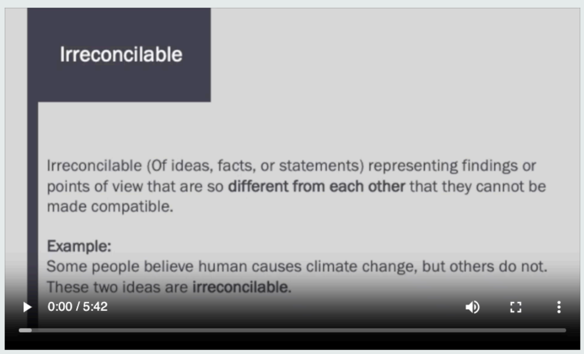
2. There is a rising consensus amongst immunologists that the observed rise in allergies in the general population can be attributed to ______ exposure to everyday germs. Known as the hygiene hypothesis, this counterintuitive idea could have far reaching implications—for one, we may now have to be more ______ those paternal prescriptions to scrub our children's hands at every opportunity.

Check Answer

20%

Vocabulary

If you need a refresher on the vocabulary, you can watch the video again. Otherwise, please answer the question below.



Select the best answer.

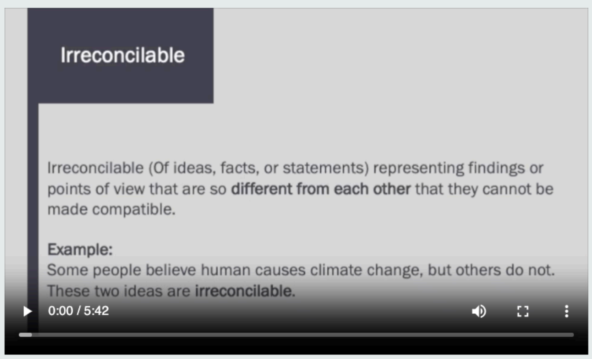
3. Researchers have decoded the DNA of the honeybee. They discovered that bee's keen sense of smell enables them to ______ kin from foe. Genes that regulate vulnerability to ______, however, are surprisingly deficient. Scientists speculate that the observed extensive grooming among hive mates ______ various diseased, thus protecting the colony.

Check Answer

23%

Vocabulary

If you need a refresher on the vocabulary, you can watch the video again. Otherwise, please answer the question below.



Select the best answer.

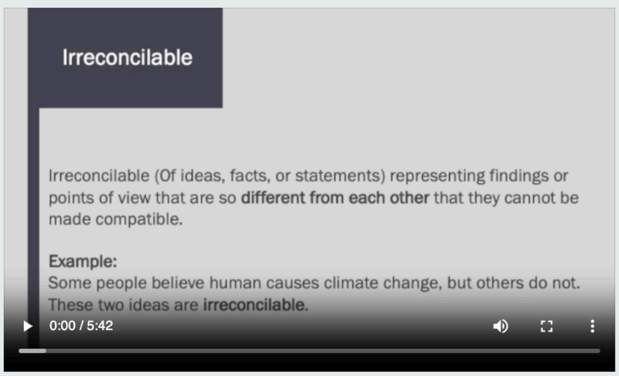
4. The ongoing salmon crisis is the result of ____ of problems, among them pollution, introduction of nonnative species, and pesticide use. Such issues speak to decades of ____ management at the political level. At this point, ____ solution will require both an understanding of history and foresight of the future challenges.

Check Answer

26%

Vocabulary

If you need a refresher on the vocabulary, you can watch the video again. Otherwise, please answer the question below.



Select the best answer.

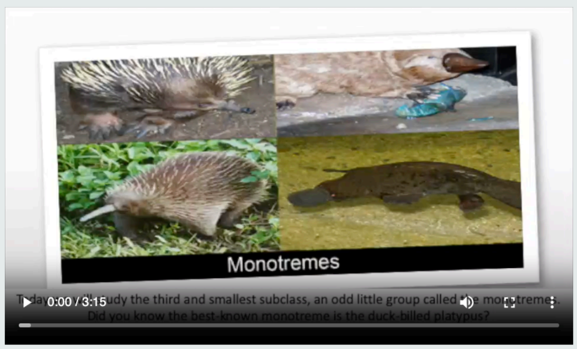
5. Many animals are ______ over the winter months, minimizing activity in order to conserve energy.

Check Answer

29%

Listening: Biology Lecture

This section of exercises is about listening. Please start by playing the video below.



After you watched the video, please select the best answer:

1. What is this lecture mainly about?

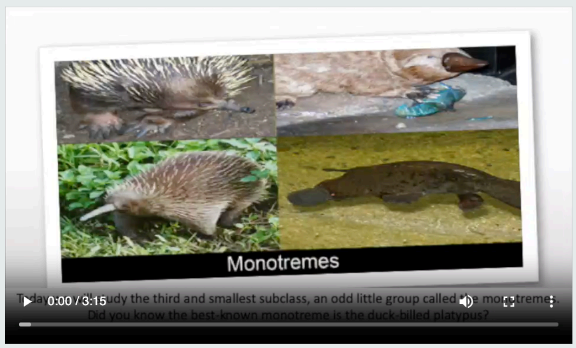
- ○ The conservation of monotremes
- ○ The smallest group of mammals
- ○ The evolution of the platypus
- ○ The animals of Australia

Check Answer

32%

Listening: Biology Lecture

If you need a refresher on the listening, you can watch the video again. Otherwise, please answer the question below.



Select the best answer.

2. How did the writer organized the lecture?

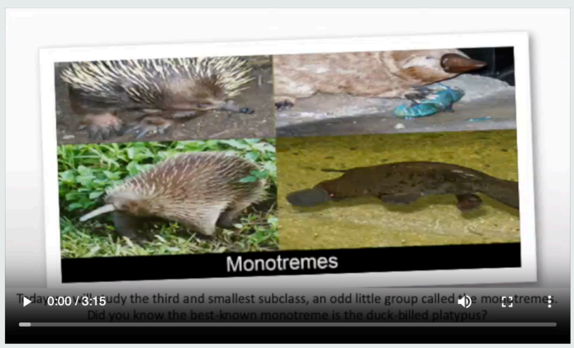
- ○ From an evolutionary standpoint
- ○ By habitat
- ○ According to geographical ranges
- ○ From general to specific groups

Check Answer

35%

Listening: Biology Lecture

If you need a refresher on the listening, you can watch the video again. Otherwise, please answer the question below.



Select the best answer.

3. What does 'monotreme' mean?

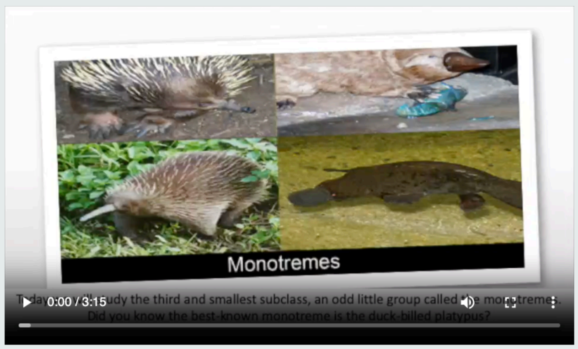
- ○ Fast-tongued
- ○ Bird-nosed
- ○ Single-holed
- ○ Tube-snouted

Check Answer

38%

Listening: Biology Lecture

If you need a refresher on the listening, you can watch the video again. Otherwise, please answer the question below.



Select the best answer.

4. Why does the professor mention a fossil from Argentina?

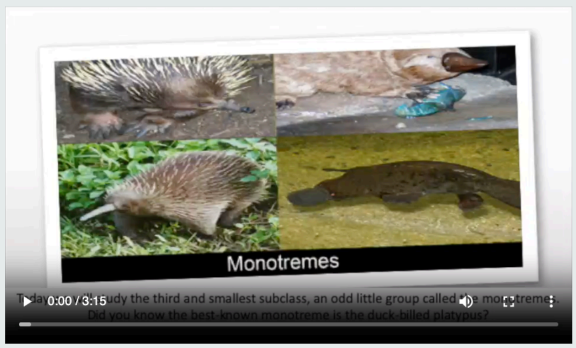
- ○ To show how old monotremes are
- ○ To show the extent of monotreme research
- ○ To show how widespread the monotremes were
- ○ To show that echidnas evolved from platypi

Check Answer

41%

Listening: Biology Lecture

If you need a refresher on the listening, you can watch the video again. Otherwise, please answer the question below.



Select the best answer.

5. All of the following are true about the monotremes EXCEPT:

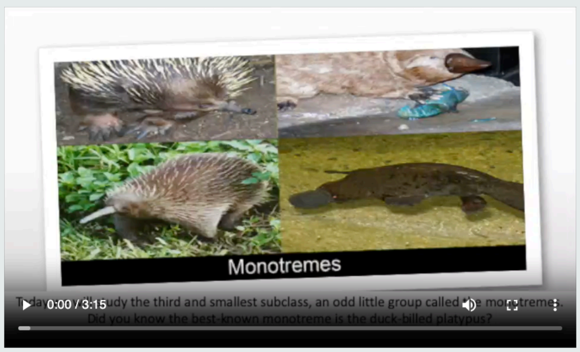
- ○ They are covered in fur.
- ○ They have reptilian dental pattern.
- ○ They lay eggs but produce milk.
- ○ They have a four-chambered heart.

Check Answer

44%

Listening: Biology Lecture

If you need a refresher on the listening, you can watch the video again. Otherwise, please answer the question below.



Select the best answer.

6. What did the early naturalists think about the first platypus specimen?

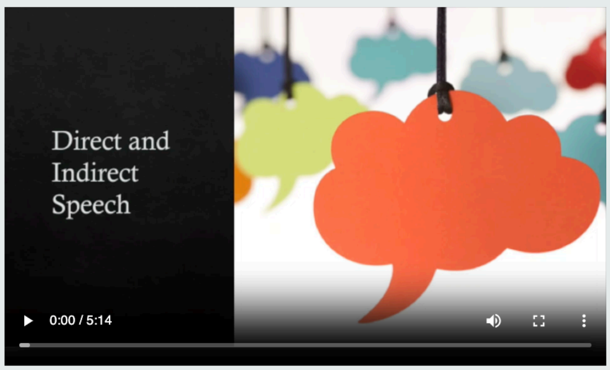
- ○ It was a new species of duck.
- ○ It was captured in India.
- ○ It was a new species of mole.
- ○ It was created by sailors.

Check Answer

47%

Grammar: Direct and Indirect Speech

This section of exercises is about grammar rules for changing direct to indirect speech. Please start by playing the video below.



After you watched the video, please select the best answer to change each sentence from direct speech to indirect speech. Think carefully about how verbs and pronouns change from one form to another.

1. "This anteater smells bad," said Tom.

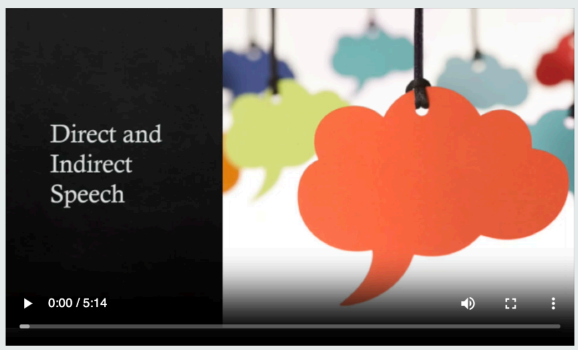
Tom said that the anteater [ ] bad.

Check Answer

50%

Grammar: Direct and Indirect Speech

If you need a refresher on the grammar rules, you can watch the video again. Otherwise, please answer the question below.



Select the best answer to change each sentence from direct speech to indirect speech. Think carefully about how verbs and pronouns change from one form to another.

2. "Skunks are known for their ability to spray a liquid with a strong, unpleasant smell" George said.

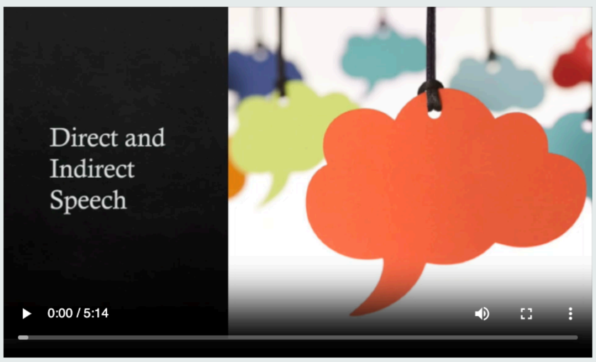
George said that skunks [ ] known for their ability to spray a liquid with a strong, unpleasant smell

Check Answer

53%

Grammar: Direct and Indirect Speech

If you need a refresher on the grammar rules, you can watch the video again. Otherwise, please answer the question below.



Select the best answer to change each sentence from direct speech to indirect speech. Think carefully about how verbs and pronouns change from one form to another.

3. "It was legal to sell elephant ivory in the US until 2016, but now we're near-total ban on commercial trade," Sam said.

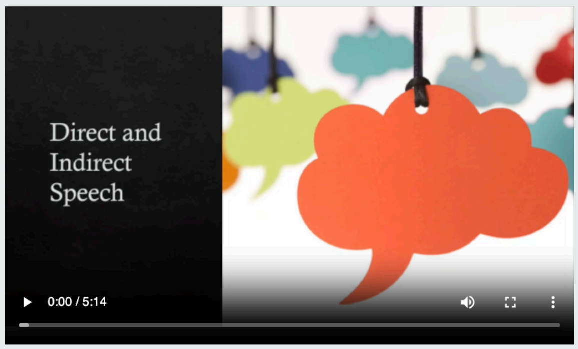
Sam said that it [ ] legal to sell elephant ivory in the US until 2016, but now [ ] near-total ban on commercial trade.

Check Answer

56%

Grammar: Direct and Indirect Speech

If you need a refresher on the grammar rules, you can watch the video again. Otherwise, please answer the question below.



Select the best answer to change each sentence from direct speech to indirect speech. Think carefully about how verbs and pronouns change from one form to another.

4. "I may have a guinea pig as a pet," she said.

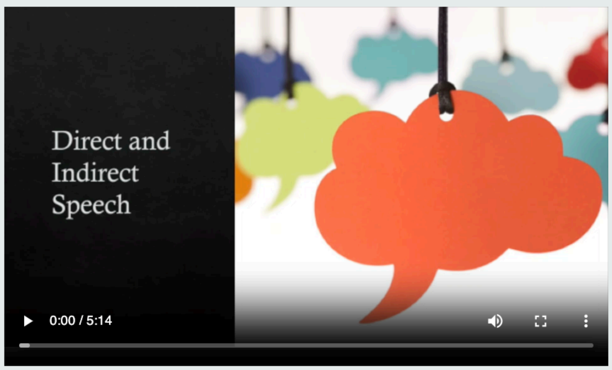
She said that she [ ] a guinea pig as a pet.

Check Answer

59%

Grammar: Direct and Indirect Speech

If you need a refresher on the grammar rules, you can watch the video again. Otherwise, please answer the question below.



Select the best answer to change each sentence from direct speech to indirect speech. Think carefully about how verbs and pronouns change from one form to another.

5. "Lions won't eat humans," Henry said.

Henry said that Lions ______ eat humans.

Check Answer

62%

Reading

This section of exercises is about reading. Please start by reading the article below. The article has 8 pages. Click **"Continue Reading"** to go to the next page of the article.

We are about to start a journey where we will be exploring animal mimicry. Have you seen animal mimicry before? We think animal mimicry is one of its most dramatic manifestations.

Do you know why animals use mimicry? They use it to survive, reproduce and pass their genes on to the next generation. Organisms that are a food source often develop techniques to protect themselves.

One of these strategies is to look like something that is not good to eat or something that is of no interest to the predator. Ok, now do you know what we call an organism that uses mimicry?

Continue Reading

1 of 8

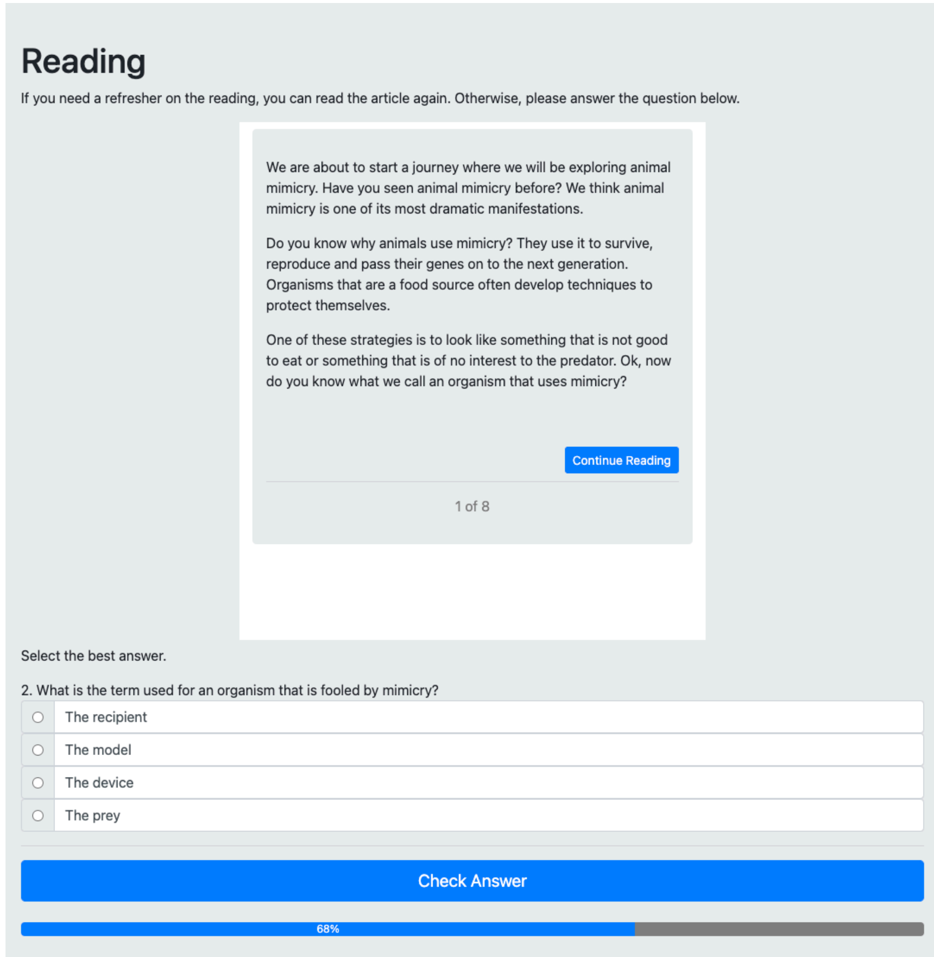
After you read the article, please select the best answer.

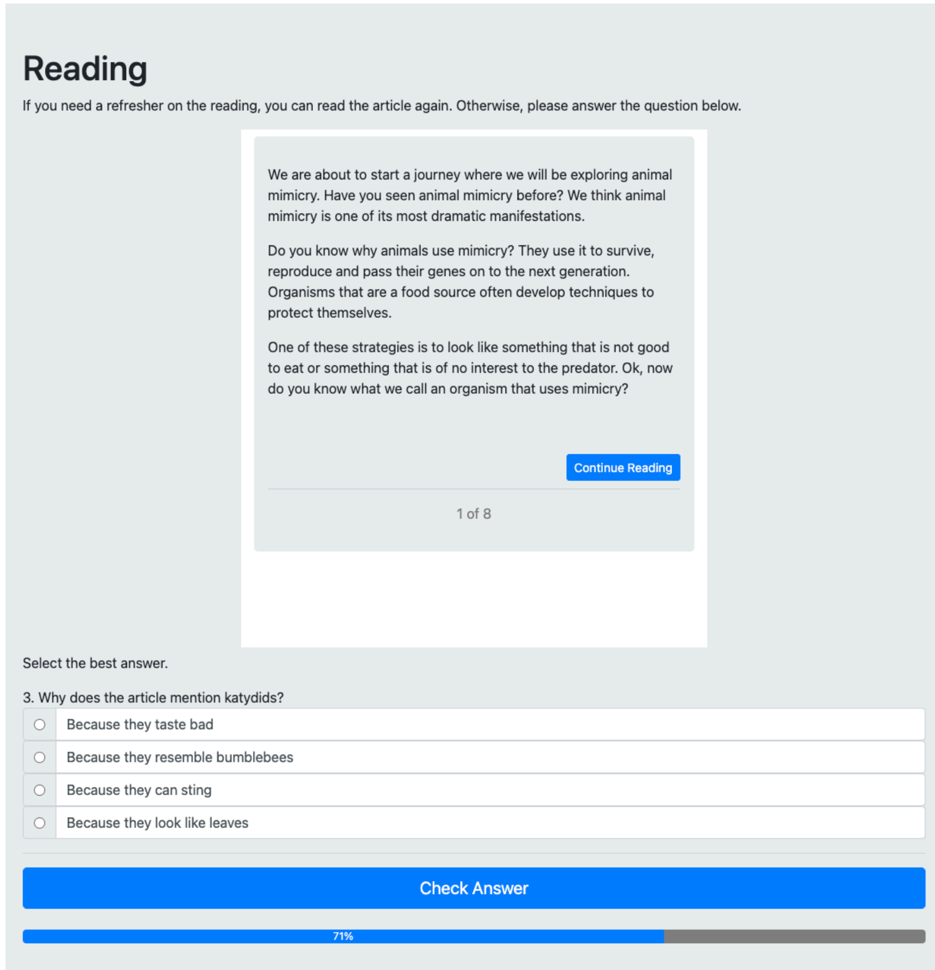
1. Which would be the best title for this article?

- Animal Behavior
- Animal Creativity
- Animal Deception
- Animal Escapades

Check Answer

65%


Reading
If you need a refresher on the reading, you can read the article again. Otherwise, please answer the question below.
We are about to start a journey where we will be exploring animal mimicry. Have you seen animal mimicry before? We think animal mimicry is one of its most dramatic manifestations.
Do you know why animals use mimicry? They use it to survive, reproduce and pass their genes on to the next generation. Organisms that are a food source often develop techniques to protect themselves.
One of these strategies is to look like something that is not good to eat or something that is of no interest to the predator. Ok, now do you know what we call an organism that uses mimicry?
Continue Reading
1 of 8
Select the best answer.
2. What is the term used for an organism that is fooled by mimicry?
The recipient
The model
The device
The prey
Check Answer
68%


Reading
If you need a refresher on the reading, you can read the article again. Otherwise, please answer the question below.
We are about to start a journey where we will be exploring animal mimicry. Have you seen animal mimicry before? We think animal mimicry is one of its most dramatic manifestations.
Do you know why animals use mimicry? They use it to survive, reproduce and pass their genes on to the next generation. Organisms that are a food source often develop techniques to protect themselves.
One of these strategies is to look like something that is not good to eat or something that is of no interest to the predator. Ok, now do you know what we call an organism that uses mimicry?
Continue Reading
1 of 8
Select the best answer.
3. Why does the article mention katydids?
Because they taste bad
Because they resemble bumblebees
Because they can sting
Because they look like leaves
Check Answer
71%

Reading

If you need a refresher on the reading, you can read the article again. Otherwise, please answer the question below.

We are about to start a journey where we will be exploring animal mimicry. Have you seen animal mimicry before? We think animal mimicry is one of its most dramatic manifestations.

Do you know why animals use mimicry? They use it to survive, reproduce and pass their genes on to the next generation. Organisms that are a food source often develop techniques to protect themselves.

One of these strategies is to look like something that is not good to eat or something that is of no interest to the predator. Ok, now do you know what we call an organism that uses mimicry?

Continue Reading

1 of 8

Select the best answer.

4. Some moths and butterflies have large, owl-like eyespots concealed on their underwings, which they can suddenly display to a predator. Which kind of mimicry is this an example of?

- Batesian mimicry
- Camouflage
- Mullerian mimicry
- Aggressive mimicry

Check Answer

74%

Reading

If you need a refresher on the reading, you can read the article again. Otherwise, please answer the question below.

We are about to start a journey where we will be exploring animal mimicry. Have you seen animal mimicry before? We think animal mimicry is one of its most dramatic manifestations.

Do you know why animals use mimicry? They use it to survive, reproduce and pass their genes on to the next generation. Organisms that are a food source often develop techniques to protect themselves.

One of these strategies is to look like something that is not good to eat or something that is of no interest to the predator. Ok, now do you know what we call an organism that uses mimicry?

Continue Reading

1 of 8

Select the best answer.

5. Why does the article mention Charles Darwin?

- Darwin was the creator of evolutionary theory.
- Darwin's theory was used to explain mimicry.
- Darwin explained mimicry for the first time.
- Darwin separated Batesian and Mullerian mimicry.

Check Answer

77%

Reading

If you need a refresher on the reading, you can read the article again. Otherwise, please answer the question below.

We are about to start a journey where we will be exploring animal mimicry. Have you seen animal mimicry before? We think animal mimicry is one of its most dramatic manifestations.

Do you know why animals use mimicry? They use it to survive, reproduce and pass their genes on to the next generation. Organisms that are a food source often develop techniques to protect themselves.

One of these strategies is to look like something that is not good to eat or something that is of no interest to the predator. Ok, now do you know what we call an organism that uses mimicry?

Continue Reading

1 of 8

Select the best answer.

6. Which organism is presented as an example of aggressive mimicry?

- ○ The Viceroy Butterfly
- ○ The Orchid Mantis
- ○ The Monarch Butterfly
- ○ The Leaf-tailed Gecko

Check Answer

80%

Writing: Punctuations

This section of exercises is about writing rules for puntuations. Please start by playing the video below.

After you watched the video, please punctuate the following text correctly by inserting commas (,), apostrophes (‘) , semi-colons (;), and periods (.) where they are needed.

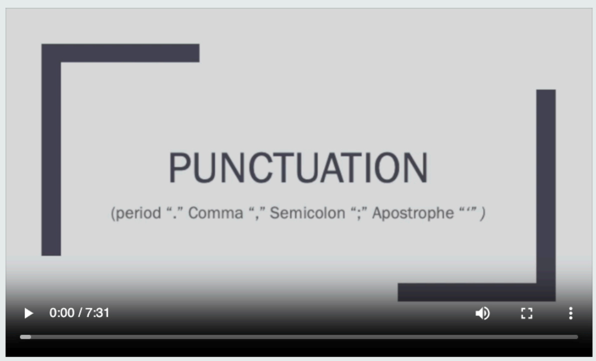
As Karl von Frisch was observing honeybees he noticed that some of the bees which he called scout bees flew out of the hive to look for food

Check Answer

83%

Writing: Punctuations

If you need a refresher on the writing rules, you can watch the video again.



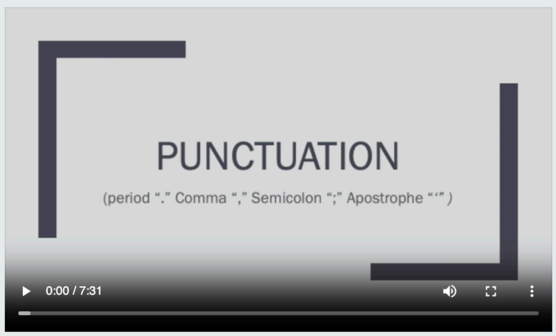
Otherwise, please punctuate the following text correctly by inserting commas (,), apostrophes (‘) , semi-colons (;), and periods (.) where they are needed.

The animal worlds largest class is mammals Mammals characteristics include being warm-blooded having a four-chamber heart and being covered in fur

Check Answer

Writing: Punctuations

If you need a refresher on the writing rules, you can watch the video again.



Otherwise, please punctuate the following text correctly by inserting commas (,), apostrophes (') , semi-colons (;), and periods (.) where they are needed.

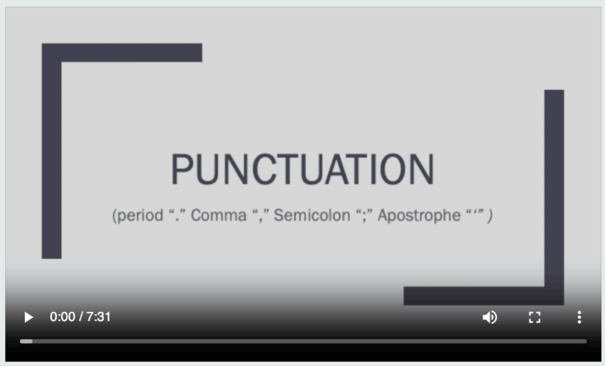
For example a gene on chromosome 7 that has been associated with cystic fibrosis is called the cystic fibrosis transmembrane conductance regulator its symbol is CFTR

Check Answer

89%

Writing: Punctuations

If you need a refresher on the writing rules, you can watch the video again.



Otherwise, please punctuate the following text correctly by inserting commas (,), apostrophes (') , semi-colons (;), and periods (.) where they are needed.

In Lincoln Park Zoo there are amphibians like frogs toads and axolotls reptiles like crocodiles snakes iguanas and turtles mammals like lions otters cows camels bears and zebras

Check Answer

92%

Appendix H

Appendix: Motivational Supportive Feedback

For each exercise, I provided distinguished motivational supported feedback based on the learner's answer. The table below shows the feedback for the right, some, and wrong answers.

Exercise	Right	Some	Wrong
1	Super job, keep it up! You did amazing work, continue the remarkable effort!	You're almost there, keep going! You did amazing work, continue the remarkable effort!	Don't worry, you will get the hang of this. You tried really hard, so stay relaxed and do the best you can.
2	Stunning work, keep going! You did an excellent job, so stay calm and continue the outstanding effort!	Almost got it, continue the good work! You did an excellent job, so stay calm and continue the outstanding effort!	Take it easy, you will figure it out! You did an excellent try, stay calm and continue the outstanding effort!
3	Wonderful job, keep up the good work! You made a phenomenal effort, continue like this and never give up!	You're so close, keep pushing! You made a phenomenal effort, continue like this and never give up!	Calm down, you will reach your goal soon! You made a phenomenal try, continue like this and never give up!
4	Amazing job, you're on the right track! Marvelous work. Relax and continue the exceptional effort!	Almost made it, keep trying! Marvelous work. Relax and continue the exceptional effort!	Be at ease, you will get it! Marvelous try. Relax and continue the exceptional effort!
5	Outstanding work, continue like this! You made a phenomenal effort, stay cool and keep up the stunning job!		Take it easy, you will work it out! You made a phenomenal attempt, stay cool and keep up the stunning job!
6	Excellent job, keep going! You did fabulous work, stay relaxed and continue the amazing effort!		Stay cool, you will get it! You made a fabulous try, stay relaxed and continue the amazing effort!
7	Great work, way to go!		Don't worry, you will find the way!

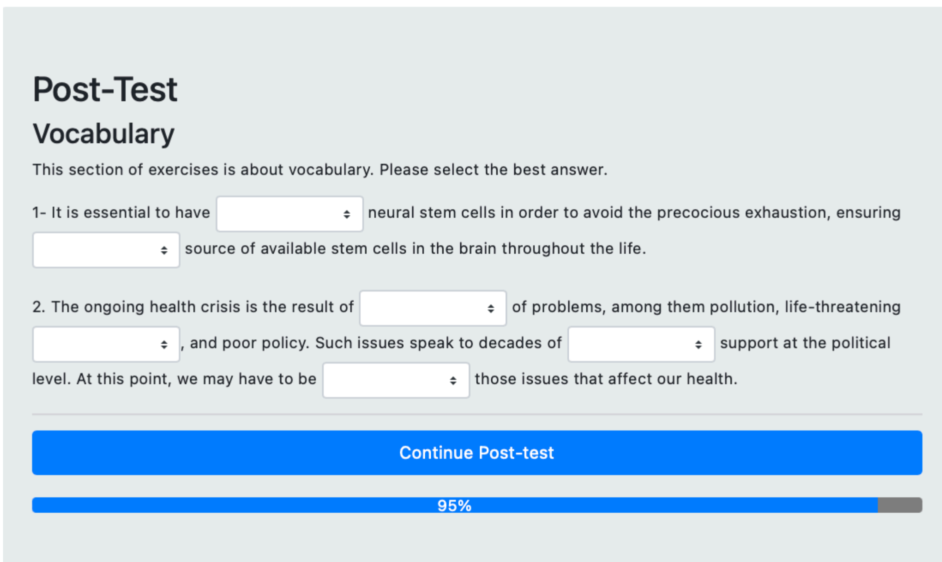
	You did an astonishing job, stay calm and keep it up!		You did an astonishing attempt, stay calm and keep it up!
8	Good job, keep up the good work! You do spectacular work. Stay relaxed and continue the outstanding effort!		That's okay, you will figure it out! You did spectacular try, stay relaxed and continue the outstanding effort!
9	Wonderful job, keep up the good work! You made an impressive effort. Take it easy and continue to succeed!		Stay calm, you will find the solution! You made an impressive effort, take it easy and continue to succeed!
10	Extraordinary job, keep up the hard work! You made an exceptional effort, Breathe deeply and reach your goals!		Things will work out, you will get it! You made an exceptional effort, Breathe deeply and reach your goals!
11	Incredible job, keep up the good work! You did an excellent job, stay calm and strong!		No problem, you will find that out! You made an excellent try, stay calm and strong!
12	Marvelous effort, continue getting better! You did an extraordinary job, keep calm and stay focused!		Relax, everything will work out! You made an extraordinary attempt, keep calm and stay focused!
13	Remarkable performance, you made it look easy! You made an outstanding effort, take it easy and continue like this!		Nothing to worry about, you will figure out the way! You made an outstanding effort, take it easy and continue like this!
14	Fabulous attempt, way to go!		It's going to be OK, you will find the solution!

	You made a remarkable effort, be calm and keep it that way!		You made a remarkable effort, be calm and keep it that way!
15	Phenomenal work, that's the right way to do it. You did an incredible job, relax and way to go!		Breathe a sigh of relief, you will figure it out! You made an incredible try, relax and way to go!
16	Outstanding job, you make it look easy! You did an excellent job, stay cool and keep this up!		Keep cool, you will get this straight! You made an excellent attempt, stay calm and keep this up!
17	Exceptional effort, you couldn't be better! You did fabulous work, settle down and keep going!		Keep calm, you will figure it out! You made a fabulous try, settle down and keep going!
18	Impressive performance, you've got the hang of it! You made a great effort. Stay cool and keep going!	Almost got it, preserve the momentum! You made a great effort. Stay cool and keep going!	Take it easy, you will find out all about this! You made a great effort. cool off and keep going!
19	Astonishing attempt, continue learning quickly! You did an exceptional job. Take a deep breath and go on like this!		Become more relaxed, you will find a way! You made an exceptional attempt. Take a deep breath and go on like this!
20	Super job, keep it up! You made a remarkable effort. Stay strong and keep up the good work!		Don't worry, you will get the hang of this! You made a remarkable effort. Stay strong and keep up the good work!
21	Stunning work, keep going! You did an impressive job, relax and keep it up!		Take it easy, you will figure it out! You made an impressive try, relax and keep it up!

22	Wonderful job, keep up the good work! You did an outstanding job, stay calm and never give up.		Stay calm, you will find the solution! You made an outstanding attempt, stay calm and never give up.
23	Amazing job, you're on the right track! You made an exceptional effort. Stay cool and keep up the good work!		Be at ease, you will get it! You made an exceptional effort. Stay cool and keep up the good work!
24	Great work, way to go! You do impressive work. Breathe deeply and keep up the good job!		Chill out, you will find the way! You did an impressive try. Breathe deeply and keep up the good job!
25	Excellent job, keep going! You made a remarkable effort. Stay strong and keep up the good work.		Stay cool, you will know it! You made a remarkable effort. Stay strong and keep up the good work.
26	Outstanding work, continue like this! You made a phenomenal effort, stay cool and keep up the stunning job!		Take it easy, you will figure it out! You made a phenomenal attempt, stay cool and keep up the stunning job!

Appendix I

Appendix: Post-Test



Post-Test

Vocabulary

This section of exercises is about vocabulary. Please select the best answer.

1- It is essential to have [ ] neural stem cells in order to avoid the precocious exhaustion, ensuring [ ] source of available stem cells in the brain throughout the life.

2. The ongoing health crisis is the result of [ ] of problems, among them pollution, life-threatening [ ], and poor policy. Such issues speak to decades of [ ] support at the political level. At this point, we may have to be [ ] those issues that affect our health.

Continue Post-test

95%

Post-Test

Listening

This section of exercises is about listening. Please play the audio clip below, then select the best answer for each of the questions.

▶ -1:12

1. What is this paragraph mainly about?

- The octopus in Indonesia
- The conservation of octopi
- The mimic octopus
- The evolution of the octopus

2. What do we learn from the discussion of crabs?

- It shows that octopi are nearly as intelligent as crab
- It shows how octopi can only imitate crab
- It offer an example of predators' mimicry
- It shows how octopi use Batesian mimicry

3. All of the following are true about the mimic octopus EXCEPT:

- Batesian mimicry
- Predators' mimicry
- Shape-shifting
- Resembling sticks

Continue Post-test

Post-Test

Grammar

This section of exercises is about grammar rules for changing direct to indirect speech. Please select the best answer.

1. "It may rain tonight," said Tom.
Tom said it ______ rain tonight.

2. "I've been out of town for a couple of days," Sara said
Sara said she ______ out of town for a couple of days.

3. "I work in the museum of science and industry," Steve said
Steve said that he ______ in the museum of science and industry.

Continue Post-test

97%

Post-Test

Reading

This section of exercises is about reading. Please start by reading the paragraph below. After you read the paragraph, please select the best answer.

> In the field of zoology, some controversy is inherent even in identifying and classifying species. Scientists don't use a rigid classification system because they are forever discovering and developing new insights about the laws of nature. Consider for example, that taxonomic rebel, the platypus. On the one hand, we would want to see these creatures as mammals because they are warm-blooded and have fur. But they lay eggs, which is more a characteristic of birds and reptiles than mammals. It is good that sometimes-rigid biological nomenclature of science makes concessions for such a remarkable creature, which not only transcends the basic tenets of its class but brings new and mystifying qualities to the whole branch of its kingdom. It is hard to believe that there is a furry, duck-billed, egg-laying, venomous mammal that senses its prey through disturbances in a surrounding electromagnetic field, at least not without a clear definition of existence and an unassailable checklist of creature features.

1. Which would be the best title for this paragraph?

- Zoologists' disagreements
- Animal ecologies
- The mysterious platypus
- Scientific classification systems

2. Why does the article mention the platypus?

- To show that mammals are venomous
- To show the flexibility of animal classification
- To explain the Zoologists controversy
- To show the rigid biological nomenclature

3. Which is NOT a common characteristic of the platypus?

- It is warm-blooded
- It produces venom
- It lay eggs
- It conceal its electromagnetic field

Continue Post-test

98%

Post-Test

Writing

This section of exercises is about writing rules for punctuations. Please punctuate the following sentence correctly.

The success of the mastectomy operation was particularly due to the efforts of Dr Ozga the general surgeon who has an innovative approach to surgery Dr Brown the plastic surgeon who first noted the patients blood clot and Dr Miller the hematologist who overcame dangerous clotting that could have traveled to the patients lungs

Finish Post-test

99%