8-20-2020 9:00 AM

The impact of multiliteracies and multimodality on ESL learners: Using Neuroimaging Technologies

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A thesis submitted in partial fulfillment of the requirements for the Master of Arts degree in Education

Abstract

Educational neuroscience has become an important role in understanding education and the association with brain development. However, few previous studies have applied neuroimaging techniques to multiliteracies research, which is an important literacy pedagogy addressing multimodal learning and cultural and linguistic diversity. This study used functional near infrared spectroscopy (fNIRS) to investigate the association of multiliteracies learning on adult English Second Language (ESL) students' performance through multimodal tasks.

Students' multimodality background was collected through a technology questionnaire. Behavioural and fNIRS data were collected before and after multiliteracies learning. Results showed that there was no significance change in behavioural responses while the model for predicting them changed after multiliteracies learning. The fNIRS data showed that multiliteracies learning is associated with activation of the learning network in the brain including the superior temporal gyrus (STG). This research has found a way for educational researchers to understand multiliteracies from neural perspectives.

Keywords

Multiliteracies, multimodality, ESL adult learners, quantitative, neuroscience, fNIRS

Summary for Lay Audience

With the development of interdisciplinary research, educational neuroscience has begun to play an important role in understanding the association of education. However, few studies have applied educational neuroscience methods to multiliteracies research, which is an important pedagogy for literacy learning, and emphasizes the use of multimodal technologies. To address this gap, this study used fNIRS, which is a neuroimaging technique that can estimate brain activity through hemoglobin concentrations to investigate the effect of multiliteracies learning on adult ESL students' brain development and multiliteracies performance.

Students were ESL learners aged 17-25 who were enrolled in an ESL course in Canada, referred to as multiliteracies learning. Three data sources were collected and analyzed by designing an experimentation using emotional videos in English. Students were asked to distinguish the actors' emotions in the videos after each video was presented. The emotions being expressed by the actors were either congruent (e.g. happy face, happy voice) or incongruent (e.g. happy face, sad voice). The technology background questionnaires were collected to understand students' multimodality background before they started the ESL course that involved multiliteracies learning. During the experiment, behavioural data including reaction time and correct responses were collected twice, before and after multiliteracies learning over a 3-month period. fNIRS data were also collected when students engaged in the multimodal experimental tasks before and after the multiliteracies learning.

Multiple linear regression (MLR) and binary logistic regression (BLR) models were used to understand the relationship between reaction time, correct responses and six independent variables including multimodal background; gender; intensity, congruency and emotion types of stimuli and question types. Results showed that there was no significant change on behavioural data while the models for predicting the behavioural data changed after multiliteracies learning. The fNIRS data showed that brain regions related to emotion, language, and multi-sensory processing were activated as well as motor regions when students were viewing and listening to the stimuli before and after multiliteracies learning.

Despite the limitations of the small sample size, this research has broadened neuroscientific findings on the association of multiliteracy learning's impact on brain development and has helped educational researchers to understand multiliteracies from a behavioural and a neural perspective.

Acknowledgements

The two years I studied in Western University was a very pleasant life experience. This is the first time I have studied and lived in a foreign country for a long time and many people have shown great kindness, support and helped me a lot during the two years and for my thesis writing.

I would firstly say thank you to my supervisor, Mi Song Kim. She is an expert in multiliteracies and introduces me to neuroscience education research which she initiated. She is always be kind and patient to me. Although she was very busy, she still spent a lot of time reviewing my thesis and gave lots of useful comments. Besides, she not only helped me a lot in my studies during the past two years, but also cared me a lot for my life.

I also want to thank my committee member, Emma Duerden. She is excellent in the field of neuroscience, always be patient to me who almost have no neuroscience experience, gave me a lot of guidance during my whole thesis progress including experimental design, data collection and data analysis, etc. I am very honored to be able to work with her in the past year.

Thirdly, I must appreciate my participants who made a great contribution for my data collection. This study will not exist without their participation.

Fourthly, I want to say thank you for all member’s in Dr. Duerden’s Developing Brain Lab. Almost every one of them has provided help or suggestions for my experiment and thesis. I am very grateful for their help and hope they will be happy and healthy every day in the future.

Last but not least, I must express my love and appreciation for my parents, my family and my friends. Although my family is far away in China, they have provided me with financial support and have always cared about my health and study. My friends in China and Canada also gave me lots of care, help and encouragement during my thesis writing. I feel very happy because of the company of these people.

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Chapter 1

1 Introduction

This chapter begins with the brief introduction of the background and development of Educational Neuroscience, and then elaborates upon the research problem, research purposes, research questions, and the significance of this study and ends with the organization of this thesis.

1.1 Background and Research Problem

Learning can lead to the permanent change in brain, which is called neuroplasticity (e.g., Draganski et al., 2006; Grushka et al., 2014; Gottschalk, 2019). Therefore, neuroscience, as an irreplaceable method to understanding students' cognitive processes in their brain, has been used more and more in educational research, which has resulted in a new research field, Educational Neuroscience. Neuroscience can help researchers and teachers better understand the neural mechanism of the learning process and can verify educational theories through a neural perspective.

Meanwhile, multiliteracies, as an important pedagogy for literacy learning through the development of multiple modes of information dissemination, are also attracting more and more attention within the Education community. Technology use or digital literacy, which leads to multimodality of communication, is also an essential aspect of multiliteracies. However, it is often hard to balance the advantages and disadvantages of using technologies for learning (Chun et al., 2016). As Jacobs (2013b) and Leander & Boldt (2012) indicate, the multiliteracies framework still needs to be reimaged. More research is needed to explore and improve multiliteracies pedagogy.

Neuroscience methodology may help us to explore multiliteracies. However, currently there is a lack of empirical research on the application of neuroscience to the study of multiliteracies pedagogy. Since linguistic diversity is also an important aspect of multiliteracies, the study of second language learning can serve as an entry point for multiliteracies studies.

While there is a growing body of research involving neuroscience usage in educational studies, research has shown that educational findings through neuroscience can be both informative and confusing (Frey & Fisher, 2010). For example, the neuronal mechanisms underlying the language processing are not fully understood (Rossi et al., 2012). There are already some studies that have used neuroscience tools to study the role of multimodal information in the second language learning process. one of the most common and most easily understood neuroscience tool is eye-tracking, which is often used to study visual information processing during learning and cognitive process (e.g., Conklin & Pellicer-Sánchez, 2016). Meanwhile, in addition to the study of visual information processing, auditory information processing is also a very important aspect relevant to the learning process of multiliteracies, especially for language learning. However, given that cognitive processing of auditory information cannot be studied using eye-tracking research methodology, brain imaging techniques do provide the possibility for more in-depth research. Although there have been many studies using brain imaging technologies to study language learning (e.g., Tuara, 2014), there has been a lack of research regarding the usage of brain imaging technology in multiliteracies language learning. Therefore, there is a clear need to conduct further research to better understand and verify the existing findings.

Among all of the neuro-imaging techniques, functional Near Infrared Spectroscopy (fNIRS) is a functional neuroimaging technique which examines the changes in blood flow in relation to the neuronal activation that occurs during a cognitive process, and is used to better understand about brain structures and functions (e.g., Ng & Ong, 2018). It is a relatively novel neuroimaging tool whose mechanism is similar to fMRI, but can offer several advantages over fMRI in language-related research, especially in terms of its ability to accept multiple modes of information simultaneously given its minimal noise levels and portability (to be more specific, see Chapter 2.4). However, because fNIRS is a relatively new tool, its advantages have not been explored in language-related research, especially with adult participants. Therefore, using fNIRS to study multimodal language learning may help better our understanding of multiliteracies.

In summary, the main research problems this study aims to address are a) the lack of studies using neuroimaging tools to study multiliteracies language learning, b) the inconclusive results of existing neuroscience studies on language learning, especially for the brain mechanisms for multimodal language learning, and c) the advantages of fNIRS in language research that have not been fully exploited.

1.2 Purposes

To address the above research problems and gaps, the overall research purpose is to understand the impact of multiliteracies learning on ESL learners by comparing their behavioural data and brain activities before and after multiliteracies learning. To be more specific, the study has two main purposes. Firstly, the study aims to explore how multiliteracies language learning background can impact participants performance on multimodal experiment tasks, and how participants' performance changes after multiliteracies learning. Secondly, the study aims to explore how brain activity (i.e., fNIRS data) is related to participants' multimodality background during multimodal information processing and how fNIRS data will change after multiliteracies learning.

In order to achieve these purposes, the relationship between behaviour data and/or fNIRS data, and congruency, intensity, emotion types of stimulus, genders of participants, students' multimodality background and question types needed to be explored through quantitative data analysis. There are three kinds of data involved, which include questionnaire data, experimental behavioural data and fNIRS data. Questionnaires were used to collect participants' digital technology backgrounds, especially regarding their multimodality background to understand the participants' multimodality levels before multiliteracies learning. In the experiment, participants would view emotional videos as stimulus trials and natural videos as rest trials. They would then answer questions regarding the content of the videos after viewing each video. For the stimulus, there are many properties of stimuli, including the emotion types, the congruency (i.e., if the emotion of the actor's face matches the emotion of the actor's voice, it is seen as a congruent stimuli and if not, it is seen as a incongruent stimuli), the intensity of the stimuli's emotion, and question type (i.e., what the question ask for, either for emotion of face or voice). The behaviour data were collected, including reaction time and the participants' answer for each question, and was then further coded into correctness. In addition, fNIRS data were recorded during the entire experiment. The data were collected twice for each participant; the first session was either before or at the beginning of participants' multiliteracies learning, and the second session was after their multiliteracies learning. In this thesis, behavioural data and fNIRS data was used for analysis.

Although neuroimaging data plays an important role in a well-designed neuroscience experiment, the behaviour data (e.g., reaction time) is the most important foundation for further analysis because it is the most direct experimental result. For an educational or psychological experiment without neuroscience tools, we always concentrate on students' behavioural data and connect them with the independent variables we are interested in; for a educational neuroscience experiment, they provide us with an intuitive overview of the participants' performance and can help with the understanding of neuroimaging data. In this study, how these behaviour data are related to students' multimodality background and other variables collected in the experiment, as well as how it may influence the experiment outcome should be considered before doing further neuroscientific analysis. Therefore, in this study, behavioural data are also an important aspect in supporting conclusions. In addition to behavioural data, fNIRS was used to study changes in brain activity before and after multiliteracies learning to better understand the changes in students' brains given the influence of multiliteracies learning. For example, comparing changes in brain activity in different brain regions before and after learning allows us to know which part of the brain can be developed through multiliteracies learning.

For the first purpose, the behaviour data, including participants' responses for each trial and their reaction time was collected and the responses data was then further coded into correctness; some of the questionnaire response were then further coded (see Chapter 3) to serve as the participants' multimodality background. Besides, some demographics information (i.e., gender, age of participants) were also collected. These data were analysed through SPSS and SAS, and ANOVA, t-tests and Chi-square were used to determine the basic relationship between different independent variables and behavioural data, as well as the differences before and after multiliteracies learning. In addition, the models of multiple linear regression (MLR) and binary logistic regression (BLR) were established to have a full view of the relationships between reaction time or correctness and all six independent variables of interest.

For the second purpose, fNIRS data was collected. The preliminary processing (e.g., coding, filtering), preliminary analysis, and comparison of data (i.e., comparison between session 1 and 2, comparison between different brain regions) were performed using NIRSlab.

1.3 Research Questions

According to the three main purposes in 1.2, the research questions of this research are:

1) What is the influence of multiliteracies learning and multimodal background on ESL students according to their experimental performance?

(1.1) What is the relationship between behaviour data and ESL students' multimodality background and other possible influencing factors (i.e., students' gender; emotion types, intensity and congruency of stimuli; question types) using emotional videos? (1.2) How does the relationship between behaviour data and independent variables change after the multiliteracies learning?

2) What is the influence of multiliteracies learning and multimodal background on ESL students according to their brain activity (i.e., fNIRS data)?

(2.1) What is the relationship between fNIRS data and students' multimodality background and other possible factors (i.e., congruency, emotion types of stimuli) using emotional videos? (2.2) How does participants' fNIRS data change after multiliteracies learning?

1.4 Significance of the Study

The main points of the significance of this study are a) given that there is almost no educational neuroscience research related to multiliteracies, this research can help fill this research gap, b) although there have been some studies on multisensory processing in brain, more research is needed to support previous conclusions and this study can provide relevant insights and c) although there has been a large amount of brain-related research in foreign language learning, the brain mechanism of language processing has not yet been fully understood and this study can help to understand it. In summary, this study enriches the field of educational neuroscience, multiliteracies pedagogy and multimodal second language learning, and provides a possible methodology for future educational practice and educational neuroscience research, especially for multiliteracies and second language research.

1.5 Organization of Thesis

This thesis is organized into five chapters detailed below.

Chapter 1: A brief introduction of the research background, the research rational and purpose, the research questions and experiment design were included and the significance of this research.

Chapter 2: The second chapter consists of a literature review of relevant literature on multiliteracies and multimodality, neuroscience and neuroimaging in education and ESL learning. It consists of five parts. First part is the overview of the literature review process, the inclusion criteria, and the brief introduction of the whole chapter. The second part reviews the literature on multiliteracies. Some existing research on multiliteracies second language (L2) learning was also reviewed and was divided into two sections: 1) the basic theories and concepts in multiliteracies, and 2) multiliteracies in ESL and foreign language (FL) learning.

The third part of Chapter 2 reviews the relevant body neuroscience literature and was divided into three sections. The first section introduces the bridging of education and neuroscience, introduces how the field of educational neuroscience arose and expands upon theories and concepts in this field; the second section reviews relevant literature and empirical research using neuroscience in educational technology and multimodality, given that there is little research on applying neuroscientific concepts in multiliteracies; the third section reviews relevant literature using neuroscience in the field of ESL and FL. The fourth part introduces the neuroimaging technique used in this study, functional Near Infrared Spectroscopy (fNIRS), in greater detail.

Chapter 3: This chapter introduces the methodologies, research contexts and the ESL participants, explains the research design and the rationale of the design and introduces the materials using for the study, the procedures of data collection, the ethics requirements and the process, hypothesis and preliminary data coding of data analyses.

Chapter 4: In this chapter the results for both the behavioural and neuroimaging data are presented.

Chapter 5: The conclusion of the study is summarized based on the findings in Chapter 4 and the possible implications of this study, further research directions and the limitations of the study are discussed.

Chapter 2

2 Literature Review

2.1 Overview

Given the paucity of literature in ESL and educational neuroscience, a systematic review of the literature was performed. The databases used for literature searches included PubMed, ERIC, Springer, Taylor & Francis Online and Google Scholar. The literature review is limited to those databases open to graduate students in the Faculty of Education, Western University. Initial search keywords including multiliteracies and educational neuroscience, but no relevant content was searched in ERIC, Springer and Taylor & Francis Online. In addition, only three journal articles in Google Scholar were considered eligible for literature review. PubMed was primarily used to find the neuroscience-related research and findings. Therefore, the next part of the literature review was summarized and analyzed from two aspects: multiliteracies and neuroscience, respectively.

Using the keywords "multiliteracies" and "ESL", "English as a foreign language (EFL)" or "second language acquisition (SLA)", a literature search was conducted in ERIC and Google Scholar, and 47 multiliteracies-related journal articles and books were examined (including those with some parts of multiliteracies such as digital literacy, multimodal literacy, etc). The basic concepts of multiliteracies was first studied, including its origins and definition, the relationship between multiliteracies and multimodality, and the pedagogy or principles put forward by key scholars on how to develop multiliteracies in this field. Then, based on the more specific research content, some specific studies of multiliteracies related to second language acquisition were reviewed, focusing on their theoretical framework, research focus, research methods and findings.

In addition, the search for relevant literature regarding neuroscience in education and language learning was examined using the keywords "neuroscience", "education", "emotion", "fNIRS" and "language", "SLA", "EFL" and "ESL". All databases mentioned above were used to conduct the literature search.

A total of 59 articles were chosen and reviewed finally, a portion were empirical studies about ESL and educational technology, others were related to the relationship of emotion and language learning in both empirical and narrative perspective, and a small part were literature reviews or narrative articles on application and importance of neuroscience in the educational field. Therefore, there are three parts of literature review for educational neuroscience: concepts, discussions, and controversies in this field; some empirical research on educational technology, multimodal literacy or digital literacy and some empirical research on ESL learning and teaching. This thesis employed fNIRS technologies, in turn this was included in the review; however, functional magnetic resonance imaging (fMRI) measures brain signals similar to fNIRS (i.e., they both measure cerebral hemodynamic activity). Additionally, fNIRS is a relatively new technology especially in language research, and the number of related studies is limited, so some fMRI studies were also reviewed. In addition, in the fourth section of this chapter, the principle, advantages and disadvantages of fNIRS are briefly discussed.

2.2 Multiliteracies

2.2.1 Basic Concepts

The Origins and Definition of Multiliteracies.

Warner & Dupuy (2018) summarized the developments and changes in the theory of literacy, such as the emphasis on prior knowledge that emerged in 1980, and the changes in role of students from passive recipients to active creators in 1990. The New London Group (1996) developed the term “multiliteracies” in response to the changes of social power (see Kalantzis & Cope, 2010), rapid development in technologies, and cultural communication in modern society, and multiliteracies calls for promotion of multimodality and the language and cultural diversity.

On the one hand, there are more modes of communication, such as the internet and social media, that enable anyone to be a reporter or producer of knowledge, and different modes of knowledge, including images, that allow greater integration, In the same time, due to the trend of globalization, the mobility of the population, and international immigration, various languages and cultures have blended together (Cope & Kalantzis, 2000; Kalantzis & Cope, 2017). Multiliteracies emphasize the process of discovery in learning and interactions between multimodal language forms, and cultural and social contexts (Paesani, 2016). A key component in multiliteracies is "multiple", which not only indicates multiple modes of information that people use to express their views and meanings but also describes "the multiple contexts in which language is used as well as the multiple factors that contribute to the make-up of those contexts" (Jacobs, 2013b, pp.270).

Given this new term, the definition of literacy changes from simply reading and writing to a social practice, which includes: using different modes of communication, applying students' prior knowledge including their mother tongue when they learn something new, applying what students learned into their daily lives, solving problems in real life for different purposes, and creating and understanding multimodal and multilingual texts (Scribner & Cole, 1981; Paesani, 2016; Leander & Boldt, 2012; Ana, 2004).

Multiliteracies and Multimodality.

As the definition of literacy has become more extensive and not limited to reading and writing, the term "literacy" can be applied to a wide range of modalities (e.g, .media literacy, cultural literacy) and today's students are surrounded by multimodal literacies (Westby, 2010). The multimodality approach pays attention to "all culturally shapes resources that are available for making meaning" (Kress et al., 2005, pp.2) and requires that students should have the capacity to draw meaning from all kinds of representations including linguistic, audio, visual, spatial and gestural. (The New London Group, 1996; Kalantzis et al., 2002). Multimodality is one of the two key components in multiliteracies pedagogy. The interdisciplinary nature of multimodal forms was considered helpful for students' learning efficacy and learning interest. Therefore, multimodality is a method that students can use to make meaning through different modes and multiliteracies is the pedagogy that is developed to learn and promote multimodality (Nabhan & Hidayat, 2018).

Frameworks to Develop Literacy and Multiliteracies Pedagogy.

Freebody & Luke (1990) developed the four related roles that a successful learner needs to play for literacy learning: code breaker, text participant, text user and text analyst. The model was further developed to a four resources model of literacy: code-breaking, meaning-making, text use and text critique. In their further notes in 1999, they commented that these four models are necessary but not sufficient to develop literacy. They viewed the four models of literacy as a family of practices and indicated that these practices should be used together in real life (e.g., community contexts) and cannot be used without each other. Specifically, in their notes in 1999, they emphasized the importance of practicing authentically repeatedly to make meaning beyond texts, and claimed that students should: "break the code of written texts by recognizing and using fundamental features and architecture…participate in understanding and composing meaningful written, visual, and spoken texts, taking into account each text's interior meaning systems in relation to their available knowledge and their experiences of other cultural discourses, texts, and meaning systems…use texts functionally by traversing and negotiating the labor and social relations around them…analyze and transform texts… their designs and discourses can be critiqued and redesigned in novel and hybrid ways" (Luke & Freebody, 1999). The four resources model also suggested that different combinations of teaching designed with different pedagogies may have different impacts for different kinds of students (Luke & Freebody, 1999).

Another aspect of multiliteracies is "design", which, as claimed by The New London Group (1996), is the one of most important parts of multiliteracies because educators are perceived as designers of students' learning environment rather than designers of textbooks and processes, and students are expected to "design" their own meaning. The term "design" includes three aspects: available designs, designing and redesigned. Available designs include all sources that can be used to create meaning and design multimodal texts, for example, language; designing means what teachers do to enrich texts to better represent meaning, and what students do to understand available designs in multimodal ways. Redesigned means students should use available designs and transform them to fit specific purposes and connect them with their own prior knowledge. Leander & Boldt (2012) also emphasized the role of "redesigned" to the explain that unintended meanings can be addressed and redesigned through producing new resources of “hybridity and intertextuality” (pp. 31) through a text-centric perspective.

Aside from the “design”, The New London Group (1996) proposed a framework for multiliteracies pedagogy, which is most widely used in multiliteracies practice design, including situated practice, overt instruction, critical framing and transformed practice. Situated practice means learning should happen using real-life experience and should utilize the designs of meaning in authentic environments and contexts. Overt instruction requires students to be “conscious awareness” (pp. 86), to have the ability to analyze meaning and the design of meaning, and to use them on their own. Critical framing refers to the ability to critically reflect and summarize what they have learned and apply it in real-life. Transformed practice should be conducted to let students revise and use transformed meaning that they have made in additional contexts from a different perspective.

A key element of multiliteracies is the design of meaning. Therefore, based on the framework and the importance of design proposed by The New London Group (1996), Kalantzis and Cope (2005) extrapolated it to develop a way to do multiliteracies called “Learning by Design”, which suggests that education should play a role in which it designs authentic experiences for students to acquire knowledge. Kalantzis and Cope (2010) also claimed that the most successful and useful people in today and in the future should be those who have the creativity to “design”, who need to take greater responsibility for their greater autonomy; and who are knowledge-producers instead of knowledge-consumers. Students should participate in learning actively, combine their interest and prior experience and create their own characters and meaning. This framework pays attention to sociocultural differences between students instead of their abilities (Kalantzis & Cope, 2010) and consists of four aspects: experiencing, conceptualizing, analyzing and applying, which correspond with the four components of the framework provided by The New London Group (1996).

In addition, each aspect is divided into two knowledge processes. Experiencing includes the known and the new, which means students should reflect on their existing knowledge and experiences and take part in the new experiences that gained when immersed in authentic contexts. Conceptualizing can be achieved by naming and with theory, which means students should have the ability to define and classify the knowledge and experiences they have had, and the ability to generalize and combine their concepts with each other. Analyzing should be done functionally and critically, which means students should know how to analyze the logical connections and function of the meaning and reflect on them critically. Applying should be done appropriately and creatively, which means learners should apply their knowledge to real-life, and transfer their meaning in a creative way to use it in broader contexts (Kalantzis & Cope, 2010). Kalantzis and Cope (2010) mentioned that they put the framework into use (i.e., The Learning Element software) for their research, and confirmed its effectiveness, for instance, increasing explicitness to design and achieve learning goals.

In addition to the above frameworks, Kern (2000) developed 7 principles to guide literacy in filling the gap between language teaching and advanced literacy learning, including: interpretation, collaboration, problem-solving, reflection and self-reflection for learning process and conventions, cultural knowledge, and language use for multiliteracies pedagogy, which is also widely used in literacy teaching.

Jacobs (2013a) summed up previous studies, arguing that assessments that simply measure the cognitive skills for alphabetic texts fail to help teachers understand students' multiliteracies skills deeply, and suggesting possible ways to take multiliteracies assessment. She inferred that the focus of assessment should be on what students will "guide students toward new skills and knowledge" (Jacobs, 2013a, pp.626). Based on qualities identified through theories of new literacies and multiliteracies, there are four possible ways of performative assessment: project assessment for in-depth tasks, performance assessment to measure creativity, quantification of collaborative skills (i.e., group assessment) and portfolio assessment to document students' works.

These frameworks are meaningful for design teaching plans or curricula and they can also be used as a reference to analyze and revise curriculum documents (e.g., Healey, 2016; Menke & Paesani, 2019). However, Leander and Boldt (2012) argued that the established framework may limit the awareness of further understanding of multiliteracies and could lead to the over-rationalized design of activities. Leander and Boldt also claimed that we should not put too much emphasis on texts; for example, they used an example of the literacies practices of a boy in out-of-school contexts instead of schooling contexts, and argued that the framework would cause misunderstanding and over-rationalized interpretation of his activities. Therefore, as called by multiliteracies, we must not only rely on the prior knowledge we had (i.e., these well-developed frameworks), but also transform our own concepts based on our own practices.

2.2.2 The Use of Technology, Digital Literacy and Multimodality in Multiliteracies Pedagogy

As mentioned above, multimodality is one of the most important components of multiliteracies. Among all the means available to promote multimodality development, the use of a variety of technology, especially digital products, has greatly promoted implementation of multimodal information in classroom. In terms of educational theory, technology-enhanced learning (TEL) curriculums support a learner-centered approach and constructivism (Weimer, 2002; Meece, Herman and McCombs, 2003 as cited in Buckenmeyer et al., 2016). Gottschalk (2019) argues that "technology use has been on the rise worldwide" (p.6) and digital technology has become an important part of students' daily lives (e.g., Gottschalk, 2019; Beach, 2012; Li, Snow & White, 2015). Buckenmeyer's (2016) study indicated that although some respondents preferred courses with no technology usage, a high proportion of respondents think technology can be useful in their academic development, especially in enhancing communication and collaboration. A survey conducted by Li, Snow & White (2015) studied the influence of technology use on language and literacy learning in adolescent students, and the results showed that technology use can have a positive impact on language learning, especially through video websites such as Youtube. Similarly, a questionnaire survey by Thompson (2013) invited university freshmen as participants to understand students' technology and multimodality backgrounds and its influence on learning. Therefore, digital literacy can also be considered as an important representative of multimodality in multiliteracies.

Digital technology can help develop students' digital literacy and multiliteracies which includes the ability to search the information online, critically analyze the accuracy and reliability of the information found online, identify deep or superficial reading online, using hyperlinks to construct the connections between variety of information, using social medias to share knowledge, enhancing collaboration and communicate with each other, and create multimodal media literacies, etc. (Beach, 2012; Son, Park & Park, 2017). A study from Bear (2012) indicated that internet usage can lead to the improvement of traditional literacy and computer literacies skills for adults during the learning process of internet auction activity; another research from Tang and Chaw (2016) also supported the assertion that digital literacy is a "prerequisite" (p.54) for students to effectively learn a technology-related learning environment. Although these digital literacies and multiliteracies do not completely overlap with each other, the improvement of digital literacy is still closely related with the improvement of multiliteracies.

However, regarding the assessment of digital literacies, both Son, Park and Park (2017) and Katz and Macklin (2007) agreed that students' self-assessment of digital literacy does not fully represent their true digital literacy level. While there have been many studies on the use of technology in education in recent years, the impact of these technologies and the rationale of their impact has not been completely explored, especially in psychological and physiological aspects (Gottschalk, 2019).

According to some questionnaire surveys, most participants have access to smartphones, tablets, computer and/or laptops, and the most frequently used digital technology includes web searching, email, social media use, etc (e.g., Thompson, 2013; Son et al., 2017; Li et al., 2015). However, the most directly related application of digital technologies on literacy learning should be online courses and online learning, and many online courses websites, such as MOOC, have been used by many students given their need for continuing education and part-time study. Research by Parker, Lenhart and Moore (2011) showed that more than 50% of college university presidents thought online learning can be equivalent to on-site campus instruction (cited in Buckenmeyer et al., 2016). In addition, online teaching also played an important role in maintaining normal classroom learning during the outbreak of COVID-19 during the preparation of this thesis and require students to have the ability to use online sources. A survey from Buckenmeyer (2016) also indicated that the students who have experiences in online courses are more likely to believe in the benefit of TEL and thus are more likely to participate in courses with higher levels of technology use. Tang and Chaw (2016) also studied the influence of digital literacies on blended learning, which blends face-to-face classroom and online learning, and the results divided digital literacies into three main factors, including "underpinnings, experiential learning and searching" (p.62) and showed that digital literacies are essential for online learning.

In recent years, a common application of digital literacy is through the introduction of digital games into classrooms, which can help the development of students' multitasking ability and involves a high volume of lot of multimodal information. Digital games have become an important method for promoting multimodality and digital literacy (e.g., Beavis, Muspratt & Thompson, 2015; Gottschalk, 2019). However, scientific game-based teaching and learning strategies have not yet fully been made available but need to be systematically developed to address possible shortcomings. A previous study from Beavis et al. (2015) investigated the phenomenon and feedback of digital learning and game-based learning in Australian schools, where, and the content of the research for students included what games they used both at school and at home, the curriculum areas in which they used digital games, and their feelings about using games in teaching. The results include differences in the types of games that boys and girls, for example, boys prefer action-adventure games compared to girls, and there are also gender differences in how different genders feel about games (e.g., boys value exploration and leadership in games more, and girls are more likely to discover personality changes and experience emotions with digital games). Similarly, a review from Beach (2012) also strongly supported the positive effects of using digital games in classrooms. However, another study from Thompson (2013) indicated that there is no significant relationship between digital games and productive learning habits, despite drawbacks from a limited sample size. The contradictions in the existing research conclusions ultimately showed that there is no firm conclusion on this area of research, and that is a need for more research exploring this issue.

In addition, the use of social media by students is also an important aspect of applying digital technology to daily life, which can be related to their social skills and problem-solving skills (Gottschalk, 2019). A paper from Buckenmeyer (2016) also mentioned social media can also be used to fulfill academic needs. Social media exposes people to more modes and sources of information, which can also be important in strengthening their multimodality and multiliteracies abilities. However, there is little research on the role of social media in education. Individuals receive and share multimodal information through social media, especially through video social media sites such as Youtube, and participation in social media has been shown to greatly improve the ability to process multimodal information including video contents, creativity, good learning habits and motivation (Beach, 2012; Li, Snow & White, 2015). Additionally, Thompson (2013) found that frequent users of rapid communication technology, which includes some social media, are more likely to do effectively web search and multitask while learning, but less likely to control their ability to multitask and reflect and read critically. Similarly, in the same research, those who use social media, multimedia creation and collaborative web tools more frequently performed worse in productive learning exercises, which involve sustained attention and deep cognitive processing. In addition to traditional social media sites like Facebook, there are also some social networking sites, such as Digital Booktalk, that were found to be useful in increasing interest in reading books and communicating with peers (Gunter & Kenny 2008), and can also be used for academic social networking (Beach, 2012).

2.2.3 Multiliteracies in ESL and FL

Technologies provide different modes of communication for language learners and teachers to reflect on their communicative practices, and how these practices can foster efficacy of communication in second language (Chun et al., 2016). Digital media also created more means of expression (e.g., the use of emotions) which can help communicators' emotional express and can also make the internet more multilingual (Lotherington, 2007). It has been demonstrated that technology and media use can improve language and literacy learning in some way (e.g., Li, Snow & White, 2015).

In addition, influence of different cultures was also seen as a part of multiliteracies and can be a bridge for FL learning (Kandhadai, 2014). As Warner and Dupuy (2018) argued, the call for diversity of multiliteracies has a significant influence on FL teaching and learning. On the other hand, linguistic diversity is also an important aspect of multiliteracies, and language is embedded in multiple modes of communication (Schmerbeck & Lucht, 2017). English, as the predominant global language, is being learned by an increasing number of students, and its usage occurs in both real-life and digital contexts (Lotherington, 2007). However, the limitations of technologies use and multiliteracies in ESL have not been fully addressed (Lee, Ardeshiri & Cummins, 2016). Hence, teaching multiliteracies in ESL or FL classroom is essential.

Kaesani et al. (2016) proposed a multiliteracies framework for FL teaching and assessment, discussed different aspects including oral language, reading and writing in multiliteracies FL learning, and the importance of multimodality and technologies in FL learning, and addressed the four pedagogical acts by The New London Group (2016). Due to the demands of modern society, multiliteracies in FL learning not only requires students to acquire strong vocabulary and grammar skills, but to discern and express meaning using foreign language (Schmerbeck & Lucht, 2017). However, there are still many challenges to use multiliteracies in FL teaching, such as the lack of professional training for teachers, the emphasis of mainstream textbooks on grammar rather than the construction of meaning (Warner & Dupuy, 2018). Therefore, more empirical research is needed to help the development of multiliteracies in ESL and FL teaching and learning. Kern & Schultz (2005) also called for more empirical research in this field and Mills (2007) suggests that there is a gap between multiliteracies theory and practice.

A recent case study using mixed methodology, conducted by Nabhan and Hidayat (2018), examined university students' literacy practices and teachers' literacy strategies with multimodal forms in ESL learning. The findings showed that digital devices are used frequently in both student' learning practices and teachers' teaching strategies, and the frequent utilization of images and videos indicated that students were predominantly audio and visual learners, which suggests that using audio and visual materials for teaching is beneficial for students' language learning and creative meaning-making. Paesani's research in 2016 also examined university students' FL learning practice through a multiliteracies perspective that used mixed methodology. Paesani argued that advanced FL ability can only be obtained when learning occurs in an authentic cultural context that can be supported by multimodal learning materials and digital technology. Moreover, a study from Pishor and Kaur (2015) also suggested that multimodal texts in multiliteracies ESL teaching showed advantages in increasing students' interest and collaboration learning. For the three studies mentioned in this paragraph, the results demonstrated the possible positive influence of multiliteracies, especially multimodality in the reading and writing process.

Angay-Crowder et al. (2013) illustrates a teaching method called "digital storytelling", which is a useful multiliteracies teaching method in previous (e.g., Yang & Wu, 2012; Ohler, 2015). The findings demonstrated that multimodal practices in this study helped students "expand their literacy repertories and means of expression" (Hull & Nelson as cited in Angay-Crowder et al., 2013) and revealed the importance of a teacher's guidance in students' learning. Similarly, Burke & Hardware (2015) also used digital storytelling as an approach to multiliteracies in their study, and the findings suggested that this approach can help students positively engage in the classroom and enrich their learning experiences. A study from Lee, Ardeshiri & Cummins (2016) explored the advantages and learning experiences from the application of multiliteracies pedagogy in ESL through a computer-assisted program. The focus of this study was on the role of technologies in multiliteracies ESL classroom, and the results demonstrated that students can use digital technologies to represent their meaning and supported the active role of digital techniques in intercultural communication, which echoes Angay-Crowder et al.'s (2013) and Burke & Hardware's (2015) research results on the advantages of digital storytelling, as introduced previously.

Leander (2009) identified four stances which English Language Arts (ELA) teachers can use regarding the use of digital technology in their classrooms: oppose the use of digital technology, replace traditional print literacy with digital technology, verify or return to traditional print literacy with digital technology, and use a combination of print literacy and digital technology through parallel pedagogy (cited in Beach, 2012). Beach (2012) also indicated that the use of digital tools can increase the performance in a print-based ELA traditional test as well, in either writing or reading. Ganapathy's (2014) and Ganapathy & Seetharam's (2016) similar research interests in technology use have yielded positive research findings through case studies and have summarized some studies have had a positive effect on the use of technology in ESL learning (e.g., Bearne et al, 2007 as cited in Ganapathy & Seetharam, 2016). Moreover, Jiang's study in 2017 also examined the use of digital techniques in ESL multiliteracies practices with the application of digital multimodal composing (DMC) which uses digital tools "to produce texts by combining multiple semiotic modes that include, but are not limited to, image, word, and soundtrack" (pp.413). Ultimately, Jiang's findings supported the active role of digital tools in ESL multiliteracies practices through a qualitative method.

Similarly, Son, Park and Park (2017) studied the influence of digital technology on English for academic purposes (EAP) and ESL students through a questionnaire, and use quantitative methods to analyze the results of questionnaires. Questions included items on participants' multimodality background and the impact of digital technology on language learning. The findings showed that most participants have a positive attitude towards digital technology. Another study from Li et al. (2015) also employed questionnaires to research the purposes to reveal how these purposes impact English language performance of adolescents. Their results showed that there are significant correlations between students' technology use and their language skills, and that some participants who reports higher language skills use technology for more purposes including blogging, homework, reading, photo sharing, etc. Besides, from the same study, Li, Snow and White (2015) also reported that those who are English language learners showed more interest on using technology for language and vocabulary learning compared with native speakers. The findings in this study may also indicate that multimodality and multiliteracies ability through technology use can have a positive influence on FL learning to some extent.

Although this thesis primarily focuses on the analysis of the influence of multimodality, especially digital literacy of multiliteracies on FL learning, it also examines how other aspects of multiliteracies, such as the integration of multiple languages and the integration of multiple cultures, also play an important role in foreign language learning. Mills (2007) used ethnographic research methods to find students' access to multiliteracies among culturally and linguistically diverse groups, and to reveal the influence of power and classroom discourses. The findings of this study emphasized the role of students' existing cultural knowledge and social power to obtain multiliteracies, and showed the importance of the teachers' role, their power and their discourses in normalizing and legitimizing the unequal distribution of literacies due to different knowledge levels and cultural backgrounds. In addition, another study by Kiss & Mizusawa (2018) showed that traditional examination-centered classroom practices had negative influences on students' learning, supporting the positive effect of multiliteracies pedagogy from the opposite side. However, conversely, a study by Puteh-Behak et al. (2015) showed that it can be challenging to employ multiliteracies in a Malaysian context given the pre-defined distant teacher-student relationship; some other studies also suggests possible difficulties of using multiliteracies in different culture contexts (e.g., Thanh-Pham, 2011 as cited in Puteh-Behak et al, 2015; Tan & Guo, 2010 as cited in Puteh-Behak et al, 2015; Burke & Hardware, 2015). Ultimately, these findings inspired us to consider cultural factors when using new teaching methods more carefully.

Kasper (2000) argued that previous studies showed that content-based instruction (CBI) is useful for ESL learning, which supported "situated practice" in multiliteracies developed by The New London Group (1996), and also viewed technologies as a tool to support authenticity, addressed complexity of tasks, and promoted multiliteracies. Kasper's research in 2000 examined a case involving the four components of multiliteracies in the learning practice and evaluated its efficacy and the use of a mixed method. The findings ultimately showed that multiliteracies pedagogy did help in students' literacy learning and final exams. Similarly, a case study from Schmerbeck and Lucht (2017) used photo projects and language learning portfolios and argued the importance of formative assessment in multiliteracies, using Kern's (2000) 7 principles of literacy and 4 pedagogical acts on multiliteracies developed by Paesani et al. (2016) to explain it and emphasized the focus of the assessment on the ability to think in the English language both "critically and creatively" (Paesani et al., 2015). Both studies by Kasper (2000) and Schmerbeck and Lucht (2017) mentioned the importance of formative assessment and attention in the learning process, which echoes Jacobs' view (2013a).

Michelson's (2018) study used a multiliteracies-based global simulation (GS) teaching method to teach FL, which is in line with situated practice in multiliteracies and the results showed that students can create positive meaning, draw links between culture and language, find social identities, and apply and reflect upon what they learned in life situation.

Aside from the aforementioned studies, some studies use multiliteracies framework to perform materials and curriculum analysis (e.g., Healey, 2016; Menke & Paesani, 2019). Due to different curriculum materials, their research conclusions are different, but could provide a common way to analyze textual ESL materials from a multiliteracies lens: code the texts, correspond the codes to each stage in the multiliteracies framework, analyze, and summarize. This kind of analysis of curriculum materials can sometimes help us understand practice in the classroom from another perspective, if we cannot access enough information from other data collection methods (e.g., interview).

In summary, there have been some evidences that multiliteracies, multimodality and digital technology could have a positive impact in language teaching. However, there are still many obstacles to the use of multiliteracies in schools, to be more specific, the use of technology and digital literacies to enhance language learning (Beach, 2012). Therefore, more scientific strategies on how to better use digital technology in multiliteracies language learning need to be developed, and more research need to be done in this field.

2.3 Neuroscience and Neuroimaging

2.3.1 Bridges and Gaps: Neuroscience in Educational Research

In recent years, interdisciplinary integration of education and neuroscience has become an inevitable trend due to the rapid development of various fields, particularly neuroimaging. Leavy (2016) defines transdisciplinary as “an approach to conducting social research that involves a synergistic collaboration between two or more disciplines, with high levels of integration between the disciplinary sets of knowledge” (pp.90). The combination of neuroscience and education has developed into a new field called educational neuroscience, which is an interdisciplinary and transdisciplinary research field. This field also draws upon and integrates research and concepts from different disciplines, such as cognitive psychology and cognitive neuroscience (e.g., Campbell, 2011; Frey & Fisher, 2010).

Cognitive neuroscience can provide insight into how physiological processes, especially neural pathways, affect the human behaviour (Howard-Jones, 2015b). Therefore, neuroscience can serve as a way to cultivate a deeper understanding of literacy and merge our understanding of both literacy and neuroscience is crucial for developing these insights. For example, while quantitative methods, such as the experiment design, are usually used in neuroscience research, most of the educational research needs to be conducted in a natural environment with qualitative methods (Krause, 2015). Moreover, compared with traditional educational research methods, this research field pays more attention to the learning processes and mechanisms in the brain rather than the learning outcome (Besty & Aloysius, 2018). Neuroscience also fosters the development and understanding of developmental, social and cognitive psychology, and may contribute to educational research indirectly given that a purely psychological approach may offer inaccurate theories which can be corrected by neuroscience findings (Grushka et al., 2014; Thomas et al., 2018).

Brain research can help us understand brain-behaviour relationships. Campbell (2011) argued that the importance of educational neuroscience is that "the focal points of educational neuroscience are living human beings, not just physiological and biological mechanisms underlying them" (pp. 8) and what educational neuroscience should do is to identify how the trajectories of brain development can influence teaching and learning in educational practices, including multiliteracies.

Donoghue & Horvath (2016) claimed that learning is a biological and neurological phenomenon. Neuroscience research have showed the strong relationship between learning, memory and brain development; particularly, the connections between neurons that changed with the interaction between individuals and the external environment (e.g., Hopkins et al., 2013; Draganski et al., 2006; Hinton et al., 2008). Halfon et al. (2001) defined this connection as "the process by which the brain responds adaptively to the environment in which a child is reared" (pp.5). Although there are some concerns that understanding brain activity may not inform classroom teaching practices, and some researchers and educators have argued that neuroscientists rarely consider how educational practices occur in classroom (e.g., Howard-Jones et al., 2015a; Ferrari, 2011), Petitto &

Dunbar (2012) pointed out that the neuroscience studies have at least 5 advantages for learning:

"(1) reveal vital information about timing in education (i.e., when is exposure to core content optimally learned), (2) tell us about the mechanisms and the developmental sequence that underlie the learning of core content and related concepts, (3) explain why certain content and concepts are difficult for students to learn in early life—and why others are easier to learn, (4) suggest ways of learning and teaching that can be used to circumvent problems associated with traditional teaching methods, and (5) reveal optimal ways to promote conceptual change in science education" (pp.186)"

Understanding the brain's learning-related activities can not only help us understand the cognitive processes, but also provides insights on possibilities to help manage learning disabilities resulting from brain damage (Riza, 2002; Arnold & Fonseca, 2004). Many scholars claimed that "neuroscience furnishes a biological and physiological foundation for effective teaching trains" (Jensen, 2005 as cited in Moghaddam & Araghi, 2013). In addition, neuroscientific discoveries can provide evidence for and help revise some educational theories and strategies, and can also verify previous educational behavioural studies. For example, recent research by Hinton et al., 2008 demonstrated that the brain are is highly adaptable based on new exposures, which supported the significance of dynamic developmental approaches in the study of learning and the importance of formative assessment. Another example of using neuroscience to support educational theory is the Meno dialog, which is a classical teacher-student interaction method developed by Socrates to help guide students in geometric reasoning and knowledge transfer, and a recent fNIRS study by Holper et al. (2013) demonstrated the applicability of the it in facilitating the application of neuroscience findings to educational theory.

Additionally, the emotion network is highly connected with the brain regions involved in cognitive processing, which provides evidence that emotion is the fundamental of learning. Students' emotional development should be a key aspect of learning in school (e.g., Munsell, 1988; Moghaddam & Araghi, 2013; Hinton et al., 2008; Arnold & Fonseca, 2004; Arnold, 2011). Arnold (2011) mentioned that emotions can result in the release of neurochemicals involved in stress processing and can target key regions involved in learning and memory.

Damasio (1994) asserted that emotion is a rational mechanism and the brain functions best without threat and stress. Schumann (1994) commented that emotion is a part of cognition and they cannot be separated (cited in Arnold & Fonseca, 2004). Many studies have showed that cognition and memory are connected to emotion and social contexts, and that recall involves experiences in different contexts (e.g., Damasio, 2012 as cited in Gtushka et al., 2014; Arnold & Fonseca, 2004). Howard-Jones et al. (2015a) designed a classroom practice by referring to the learning principles implied by neuroscience research, and thus supported the effectiveness of their method. In addition to the overall effect on cognitive function, language learning is also impacted by affective processes (e.g., Arnold, 2011; Arnold, 2019). Arnold (2011) claimed that the ignorance of the affective side of language learning will cause difficulty and language learning should take place in a low-anxiety and experience-related environment.

Cultural differences have been reported to evoke differential patterns of activation in response to emotional stimulus, for example, a study from Immordino-Yang (2016) showed that American group showed activation in cortices that represent the musculoskeletal body in space (e.g., superior lateral parietal regions) when feeling emotions while Chinese individuals demonstrated an opposite pattern of activation. Therefore, previous research results may not be applicable to some populations.

Additionally, some findings showed that learning is more efficient when learning is made more meaningful (i.e., learning in a meaningful environment that can help connect new knowledge with existing knowledge, do real-life tasks and gain learning experiences) than rote learning (Brown, 2000; Lovat & Smith, 2013 as cited in Grushka et al., 2014; Campbell, 2011), which echoes the theory of multiliteracies.

The above examples show that the bridge that connect neuroscience and education is necessary, and that bridge is conducive to our further development of our educational theories and understanding. Therefore, developing a teaching plan based on the development principles of the brain can maximize learning efficiency (Moghaddam &

Araghi, 2013). Conversely, education can also provide inspiration for neuroscience research given that educational research can have some problems and conclusions drawn from practice, which requires more scientific verification through neuroscience (Sigman et al., 2014).

Although the new field of educational neuroscience is being developed, there still exists challenges and gaps in educational neuroscience research. First, Ng & Ong (2018) argued that “findings from neuroscientific research typically draw on small sample sizes and are not generalizable” (pp.118). Moreover, neuroscience research is less commonly used in schools, especially in universities contexts, compared with its widely widespread usage in hospital settings, thus more research is needed to fill this gap. Thirdly, given that different neuroscience tools have different focuses areas, the combination of multiple tools may help us better understand the brain mechanisms that underlie learning (e.g., Ng & Ong, 2018). However, how to best combine them in an effective way still needs to be explored. Fourthly, as the result of the pseudoscience of “brain-based learning”, the public may have misgivings about the effectiveness of neuroscience education (Busso & Pollack, 2015). Fifthly, although brain has strong relationship with learning, learning is still only one aspect of education that requires more multidisciplinary communication and collaboration between scholars (e.g., teachers, policy makers, neuroscience scientist, educators) (Thomas et al., 2018). Finally, we should emphasize that our final goal is to apply neuroscience findings to educational practices.

Some scholars believe that the combination of neuroscience and education may be futile, given the notion that its results have not adequately been applied in real classroom settings (Sigman et al., 2014; Frey & Fisher, 2010) or that neuroscience can only inform education indirectly (Busso & Pollack, 2015). Howard-Jones et al. (2015a) commented that if some neuro-imaging studies can include more interviews with participants, the findings may be more meaningful for “the construction of neuro-educational concepts” (pp.229). Ferrari (2011) also argued that the biggest crisis and challenge of educational neuroscience is how to apply the discovery of neuroscience into improving the reality of life.

2.3.2 Neuroscience in Educational Technology, Multimodality and Multiliteracies

The use of educational technology allows students to access and process more information at the same time, stimulating more brain regions in multimodal ways (Riza, 2002). Additionally, the development of neuroimaging techniques provides ways to explore "knowledge of the architecture and the functioning of the brain" (pp. 360) ,which coincides with Gruskha's notion of "the proliferation of multimedia devices" (pp.360) (Grushka, 2014). Furthermore, both multiliteracies pedagogy and evidence from neuroscience research demonstrated the importance of experimental nature learning and creating the ideal learning environment, which can both be better constructed and developed by multimodality (Grushka et al., 2014).

A review from Anderson, Bradley and Meng-Jung (2014) also mentioned many applications of neuroscience in the study of influences and limitations of educational technology, especially in mathematics and science education. For example, using brain-based methods to study brain activity and mental processes in solving mathematics and science problems (e.g., Waisman, Leikin, Shaul & Leikin, 2014). Ferrari (2011) claimed that "the physical environment has as important an effect on the brain as the brain has on our capacity for learning" (pp.33), which indicated that the research on multiple aspects of the physical learning environment is important.

Howard-Jones et al.'s review (2015b) mentioned that some studies (e.g., Rosser et al., 2007; Koepp, 1998; Weinstein, 2010) showed that uncertain rewards may activate the increase of dopamine in the brain, which is associated with stronger plasticity and an "improved ability to store and to explicitly recall information (declarative memory)" (p.14). The results may indicate that game-based learning can increase positive effect on learning, can support the significance of using multimodality in educational environment, and can demonstrate that computer games may have positive influences on brain development. Prensky (2001) also claimed that digital games and other digital technologies can help the brain development, particularly with visual skills, hand-eye coordination, multitasking, and reaction on unexpected events (cited in Thompson, 2013).

Goswami's (2008) study showed that digital and multimodal learning environment can strengthen the connections between different areas of the brain, but we still need more research to see whether these connections represents "stronger learning" (pp.390) and how we can utilize these findings to support students' learning (cited in Grushka et al., 2014). Andreano et al. (2009) used virtual reality (VR) to study the influence of multimodality on brain and found that adding audio information in VR environment can cause stronger activation in the hippocampus, which is thought to be associated with memory and learning (as cited in Howard-Jones et al., 2015b).

Findings from Wang & Hsu (2014) used EEG and showed that the increased experience achieved through multimodal environment can improve learning performance. Howard-Jones et al. (2015b) used evidence from Kim and James (2010) to assert that shape information can be transferable between vision and haptics, which may be useful for designing educational tangibles. Furthermore, a study from Small and Vorgan (2008) claimed that extensive use of technology can lead to enhanced plasticity performance in brains especially in dorsolateral prefrontal cortex area. However, in the same book, they also proposed the possibility that digital technologies may lead to the overdevelopment in some brain regions like temporal lob, and suppress other regions such as the frontal lobe, which may lead to less profound or deep and critical thinking. Another application of using neuroscience to study technology-related education is using neuroscience and other digital technologies to develop computer-based brain-training software or computer games (Howard-Jones et al., 2015b). Although there are very few products of this type, the prospect of using brain-based facilities to help brain development cannot be denied.

Multimodal learning stimuli, for example, videos of emotional faces with both visual and audio information, may influence students' emotions, which has been thought to have a strong relationship with learning (see 2.3.1) (e.g., Munsell, 1988; Moghaddam & Araghi, 2013; Shen et al., 2009 as cited in Ng & Ong, 2018; Bavelier, Green and Dye, 2010 as cited in Gottschalk, 2019). The design of a multimodal educational environment, including the integration of multiple cultures into the environment, may lead to richer interactions between the environment and students, and may have a positive impact on social emotions. Studies have shown that the neural systems related to social emotions may be associated with high-level cognition and abstract thinking (Haidt & Morris, 2009 as cited in Immordino-Yang, 2016). Articles from Immordino-Yang (2016) and Immordino-Yang and Gotlieb (2017) also supported the essential role of cultural learning in social emotion and brain development, and learning in a multicultural environment, as mentioned earlier, is an important part of multiliteracies. In addition, Gottschalk's (2019) review also mentioned that the use of social media by digital technology may be associated with increased gray matter in the amygdala, which is a region of the brain associated with emotional learning and memory.

Contrarily, although digital technology has helped students gain new cognitive skills such as multitasking and spatial orientation, the heavy use of technology has also been suspected to have some negative effects on student learnings. For example, in a review article from Cavanaugh, Giapponi & Golden et al., 2016, it was mentioned that a study from Greenfield (2009) also demonstrated that digital technology was found to negatively affect students' deep processing skills including critical thinking and self-reflection in brain. Digital reading is also mentioned in this review and is thought to cause the brain to minimize sufficient deep cognitive function (e.g., Wolf, 2007 as cited in Cavanaugh et al., 2016). This review also mentioned that Small and Vorgan (2008) claimed that cognitive high pressure can be caused by continuous partial attention and multitasking, and therefore can lead to decreasing time for reflection and contemplation.

Landhuis et al. (2007) demonstrated that long periods of TV watching may cause attention problems during children's growth (cited in Gottschalk, 2019). Another two studies (Bergen, Grimes & Potter, 2005; Hembrooke & Gay, 2003) in this review showed that digital technology may lead to shorter working memory. However, Cavanaugh et al. (2016) also clarified that these neuroscience studies only sufficiently formed “suggestive correlations” (p.383) instead of “linear causes and effects” (p.383), and that more research is needed to provide further insight. Studying the shortcomings of digital technology through neuroscience technology, as explored in the previous examples, may help us find ways to improve the methods of applying digital technology in teaching and learning from cognitive perspective and provide evidence-based suggestions for teaching design.

The previous research findings indicated that using neuroimaging tools to develop insights on how multimodality and educational technology may support or influence the brain development is both important and possible. Besides, neuroscience findings can also be used to design and develop educational learning techniques (e.g., Jordan & Levine, 2009 as cited in Howard-Jones et al., 2015b). For example, Dahlstrom‐Hakki et al. (2019) imagined the possibility of using neuroscience tools as a method for assessing implicit knowledge and applying it in a classroom environment. However, little work has been done to use neuroscience to "inform the design and use of technology-enhanced learning (TEL)" (Howard-Jones et al., 2015b). Neuroscience also has the potential to help us understand which multimodal learning environment design is effective or not, and the reasons behind their efficacies. However, Ng & Ong (2018) argued that neuroscience research is limited in the field of digital learning environment (DLE), which is an important application of multimodality. Ng & Ong (2018) argue that more research is needed to explore this field, especially regarding how to use multimodality to improve learning instead of only paying attention to learning outcomes.

In addition, given that multimodality is an essential part of multiliteracies, the brain's multisensory processing abilities (e.g., the visual and auditory stimuli used in this experiment) which remain largely unknown (Gentile et al., 2017) is important. Studies have shown that multisensory processing is spatially separated from modality-specific neurons (e.g., Schroeder et al., 2003 as cited in Gentile et al., 2017). Superior Temporal Gyrus (STG) is well-knowned for its importance in phonetic processing (Petittl & Dunbar, 2012); some studies have found that superior temporal gyrus (STG) is also related to the processing of multisensory information, and can respond to "both visual and auditory inputs, and where responses are enhanced for audiovisual inputs compared with when each input is presented alone" (Gentile et al., 2017, pp.10105).

Gentile et al (2017) examined the activation of the STG region by presenting separate visual or auditory stimulus or presenting two congruent or incongruent stimulus simultaneously (bimodal). The findings supported previous relevant research and suggested that bimodal STG (bSTG) was "not exclusively composed by bimodal voxels" (pp.10110) but can respond to both unimodal visual or audio inputs and bimodal inputs. In addition, an important finding relevant to the design of this experiment revealed that "natural/nonlanguage stimuli and artificial/language stimuli activated the bSTG in different manners" (pp.10110-10111), which suggests that bSTG region can be related to literacy and language learning (Gentile et al., 2017). Although these existing neuroscience studies have identified some of the neural mechanisms related to the effects of multimodal and multisensory processing and technology on brain development, more research is still needed in this field.

2.3.3 Neuroscience in ESL and FL

With the development of research questions and technologies, there are increasing methods to conduct FL-related research, including using neuroscience tools to measure cognitive process (Mackey, 2014). Neuroscience and neuroimaging techniques can provide researchers with understanding of how brain processes language and how different factors affect this process (e.g., Sabourin, 2009). Although neuroscience has become more widely used in language-related research and has shown its great potential (e.g., provide scientific foundations for the design of language teaching) in this field, the neural mechanism under language learning and processing has not yet to be fully understood. There are also some debates, misunderstandings or over-generalized claims of existing findings that still need to be further explored (Nouri, 2015; Sabourin, 2009). Sabourin (2009) also argued that while the traditional educational research method is important, neuroscience can provide "extra information" (pp.7) vital to understanding some controversy in the field of language learning research. This part briefly sums up some experiment designs, conclusions and findings regarding FL learning and teaching that related to this study the neuroscience perspective.

Many neuroimaging and neuroscience tools can contribute to the understanding of language and FL learning. Rossi et al. (2012) claimed that electrophysiological approaches (e.g., EEG, MEG) which have high temporal resolution performed a "cornerstone" (pp.152) role in neuroscience-language research but usually have relatively low spatial resolution. Additionally, Rossi et al. (2012) also argued that vascular-based techniques such as fMRI, PET have better spatial resolution but usually have large volume which cannot provide a natural environment. However, fNIRS can be used in a relatively natural environment, which can make it useful in language learning settings (see next part).

Nouri (2015) argued that learning in both the first language and foreign language can promote each other, which strongly denied some remarks that FL learning will interfere with first language learning and supported the role of prior knowledge. Petitto & Dunbar (2012) also saw this as a milestone for neuroscience application in bilingual research and as a meaningful method for teaching practices. Moreover, recent studies have showed that auditory training is an important part of FL learning (e.g., Winke, 2013), which supports the idea that students will perform better in experimental trials that require them to distinguish the emotion in voices after their ESL learning.

Besides, another important aspect of language and FL learning in neuroscience findings is that the brain is somewhat modular (e.g., Munsell, 1988), in other words, some brain areas are essential for specific functions, even though no brain regions can function independently from one another. The phonological processing in the brain, especially phonetic perception, is the most thoroughly investigated research area in terms of brain structure (e.g., Wen, Biedroń, & Skehan, 2016). In earlier studies, several brain regions that are important for language have been summarized and are called language centers, including Broca’s Area, Wernicke’s Area, Angular Gyrus, and Insular Cortex. A well-known phenomenon, demonstrated through many studies, showed that damage in Broca’s Area or Wernicke’s Area leads to language-related disabilities. Among them, the Broca’s Area was found to be related to phonological, semantic, and syntactic processing as well as working memory, in which the anterior part of this area participates in the semantic process and the posterior is more related to the phonological process (Bohsali et al., 2015). Wernicke’s Area is considered to be related to language understanding; in addition to Wernicke’s Area, other areas around it include the left posterior superior temporal gyrus (pSTG), middle temporal gyrus (MTG), inferior temporal gyrus (ITG), supramarginal gyrus (SMG), and angular gyrus (AG) have all been found to have relationships with language understanding (e.g., Binder, 2015; Weber et al., 2016 as cited in Ng & Ong, 2018).

Among them, angular gyrus can help process both concrete and abstract words, symbols and concepts and also participates in visual memory (Seghier, 2012).

The insular cortex can also participate in language processing as well as other functions such as motor control, emotion, sensory and self-awareness (Oh, Duerden & Pang, 2014). However, insular cortex is difficult to be detected by the neuroimaging technique used in this research, fNIRS, because it is buried deep beneath the outer lobes of the cerebral cortex.

According to Balaguer and Rodríguez Fornells (2010), both the prefrontal cortex (PFC, including the inferior frontal gyrus, IFG) which is also related to emotional processing (e.g., Balconi, Grippa, & Vanutelli, 2015), and temporal cortex (including MTG and STG) is related to morphosyntactic processing; besides, a review from Quaresima et al. (2012) indicated that most language-related neuroimaging studies paid attention to the frontal and temporal areas in the brain, although some of them also included the parietal area. Morgan-Short et al. (2010) also demonstrated the importance of using the longitudinal design to study language learning to understand the learning process.

In addition, the left and right hemispheres of the brain also have different functions regarding language processing. When processing language-related infomration, different areas of brain are activated. For example, although language processing is predominantly processed in the left hemisphere in over 90% of right-handed people, the right hemisphere can also be important for other language-related tasks, such as modulating speech to make meaning clear; in addition, the right hemisphere is often considered to be related to emotional and perceived tasks (Taura, 2014; Riza, 2002; Mayers, 1993 as cited in Riza, 2002).

Moreover, the lateralization of the brain is different between bilingual and monolingual populations, although this difference is related to the age of exposure to foreign languages (i.e., people who are late in being bilingual often show more bilateral activation and more cognitive efforts) (e.g., Kim, Relkin, Lee & Hirsch, 1997 as cited in Petitto & Dunbar, 2012). Munsell (1988) argues that modular is much more important than the lateralization of the brain. Jasinska's (2013) study showed that bilinguals can activate the right brain to a greater extent than monolinguals and FL learning may promote the language processing of double hemispheres. A study from Sugiura et al. (2011) developed a similar conclusion that FL learning leads to hemispherical asymmetry in language processing in elementary school students in Japan, especially in the inferior frontal region and inferior parietal regions. Specifically, when dealing with unfamiliar foreign language words, students relied more on the right hemisphere (especially in the SMG region), while the left hemisphere had stronger activation when processing high-frequency words (especially in the angular gyrus area). All these studies have shown that in the study of language, especially for FL learning, research on both hemispheres is necessary.

2.4 Functional Near Infrared Spectroscopy (fNIRS)

Both fNIRS and fMRI are functional neuroimaging techniques which can examine changes in blood oxygen changes in the brain (e.g., Ng & Ong, 2018). fNIRS is a non-invasive neuroimaging technology that measures cerebral hemodynamic response in oxygenation (HbO) and deoxygenation (HbR) states in the brain. During a task or initiating a movement, oxygenated blood will rush to regionally-specific bran regions and there will be a compensatory change in deoxygenated blood and this can be imaged with fNIRS and thus to “observe” brain activity (e.g., Petitto & Dunbar, 2012; Ansaldo, Kahlaoui & Joanette, 2012; Quaresima et al., 2012; Plichta et al., 2011).

Increased oxyHb and decreased deoxyHb parameters are thought to correspond to increased changes local brain activity (Lloyd-Fox et al., 2010 as cited in Ravicz, 2015). To explain it from an single neuron level, oxygen that, can be transported to neural tissue via oxy-hemoglobin in the blood, is required to metabolize the glucose to provide energy for neuron activity when the brain region got activated; after oxy-hemoglobin delivers out the oxygen, it is transformed into deoxygenated hemoglobin (Heeger & Ress, 2002). Therefore, the rise and fall of oxygenated hemoglobin levels (and the fall and rise of the deoxygenated hemoglobin levels) in a specific brain region can indicate the occurrence and end of an event in that brain region. The fNIRS instrument calculates parameters of oxyHb and deoxyHb by emitting light and detecting reflected light and can therefore reflect activity in a certain area. Although its principles are similar to fMRI, fNIRS is more portable than fMRI and also has better temporal resolution than fMRI. In addition, compared with EEG, which also has good temporal resolution and portability, it has better spatial resolution.

Regarding this study, fNIRS is important to language studies and “has proven to be very valuable in providing a rough localization of the brain areas underlying language processes” (Rossi et al., 2012, pp.154), because it is quiet and will not be disturbed by environmental noise, which means participants will not need a dedicated environment and can receive audio stimuli when they are measured for brain activity. The portability of fNIRS allows experiments to be conducted in any setting (i.e., natural environment) instead of being limited to strict laboratory environments, which compares favourably with the limitations of other functional neuroimaging tools (Ansaldo et al., 2012; Holper et al., 2013; Dahlstrom-Hakki, 2019). Howard-Jones (2015b) argued that EEG is portable but has low spatial resolution, and that fMRI has good spatial resolution but involves a noisy environment, and fNIRS can solve these disadvantages of other brain imaging techniques in some way. Besides, fNIRS allows a long-time measuring - which means participants can be observed during their long educational activities (Quaresima et al., 2012). It also has tolerance for subtle movements which means participants do not need to hold their heads still (e.g., Petitto & Dunbar, 2012; Tuara, 2014; Ansaldo et al., 2012; Scherer et al., 2012; Plichta et al., 2011). Aside from those, fNIRS is relatively inexpensive compared with the fMRI or PET (Scherer et al., 2012; Ansaldo et al., 2012).

Rossi et al. (2012) mentioned that “an important advantage of fNIRS is the sensitivity to long-lasting or slowly evolving stimulus features, critical for the investigation of prosody”, which fits our experimental design using emotional stimulation that actors speaks in different prosody. All those advantages of fNIRS helped to supplement neuroscience research on language development.

A recent study from Li et al. (2020) used fNIRS to test the activation in the prefrontal cortex (PFC) and temporo-parietal junction (TPJ) (including SMG and STG) in Chinese ESL adult learners. Research findings suggest that activation in TPJ is inversely related to auditory input processing while activation in PFC is positively correlated with listening proficiency. This study demonstrates the feasibility and superiority of using fNIRS for experiments in auditory-related FL learning research.

In addition to its superior applications in language learning, fNIRS is also useful in measuring sensory and multisensory interactions, and many fNIRS studies have suggested that PFC and STC are strongly related with emotional activation, visual stimulation and multisensory processing (e.g., Balconi, Grippa, & Vanutelli, 2015). The study from Balconi, Grippa and Vanutelli (2015) also suggested that negative emotion can lead to lateralization effect (i.e., more right-PFC activity). For example, a study from Ravicz, Perdue, Westerlund, Vanderwert and Nelson (2015) used fNIRS to measure infants' prefrontal cortex neural responses to facial emotions. In addition, Wiggins and Hartley's (2015) research is the first application investigating multisensory processing in adults by studying the influence of sounds on the visual cortex in occipital lobe, which showed that it is feasible to study brain structure in perception by fNIRS. Schneider's (2014) fNIRS study used a speed judgement task as a control group to study on the influence of emotion stimuli on brain, and found that negative emotion was related to increased brain activity in right extrastriata body area (EBA, located within the lateral occipitotemporal cortex), right ITG, left TPJ and left superior temporal sulcus (STS).

Although fNIRS has some advantages in language, emotion and sensory-related research, it also has some disadvantages, including its inability to provide anatomical images. This may require us to accurately define the areas we are interested in, and apply them for further analysis (e.g., Plichta et al., 2011). Moreover, the spatial resolution of fNIRS is not very high and it cannot be used to detect brain regions "deeper than the outermost 10-15mm of intracranial space" (Strangman, Li & Zhang, 2013 as cited in Wiggins & Hartley, 2015, p.15). However, these disadvantages did not affect our analysis given that all the general locations of brain activity can be detected by fNIRS and these regions were all that were required for this study. Besides, the spatial resolution that fNIRS can provide is approximately 1cm^2, thus the findings were limited to superficial cortical regions of the brain (e.g., Miguel et al., 2019).

Although fNIRS has shown its superiority in language studies, there are still plenty of gaps in this field. Ansaldo et al. (2012) argued that despite its strong advantages, fNIRS is not a popular choice for brain science research in language. Therefore, this study has the potential to enrich the research of fNIRS in the field of language. Quaresima et al. (2012) summarized that most of fNIRS studies performed on adults in the domain of language paid attention to "underlying metabolic mechanism during vocalization and semantic processes, categorical perception of phonemes, speech recognition, discourse processing, language comprehension, etc" (pp.83), which suggests only a few of these studies were designed to include both multiliteracies pedagogy and FL learning. In addition, the application of fNIRS in adult research is much less common than with infants and young children. However, Ravicz et al. (2015) mentioned that "the brain topography is less well mapped for infants than adults" (p.6), which indicated that fNIRS may work better on adults than infants. A paper from Obrig (1999) also discussed the time advantage of fNIRS compared with fMRI regarding the adult brain and used three experiments to support the potential role of fNIRS in functional research of the adult brain.

Chapter 3

3 Methodology

This chapter explains the methodology used in the study. This chapter begins with the context of this research, and then comes to the ontology and epistemology used in this study. Next, the third part introduces the specific research design and data collection procedure, while fourth part is the description of the study participants. Then, the materials (i.e., the stimulus used in the e-prime experiment) and the instruments (i.e., the questionnaires and interview questions used in the research) are introduced. Finally, the data analysis process was elaborated upon, which includes the preliminary data analysis, data coding, and the hypothesis before data analysis.

3.1 Research Context

The context of this research is in London, Ontario, Canada. To find more eligible participants, the recruitment scope was expanded upon from an ESL program in the Western English Language Center (WELC) to all ESL programs or courses in all language schools in London, Ontario. Although the initial plan was to compare the behaviour data and brain activities data of subjects before and after their language learning, the first session of the experiment was primarily in the middle of language learning due to the slow progress of the recruitment process, which may lead to insignificant outcomes when analyzing. However, all the participants in the experiment have had several years of experience in learning English before entering the ESL programs from which I worked on, so this error is considered acceptable to some extent. The experiment was conducted at the Western Interdisciplinary Research Building (WIRB).

3.2 Ontology and Epistemology

The ontology used in this study is materialism and the epistemology of the study is rationalism because the content of the study (i.e., how can brain activities be related to multiliteracies learning) is considered to objectively exist, will not be interfered by human will, and we can find reason underlying it with a rational method. The worldview adopted by this research is pragmatic worldview, which utilizes pluralistic approaches to conduct studies, believes mixed methods of quantitative and qualitative can provide the best understanding of the research problem, and guarantees that researchers have freedom to choose research methods (Creswell, 2014). Although the initial plan was to include an interview in a mixed method design, due to the influence of COVID-19, the interview was not conducted, and this research featured a quantitative research design. The experimental design of the quantitative method is longitudinal, which will be further explained in part 3.3.

3.3 Research Design and Data Collection

The experiment design of this study is a longitudinal experiment – participants need to participant in two sessions in the middle of and after their multiliteracies learning. In addition, students need to complete a pre-test of six questionnaires on language experience and proficiency, handedness, technology usage, empathy, and social responsiveness in the 1st session and complete a post-test of one questionnaire on language experience and proficiency in the 2nd session. The experiment of each of the two sessions followed the same procedure: during the testing, the participant sat in front of the computer screen; they were then required to use iPad to complete a mirror tracing tasks and the time spent on completing it was recorded; After these tasks, participants wore the fNIRS cap which had 32 sources and 32 detectors (see Figure 1) to record the hemoglobin states in brain during the entire e-prime experiment. In this experiment, participants did the multimodal tasks on computer which asked them to determine the emotion of the actors in each video for stimulus trials, as well as provide the basic information of the video for the rest trails by making multiple-choice responses on the computer where their reaction time and answer were recorded. Each experiment included 128 trails with 64 emotional stimulus and 64 rest trails (see Figure 2) and the design was balanced, which meant there were 32 congruent trials and 32 incongruent trials in each experiment. The questions for emotional stimulus were: what emotion best matches the voice/face and the questions for rest trials were questions about the content of the video (e.g., what sound do you hear in the video?). All questions were demonstrated read-only (i.e., with no voices). All stimulus that were used in the study were from RAVDESS (see 3.5). FNIRS data were collected through the whole experiment.

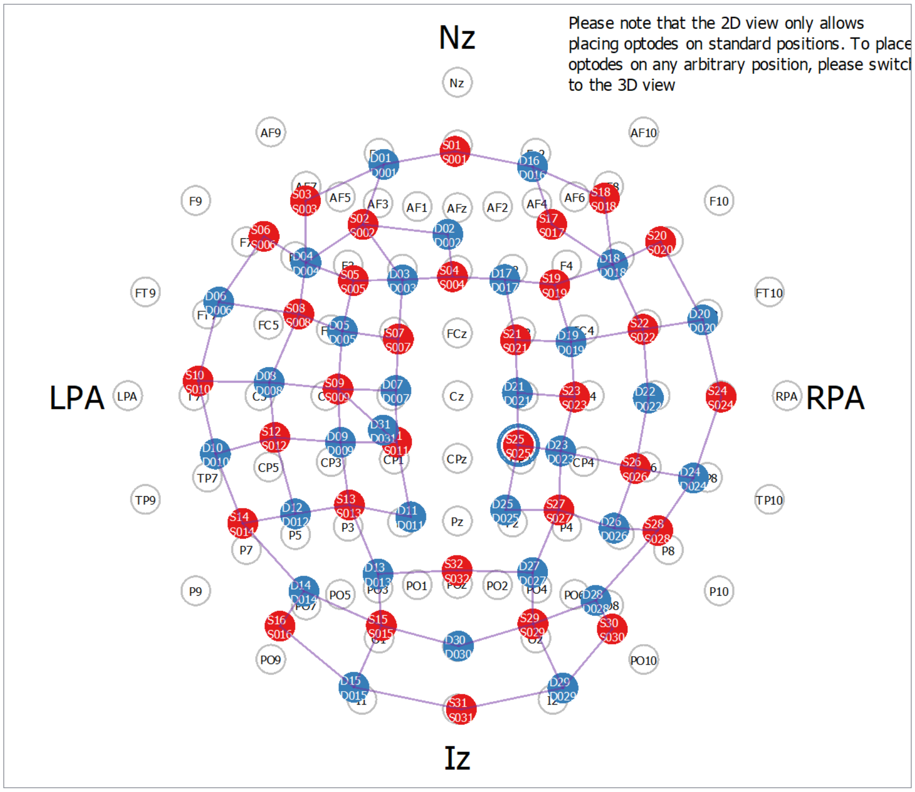

Figure 1: The Probe Layout for the Study (s represents sources and d represents detectors)

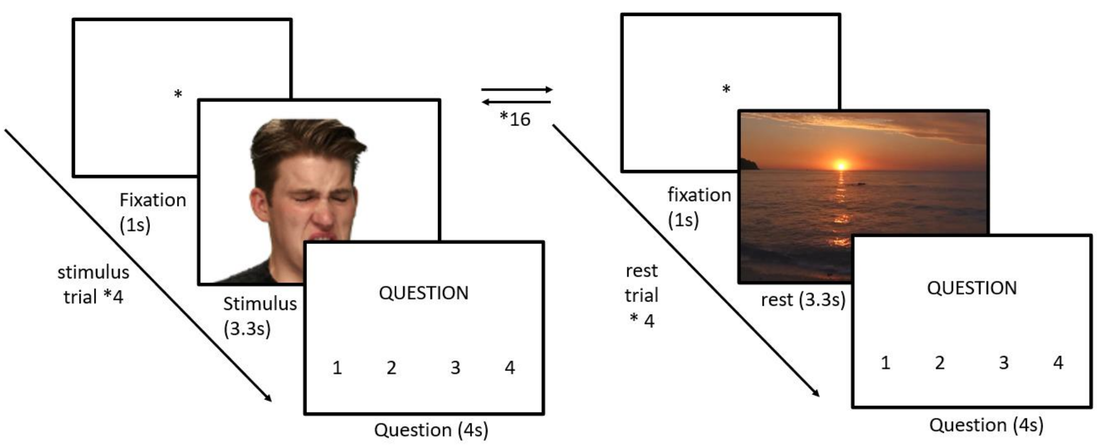

Figure 2: E-prime Experiment Procedure

All quantitative data were collected throughout the two sessions of experiment and in Fall 2019 and Winter 2020. Table 1 summarizes the five main kinds of data that were collected for this study.

Table 1: Data Sets and Types

Data Set	Data Type	Data collection Method
Questionnaire data	Quantitative	Six questionnaires in session 1 (n=6); and 1 questionnaire in session 2 (n=5)
Mirror tracing task data	Quantitative	Mirror tracking task on iPad (n=6 in session 1 and n=5 in session 2)
Behavioural data (multiliteracies tasks performance data)	Quantitative	E-prime experiment (n=6 in session 1 and n=5 in session 2)
fNIRS data	Quantitative	fNIRS (n=6 in session 1 and n=4 in session 2)

The independent variables in this thesis include: 1) time of experimentation (i.e., before and after multiliteracies learning; 2) different kinds of emotion (i.e., happy, neutral, angry and fearful); 3) congruency of experimental stimulus (i.e., a congruent stimuli means the actors have the same emotion of voice and face, while incongruent stimuli means the actors have different emotion for voice and face); 4) the intensity of the emotion in stimuli; 5) the score of digital literacy background of students which was coded and calculated from the technology questionnaire; 6) gender of participants and 7) question type (i.e., for the stimuli trials, there was one question for each trial which asks for each face or voice, and the question type are face-related questions and voice-related questions). The dependent variables of this study include behavioural data (i.e., reaction time and the correctness of the answer) and fNIRS data.

Table 2 summarizes how each variable served as independent and dependent variables to answer the three research questions.

Table 2: Summary of Variables Used for Answering Research Questions

Research Question	Independent Variable	Dependent Variable	Data Set
RQ1.1	multimodality background, congruency, emotion types and intensity of stimuli, gender of participants, question types	reaction time; correctness;	Behavioural data; Questionnaire data
RQ1.2	Time (session 1 & 2), congruency types, emotion types		
RQ2.1	multimodality background, congruency types, emotion types	fNIRS data	Questionnaire data; fNIRS data
RQ2.2	Time (session 1 & 2), congruency types, emotion types		

3.4 Participants

Participants were in the age range of 17-25 years old (i.e., the most common university and college age), enrolled in an ESL program or course during the two sessions of the study. They were required to have some English foundation to complete the relevant questionnaires and experiments. In addition, participants could not have red hair, which has been found to interfere with fNIRS data collection significantly. At the end of each session, participants were eligible to receive a gift card ($20 for the 1st session and $40 for the 2nd session) as compensation for their time.

The final number of participants was 6, which did not achieve the initial recruitment expectations because of the interruption of data collection due to the COVID-19 outbreak. Among the 6 participants, all 6 participated in the first session while only 5 participated in the second session, and 1 collection of fNIRS data in the 2nd session was damaged due to the hardware complication. Four participants were female, and two participants were male in the first session, and four participants were female, and one participant was male in the second session.

Among all participants, five of them were participating the ESL program is Western English Language Centre (WELC) in order to fulfill the requirement of entering into grade 1 of university; one of them was participating the ESL program in a college in London, which also aims to fulfill the requirement of entering into grade 1 of college. There are some related questionnaire results indicating that they have used science and technology in the classroom and exposed to multimodal information including videos, pictures, etc. during their ESL learning, but the more specific classroom practice was unknown.

3.5 Research Materials and Instruments

3.5.1 Questionnaires

Six questionnaires were used to understand participants' background before and after multiliteracies learning including questionnaires on language experience and proficiency, handedness, technology usage, empathy, social responsiveness, and demographics. As this paper mainly focuses on the impact of the multimodal part of multiliteracies, only the questionnaire regarding technology usage was used and coded for data analysis in this thesis. Given that the questionnaire primarily focused on the use of digital technology, the coded questionnaire was considered to represent the participants' multimodality background, which is also an important part of multimodality and multiliteracies.

To ensure the reliability and validity of the questionnaire, all questionnaires used have been widely accepted and have verified scales, except for the demographic questionnaire and technology usage questionnaire. For language experience and proficiency, The Language Experience and Proficiency Questionnaire (LEAP-Q), developed by Marian, Blumenfeld and Kaushanskaya (2007), was used. For handedness, the 10-item Hand Preference Questionnaire with Three Response Categories, developed by Porac (2016), was used. For empathy, the Toronto Empathy Questionnaire, developed by Spreng et al. (2009), was used. For social responsiveness, the Social Responsiveness Scale (SRS), developed by Constantino and Gruber (2012), was used.

For the technology usage questionnaire, the majority of this questionnaire was developed by my lab members and thesis committee member, and a small portion of the questions and baseline/concepts were selected from several sources, including the Student Technology Survey by Western and Lawson Research, Internet Skills Scale (ISS) developed by Alexander et al. (2016) and Everyday Technology Use Questionnaire (ETUQ) developed by Nygard (2002) and verified by Rosenberg, Nygard and Kottorp (2009). Only parts of these questions were chosen for evaluating participants' multimodality background in this thesis (see Chapter 4).

3.5.2 Mirror Tracing Task

The mirror tracing task is a procedural or implicit memory task and uses eye-hand coordination and motor learning (Telles, 2006; Frase et al., 2020). Procedural memory refers to the memory of how to do certain procedures such as how to ride a bike, and it is related to the motor skills. In this task, participants should firstly draw a pentagram pattern based on the template on the website, and then draw a mirror pentagram pattern. The time spent on drawing initial pattern and the mirror pattern was recorded. The participants had no training on this task and therefore should show no change in performance over time. Only the time using on this task was recorded so there would be no comparisons on deviations from template. The selected task is a free task found on the Internet (https://projectneuron.illinois.edu/games/mirror-tracing-game?shape=star5).

3.5.3 E-prime Experiment Stimulus Materials

The reason why we chose emotional videos as the stimulus was to ensure that the videos have both visual and audio stimuli which can therefore activate bimodal information processing in the brain and allow me to study the cognitive mechanisms behind it. Additionally, many neuroscience studies have shown that emotions have a strong connection with learning and language, including language learning, which may contribute to the development of emotional intelligence (e.g., Brand, 1999; Hinton et al., 2008; Chwilla et al., 2011). This ultimately indicates that, language learning may enhance the judgment and perception of emotions. Thirdly, a study by Vouloumanos, 2009 showed because participants can connect people's face with their speech from their infant period, the use of both facial and auditory stimuli may provide feedback on their perception of semantic language. Additionally, a fNIRS study from Plichta et al. (2011) showed that emotional stimuli can lead to an enhanced activation of sensory areas in brain, involving both the visual and audio cortex. Another study from Schneider et al. (2014) similarly showed that visual emotional stimuli can lead to increased oxygenated haemoglobin (oxyHB) and mentioned the dynamic stimuli (e.g., video stimuli) can lead to enhanced emotional perception (Grèzes et al., 2007 as cited in Schneider et al., 2014). These results also support the proposal that emotional stimuli can be related to multisensory perception, which is strongly related to multimodal and multiliteracies learning.

The multimodal emotional video datasets used for this study is RAVDESS. According to Livingstone and Russo (2018), one of the main advantage of this dataset is its richness, as it has 7356 clips; In addition, it provides two intensities of each emotions (normal and strong); it also have two baselines of emotion including neutral and calm, and neutral emotion are selected as the baseline emotion in this study. Correspondingly, the actors in RAVDESS are all native North American English speakers, and the content of speech (i.e., the content of the statement) is neutral (i.e., kids are talking by the door). In addition to the two baseline emotions above, RAVDESS also contains six emotional states that are common in all cultures (i.e., happy, sad, angry, fearful, surprise and disgust), although only 3 emotional states (i.e., happy, angry fearful) and one baseline emotion (i.e., neutral) were chosen for this study. All these advantages provide ample experimental stimulus choices, with only minor errors due to different actors and the content of speech. Therefore, RAVDESS was the ideal choice for this study. Figure 3.2 shows four still image frames examples of each of the emotional expressions used in this study.

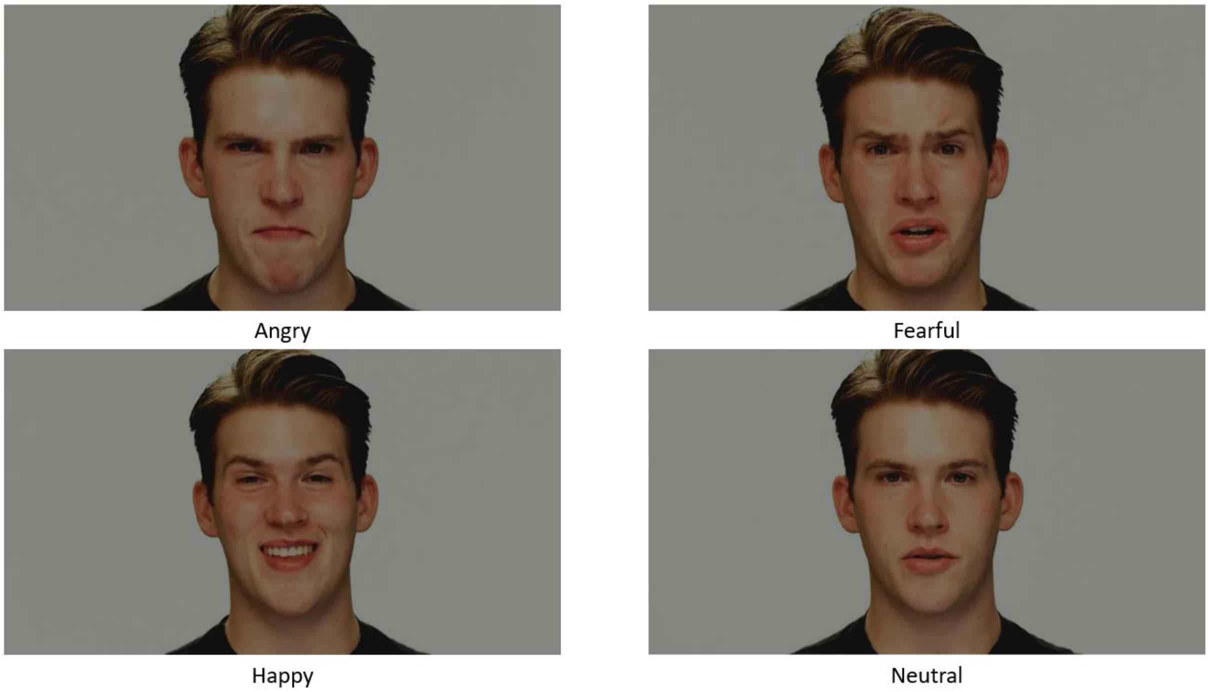

Figure 3: Still Image Frame Examples of Four Used Emotions

3.6 Data Analysis

3.6.1 Data Coding

Data Coding of Technology Usage Questionnaire.

Due to the large quantities of questions in Technology Usage Questionnaire (see Appendix A) and the limited number of participants, the questions of the science and technology questionnaire were further screened and coded.

Firstly, Q28 was excluded given that some answers were missed for this question. Then, 8 questions were excluded because the answers for the six participants for these 8 questions were the same and had no statistical significance including Q23, Q24, Q30, Q33, Q34, Q36, Q37, Q50. Thirdly, the 9 statements under question Q43 (from Q43_1 to Q43_9) were deleted because they used a different scale (3-level) with other questions and could not be analyzed without much difficulty. The other reason for deleting these 9 statements was that they had too much overlap with statements in Q42. Fourthly, four questionnaire questions or statements (Q4, Q20, Q25, Q31) were considered less relevant to multiliteracies or multimodality, and thus were excluded.

Fifthly, the values for answer were recoded for questions Q1, Q2, Q3, Q5, Q6, Q7 and Q8 because the statements for these questions were negative and the statements of other questions were all positive. For these questions, 1 was coded as "very true of me", 2 was coded as "mostly true of me", 3 was coded as "neither true nor untrue of me", 4 was coded as "not very true of me" and 5 was coded as" not at all true of me ", which was the opposite of the coding order of other questions or statements. Similarly, the answer items for Q41 were also recoded for their order difference with other questions' answer items.

In the initial design of the questionnaire, the questions in the questionnaire were divided into five categories, namely computer use, information navigation, social skills, creative skills and operational skills.

Reliability. Due to the limitation of the number of subjects, it is impossible to calculate the test-retest reliability (i.e., external reliability) of the questionnaire. Therefore, only the internal reliability of the questionnaire, that is, the Alpha reliability was calculated. As shown in the Table 3.3, the alpha reliability value of the questionnaire after screening was 0.883, indicating that the questionnaire had good internal consistency. Among them, for the computer use part (from Q40 to Q42 and from Q45 to Q56), the alpha reliability value was 0.861; for the information navigation part, the alpha reliability value was 0.647; for the social skills part, the alpha reliability value was 0.701; for the creative skills, the alpha reliability value was 0.732; for the operational skills, the alpha reliability value was 0.801. In summary, the reliability of each part of the questionnaire was qualified, and the reliability for most parts of the questionnaire and the whole questionnaire was high enough to prove the reliability of the questionnaire.

Validity. For content validity, because there was no questionnaire that fully met the requirements of this study, as mentioned above, the questionnaire was developed after reading multiple references related scales. This questionnaire was therefore considered to have good content validity. For construct validity, due to the limitation of the number of subjects, KMO test could not be used to analyze structural validity, so only principle components analysis (PCA) was used to analyze content validity. SPSS was used to conduct PCA and using varimax for rotation and the extraction was set to base on 5 factors as mentioned above. In order to make the analysis results clearer, a filter was conducted to show only those with the absolute value of the correlation coefficient greater than 0.5 in the table (as shown in Figure 4).

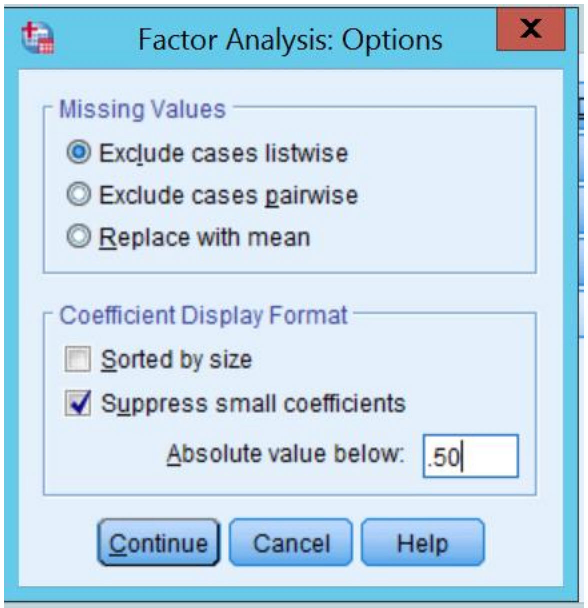

Figure 4: Filter the Value of the Correlation Coefficient Greater than 0.5

The results of the first PCA analysis are shown in the Appendix B. Although the five factors can explain 100% of the variance, some components have the problem that they can explain more than one factors, or that they do not belong to the initial factor.

The first factor should have been computer use and should have contained questions Q40 to Q42 and Q45 to Q56. However, the components Q42_1, Q42_4, Q42_6, Q42_7, Q42_15, Q45, Q46, Q47, Q48, Q51, Q53, Q54, Q55 did not explain the first factor. Therefore, these 13 questions should be deleted. Similarly, Q26 was deleted because it cannot explain the second factor, which should be operational skills; Q15, Q18, Q21 were deleted because they cannot explain the third factor, creative skills. There were two questions in both remaining two categories that could explain the factor 5. However, because the questions that belongs to the information navigation (from Q1 to Q8) part explained a higher variation for factor 5 (0.888 and 0.964), it was considered that the factor 5 should be information navigation, and the factors that cannot explain the factor 5 were deleted including Q1, Q2, Q3, Q5, Q8. Consequently, Q9, Q10, Q12, Q13, Q14 were deleted because only one of them (Q14) could explain the factor 4 and it could explain more than one factors, which would cause confusion. Thus, only 4 factors were left.

After deleting the above components, the second PCA was conducted. Q42_3, Q42_8, Q42_12, Q49 and Q52 could explain more than one factors which would cause confusion, so they should be deleted; Q29 could also explain more than one components, but it was temporarily retained because there are only four components remained for the factor 2 (i.e., operational skills).

Then, the third PCA was conducted, which showed that Q56 should be deleted because it could explain more than one factors; Q19 and Q29 could also explain more than one components, but they were temporarily retained because there were only four components remaining for the factor 2 (i.e., operational skills) and 3(i.e., creative skills).

Then, the fourth PCA was conducted and the results were acceptable even though Q19 and Q29 could explain more than one component. Q40, Q41, Q42_2, Q42_5, Q42_9, Q42_10, Q42_11, Q42_13 and Q42_14 belongs to factor 1, which should have been computer use; Q27, Q29, Q32, Q35 belongs to factor 2, which should have been operational skills; Q16, Q17, Q19 and Q22 belongs to factor 3, which should have been creative skills. Q6 and Q7 belongs to factor 4, which should have been information navigation.

After the above steps, the internal consistency reliability (alpha reliability) of this questionnaire was calculated again to be 0.816. Therefore, the questionnaire composed of the remaining questions and statements was considered to have good reliability and validity, and thus can be used for further analysis.

Since the answers to the questions have been recoded in the previous steps and all questions have used the five-level scale, the scores in this questionnaire for each participant were calculated by adding all values for each question. According to the scoring method described previously, the total scores of the six subjects were 74, 84, 54, 76, 75 and 71 respectively. Participants were divided into two groups: group with high multimodality background (G1) and group with low multimodality background (G2) based on the score. G1 had 5 subjects (the score of 74, 84, 76, 75 ,71) while G2 had only 1 subject (the score of 54, a female subject). The independent sample t-test was conducted to compare the difference between the two groups and the results showed the difference was significant ($t = 4.143$, $p = .014$). Research question 1.1 and 2.2 were based on the two groups.

3.6.2 Data Analysis Procedure for Each Research Question

Research Question 1.

The research question 1 was based on the behavioural data and could be analysed directly through SAS. There are two dependent variables: the reaction time for each trial of response which is a continuous variable, and whether the response is correct (i.e., the correctness) which is a binary variable. The independent variables include the multimodality background, the type of question used (face-related or voice-related), gender of subjects, whether the stimulus is congruent, the type of emotion, the intensity of emotion. The analysis methods used includes descriptive statistics that demonstrated the basic information for all kinds of data, the bivariate relationship analyses which used t-test, ANOVA and Chi-square to show the relationship between each independent variable and the dependent variable, and the multiple linear regression (MLR)/ binary logistic regression (BLR) for the main analysis which established a model to showing the relationship between all independent variables and dependent variables..

Firstly, the descriptive analysis was performed to show the mean and the standard deviation for continuous variables, as well as the number and percentage (i.e., frequencies) for each type for nominal variables of the each group within both research question 1.1 and 1.2. For research question 1.1, the higher multimodality background means group 1 and the lower multimodality background means the group 2; for research question 1.2, only the data for session 2 was used for descriptive analysis. Consequentially, all descriptive statistics were conducted only for test trials using “filter data” function and rest trials were excluded.

Secondly, t-test, ANOVA and chi-square were used to see, first, if there is a relationship between each independent variable with each other, and second, if there is a relationship between each independent variable and each dependent variable. Ultimately, this was to guarantee that the MLR/BLR model was suitable for this research.

Thirdly, MLR was conducted to see if the multimodality background, the type of question used (face-related or voice-related), whether the stimulus is congruent, the type of emotion, the intensity of emotion, gender of subjects can predict participants' performance (i.e., the reaction time) in this experiment. Additionally, for research question 1.2, the comparison for the two MLR models for data collected in session 1 and session 2 were included.

The null hypothesis for the MLR model for reaction time the regression model does not fit the data better than the baseline model. None of the coefficients will differ from 0. $\beta 1 = \beta 2 = \ldots = \beta k = 0$. The alternative hypothesis is that the regression model does fit the data better than the baseline model. At least one of the coefficients will differ from 0, and not all βis will equal zero. To be more specific, in a multivariate model, higher multimodality background, congruent stimulus, angry emotion, stronger intensity of stimulus, face-related question and female subjects will lead to less reaction time compared with other kinds of independent variables. Besides, for the comparison between the session 1 model and session 2 model, the influence of the different kinds of independent variables will become lower because they have better understanding on English and multiliteracies.

Fourthly, BLR was run to see if the multimodality background, the type of question used (face-related or voice-related), whether the stimulus is congruent, the type of emotion, the intensity of emotion, or the gender of subjects could predict participants' performance (i.e., whether the answer is correct) in this experiment. Like the analysis in the third step, for research question 1.2, besides, the comparison for models with data collected in session 1 and session 2 was included.

The null hypothesis for the BLR model is that the regression model does not fit the data better than the model with no predictors. None of the coefficients will differ from 0. The alternative hypothesis is that the regression model does fit the data better than the model with no predictors, and that at least one of the coefficients will differ from 0. In a multivariate model, higher multimodality background (vs. lower multimodality background), congruent stimulus (vs. incongruent stimulus), angry emotion (vs happy, neutral and fearful emotion), strong intensity of stimulus (vs. regular intensity of stimulus), face-related question (vs. voice-related question) and female subject (vs. male subject) are more likely to be correct for each test trials. Similarly, for the comparison between session 1 model and session 2 model, the influence of the different kinds of independent variables will become lower given that they have both a better understanding of English and multiliteracies.

Finally, simple comparisons for the difference of the reaction time and correctness in session 1 and session 2 were also calculated using t-test in SAS to show an overview of the difference before and after multiliteracies learning. Given that it is hard to directly use t-test to compare the difference of correctness before and after learning, the accuracy of each participant in each session was calculated by correctness. The t-test comparison result for accuracy was considered to represent the difference of correction before and after multiliteracies learning. Two kinds of accuracy were calculated, one with no answer's trial and one without. Only the accuracies for stimuli trials were calculated and the rest trials were excluded. For example, for the first participant in session 1, there were 13 incorrect trials, 48 correct trials and 3 trials with no answers. The accuracy for first participant in session 1 without no answer's trial was 48/61 = .787 and the accuracy with no answer's trial was 48/64 = .750.

The null hypothesis for the simple comparison was that there will be no significant difference in reaction time and accuracy in session 1 and session 2. The alternative hypothesis for the simple comparison were the reaction time in session 2 will be significantly shorter than that in session 1 and the accuracy will be significantly higher.

Research Question 2.

The research question 2 was based on the fNIRS data. Firstly, NIRSlab was used to preprocess and analyze the data; then, in order to make the results of the analysis more accurate, part of the datawas imported into SPSS for further analysis.

Preprocessing. During the subsequent analysis, it was found that when the different events markers overlapped with each other, there would be problems in the analysis results.

Therefore, two sets of pre-processing were performed on the data of each participant in each group to include all the events that needed to be analyzed.

The first step of preprocessing was setting markers for different event files, which were different for each set of pre-processed data for each participant and each session. For each data set, the first set included the event markers of fixation, congruent stimulus, incongruent stimulus and response for stimulus; the second set included the event markers of fixation, congruent stimulus with angry, happy and fearful emotions, congruent stimulus with neutral emotion, face-related response for incongruent stimulus trials and voice-related response for incongruent stimulus trials.

The second step for pre-processing was truncating time series. Since we have marked the time when each event started in the previous step, this step was not performed except for the subject 3 in the first session in which the data was still collecting for about 40 seconds after the experiment is end, which caused disorganized data for the last 40 seconds and would lead to problems for further steps. For the subject 3 in the first session, the truncation was conducted to record only keep five seconds after the last event marker.

The third step for pre-processing was removing discontinuities and the STD threshold value was set to be 5.

The fourth step for preprocessing was to check data quality for each channel. Gain Setting value was set to be 8 and CV value was set to be 7.5%. After automatic screening, each channel that was defined as bad was checked again to further determine whether it should be finally included in the subsequent analysis. The data that was still considered acceptable was marked as good (see an example for Figure 3.3 and 3.4). For subject 1 in the first session, the channels which were detected as bad but marked as good included 29, 55, 61, 67, 92, 97 and 98; for subject 2 in the first session, the channels which were detected as bad but marked as good include 2, 8, 10, 12, 16, 22, 23, 29, 30, 31, 35, 39, 42, 44, 47, 50, 56, 58, 61, 65, 66, 67, 73, 79, 81, 84, 89, 92, 96, 97, 98; for subject 3 in the first session, the channel which was detected as bad but marked as good was 96; for subject 4 in the first session, the channels which were detected as bad but marked as good included 6, 7, 15, 16, 17, 18, 21, 22, 23, 24, 25, 26, 27, 29, 30, 31, 33, 36, 38, 44, 45, 46, 50, 52, 53, 54, 55, 56, 60, 61, 65, 66, 67, 68, 73, 92, 93; for subject 5 in the first session, the channels which were detected as bad but marked as good includde 23, 25, 28, 29, 30, 38, 44, 45, 51, 64, 94, 95; for subject 6 in the first session, the channels which were detected as bad but marked as good included 7, 11, 12, 15, 23, 24, 25, 29, 32, 34, 35, 38, 57, 58, 61, 62, 63, 65, 66, 68, 70, 74, 75, 81; for subject 2 in the second session, the channels which were detected as bad but marked as good includef 17, 18, 22, 23, 24, 36, 46, 48, 51, 53, 63, 66, 67, 68, 80, 85, 95, 98; for subject 3 in the second session, the channels which were detected as bad but marked as good included 25, 26, 32, 34, 37, 39, 50, 51, 61, 82, 84, 86, 94, 95 (all channels were marked as good because subject 3 was the only one in the second group which had a lower multimodality background and all data for this subject was needed); for subject 4 in the second session, the channels which were detected as bad but marked as good included 15, 20, 30, 32, 41, 47, 68, 82, 88; for subject 5 in the second session, the channels which were detected as bad but marked as good included 13, 14, 15, 16, 19, 20, 21, 24, 25, 26, 28, 30, 31, 32, 33, 34, 35, 38, 39, 41, 42, 43, 44, 45, 46, 47, 48, 50, 51, 52, 61, 62, 64, 67, 68, 70, 72, 73, 90, 91,92, 93, 95, 96, 97, 99.

The fifth step for preprocessing was data filtering. The filter type of band pass and all parameters were kept as default.

The last step for preprocessing was setting parameters for Beer-Lambert law which used the Spectrum proposed from W.B. Gratzer and computing hemodynamic states for further analysis. All parameters were kept as default.

Data Analysis in nirsLAB. The data analysis that can be conducted in nirsLAB is statistical parametric mapping (SPM) level 1 and level 2. Level 1 is for the single subject and can conduct the analysis between different events within the single subject; level 2 is for multiple subjects and is used to conduct comparison between different subjects or different subject groups. The data analysis that needed to be performed used the analysis results from SPM level 1, so the analysis for SPM level 1 was necessary for each dataset.

SPM level 1. As mentioned above, each dataset needed to be analyzed with SPM level to set parameters and estimate general linear model (GLM) coefficients for further analysis.

The hemoglobin data that needed to be use in this research includes oxyhemoglobin, deoxyhemoglobin, and total hemoglobin.

For parameters setting, all datasets were set to use hrf basis function and nirsLAB condition file which we created in the preprocessing steps. All other parameters were kept as default because the filtering was completed in the pre-processing steps and pre-coloring was not needed for the analysis for this research. Subsequently, the GLM coefficients were estimated automatically by the software and were saved for SPM level 2 analysis. The number of coefficients for each channel in each dataset was n+1, in which n refers to the number of conditions/events set in previous step. The last one was a constant parameter developed by nirsLAB.

SPM level 2. There were two main parts for Research Question 2, and the data analysis for these two parts was as following:

Research question 2.1 How does participants' fNIRS data in the first session relate to their multimodality background (assessed through the technology questionnaire). The subjects were divided into 2 group as mentioned above: subjects 1, 2, 4, 5, 6 were in the first group with high multimodality background while subject 3 was in the second group with low multimodality background. There were five contrasts of fNIRS data that were done for this part between these two groups: a) the difference for observing congruent stimulus in group 1 vs. group 2; b) the difference for observing incongruent stimulus in group 1 vs. group 2; c) the difference between observing congruent and incongruent stimulus in group 1 vs. group 2; d) the difference between observing fluctuating emotions stimulus (include angry, fearful and happy) and baseline emotion (neutral) in group 1 vs. group 2 and e) the difference between face-related question and voice-related question in response part in each trial in group 1 vs. group 2. Among the five contrasts, the first two were simple t-contrasts because they simply needed the contrast between two groups; the last three comparisons were F-contrasts because what needed to be known was whether the difference in the hemodynamic response in two events in group 1 is different from that in group 2. More than 1 contrasts should be conducted to verify this kind of difference, and F-contrasts (i.e., ANOVA) can use a matrix to calculate it perfectly. For all those contrasts, only the channels that had a significant difference (i.e., *p* value was set to be 0.05) were set to shown in the results because there were 99 channels in total and showing all of them would have caused confusion. The *t* values and *F*- values were exported through nirsLAB and *p* values were then calculated with these values and degrees of freedom. All *t* values and corresponding *p* values were shown for t-contrasts in Chapter 4, but the *F* values and *p* values were not shown because we cannot simply use degrees of freedom and *F* values to calculate the *p* values; if we used the degrees of freedom to calculate the *p* values, the results would not match the SPM image.

Research Question 2.2. How does participants' fNIRS data change before and after multiliteracies learning. The datasets were divided into two groups: the first group are the datasets that were collected for the first session, which occurred during the early period of multiliteracies learning; the second group are the datasets that were collected for the second session, which occurred after one semester's multiliteracies learning. There are three contrasts for fNIRS data for this part of Research Question 2 between the aforementioned two groups: a) the difference for observing congruent stimulus in group 1 vs. group 2; b) the difference for answering stimulus-related question in response part in group 1vs. group 2; and c) the difference between observing fluctuating emotions stimulus (include angry, fearful and happy) and baseline emotion (neutral) in group 1 vs. group 2. Similar to the previous part, the first two contrasts for this part were completed with t-contrasts; and the last contrasts were completed with a F-contrast. Like RQ 2.1, all *t* and *p* values related to t-test are shown in the next chapter but *F* values and corresponding *p* values for F-tests (i.e., ANOVA) are not shown.

In this step (i.e., SPM level 2) and for both two parts of the research question 2, the brain maps related to all above comparisons were saved and can be seen in next chapter; besides, all data was saved in the ASCII to further analyze to get exact *p* value. All these contrasts were performed for three kinds of data: oxyhemoglobin, deoxyhemoglobin, and total hemoglobin.

The hypotheses for fNIRS data are: before multiliteracies learning, the brain area related to language processing (e.g., PFC, IFG), emotional processing (e.g., PFC and STC) and multisensory area (e.g., STC) will be activated more in incongruent stimulus than congruent stimulus and in happy, angry, fearful emotion than in baseline emotion (i.e., neutral); STG will be less activated for those who have higher multimodality background; after multiliteracies learning, fNIRS data in brain regions related to emotional processing, language processing and multisensory processing, especially in PFC and STG areas will show differences compared to the data before multiliteracies learning data.

Chapter 4

4 Results

4.1 Research Question 1.1 What is the Relationship between Behaviour Data and ESL Students' Multimodality Background and Other Possible Influencing Factors Using Emotional Videos?

4.1.1 MLR model for reaction time

Preliminary Analysis.

The descriptive statistics for reaction time and frequencies of independent variables for preliminary analysis were shown in Table 3. The mean of reaction time was 2168.09 (*SD* = 729.56). From the frequencies table, we can see most of properties for stimulus itself (i.e., emotion type, question type and congruency) were balance-designed. Besides, there were not enough cases for intensity of questions, because neutral emotions would not have intensity.

Besides, t-tests and ANOVA were used to check the relationship between each independent variable (i.e., multimodality background, emotion types, congruency and intensity of stimuli, gender of subject and question types) and dependent variable (i.e., reaction time). The results were showed in table 4. Most independent variables except for gender (t (293) = -5.41, p < .0001) did not show a significant correlation with the dependent variable, which may be caused by the limited number of subjects. However, further analysis was still performed because no other independent variable could be involved.

Table 3: Frequencies for Independent Variables

Variable	Frequency	Percent	Cumulative frequency	Cumulative percent
Multimodality background of ESL Students				
High	256	80	256	80.00
Low	64	20	320	100.00
Emotion Types of Stimuli				
Happy	80	25.00	80	25.00
Angry	80	25.00	160	50.00
Fearful	80	25.00	240	75.00
Neutral	80	25.00	320	100.00
Congruency of Stimuli				
Congruent	160	50.00	160	50.00
Incongruent	160	50.00	320	100.00
Question Types				
Face-related	160	50.00	160	50.00
Voice-related	160	50.00	320	100.00
Intensity of Stimuli				
Regular	95	39.58	95	39.58
Strong	145	60.42	240	100.00
Gender of Students				
Female	256	80	256	80.00
Male	64	20	320	100.00

Table 4: Bivariate Relationships between Independent Variables against Reaction Time

Variable	Df	*t/F*	*p*
Multimodality Background	293	1.55	.12
Emotion Types of Stimuli	3	1.69	.17
Gender of Subject	293	-5.41	<.0001
Congruency	293	-.53	.59
Question Type	293	-1.06	.29
Emotion Intensity of Stimuli	293	.61	.54

Collinearity Detection.

All independent variables except multimodality background and gender of subjects were considered separately and there properties were fixed when designing the experiment. Therefore, all independent variables except multimodality background and gender of subjects would not have a relationship with each other, and Chi-square only needed to be conducted between gender and multimodality background (see Table 5). The relationship between gender and multimodality background was significant, $\chi^2(1) = 20.00$, $p < .0001$. Besides, the statistics of collinearity (VIF) were all acceptable (<5, see Table 6); besides, none of the Condition indexes exceeded 10. These results indicated that although there was a significant relationship between gender and multimodality background, there was no collinearity issue in this model.

Table 5: Collinearity of Gender of Subjects against Multimodality Background

Variable	**multi_high**	**multi_low**	**Total**	**χ^2(1)**	***p***
Female	60.00	20.00	80.00	20.00	<.0001
Male	20.00	0.00	20.00		
Total	80.00	20.00	100.00		

Table 6: Multiple Linear Regression Analysis Summary for Variables Predicting Reaction Time

Variable	**Df**	**Parameter estimate**	***SE(B)***	***t***	***p***	**Variance inflation**	**95 % Confidence Interval**	
Intercept	B	2574.49	197.23	13.05	<.0001	0	2185.67	2963.30
High multimodality background	B	117.52	122.95	.96	.34	1.06	-124.87	359.92
Low multimodality background	0	0						

Variable	Df	Parameter estimate	*SE(B)*	*t*	*p*	Variance inflation	95 % Confidence Interval	
Emotion_angry	B	215.26	118.59	1.82	.07	1.35	-18.53	449.05
Emotion_fearful	B	36.21	116.40	.31	.76	1.36	-193.26	265.68
Emotion_happy	0	0						
Female subject	B	-633.07	131.45	-4.82	<.0001	1.05	-892.22	-373.92
Male subject	0	0						
Face-question	B	-153.38	95.99	-1.60	.11	1.01	-342.62	35.85
Voice-question	0	0						
Regular intensity	B	87.66	99.46	.88	.38	1.04	-108.42	283.74
Strong intensity	0	0						
Congruent stimulus	B	-53.12	96.20	-.55	.58	1.02	-242.77	136.53
Incongruent stimulus	0	0						

Note. Adjusted R^2 = 0.1162

Validation and Influential Observation Detection.

The independence of observations and residuals was satisfied to some extent because the participants did not know each other.

The assumption of linearity does not need to be checked because all the independent variables are categorical variables.

The assumption of normality of residuals was evaluated using Kolmogorov-Smirnov test of normality. The distribution of residuals did not satisfy the assumption (Kolmogorov-Smirnov D = 0.05, p >.015). However, normal probability and Q-Q plots of residuals (see Figure 4.1.1) indicated no strong departures from normality, so the data could be further analyzed.

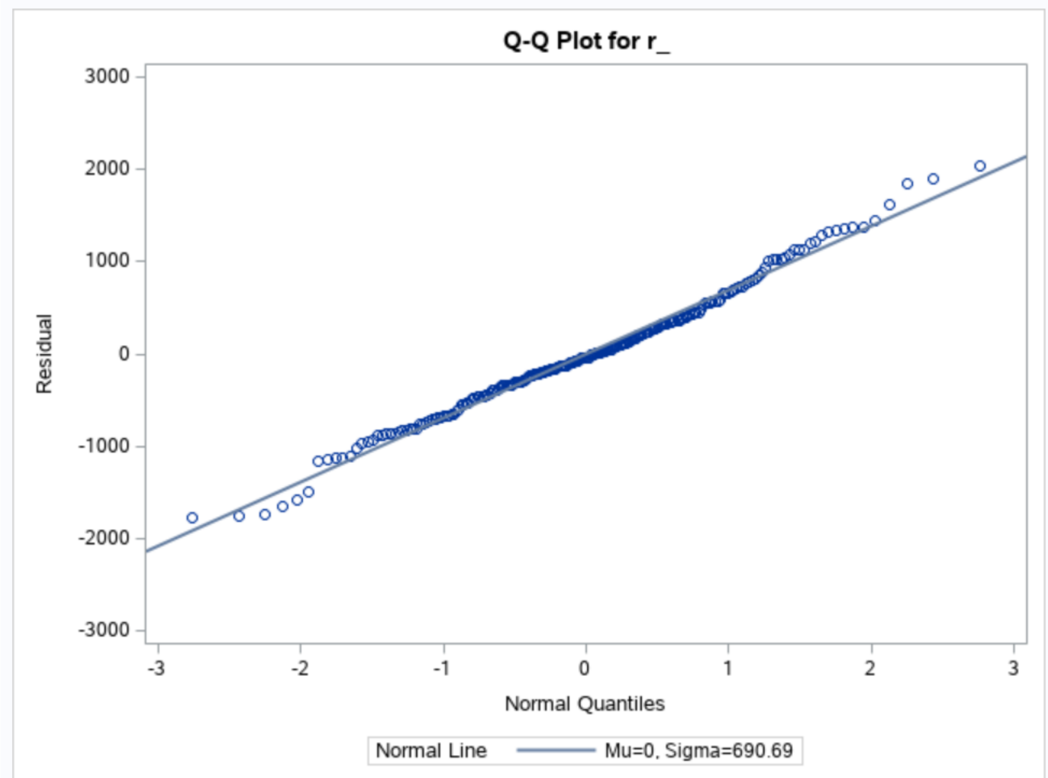

Figure 5: Q-Q Plots of Residuals for MLR in Session 1

The assumptions of homogeneity of variance of residuals was examined using plots of residuals against predicated values and residuals against the independent variables which indicated no clustering or patterns (see Figure 6). The results of White test showed that the heteroscedasticity was not significant, $\chi 2$ (29, N = 217) = 20.96, p = .86. The plot of residual by regressors for reaction time was showed in Figure 7-9. Therefore, the assumption of constant variance was satisfied.

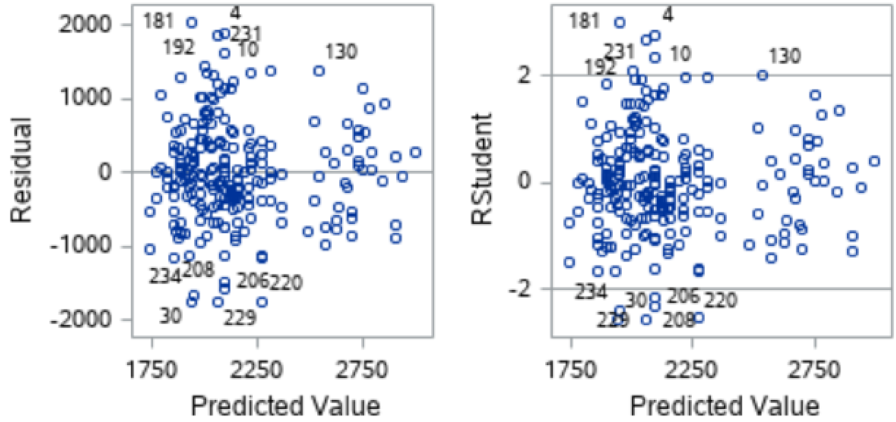

Figure 6: Plots of Residuals against Predicated Values and Independent Variables for MLR in Session 1

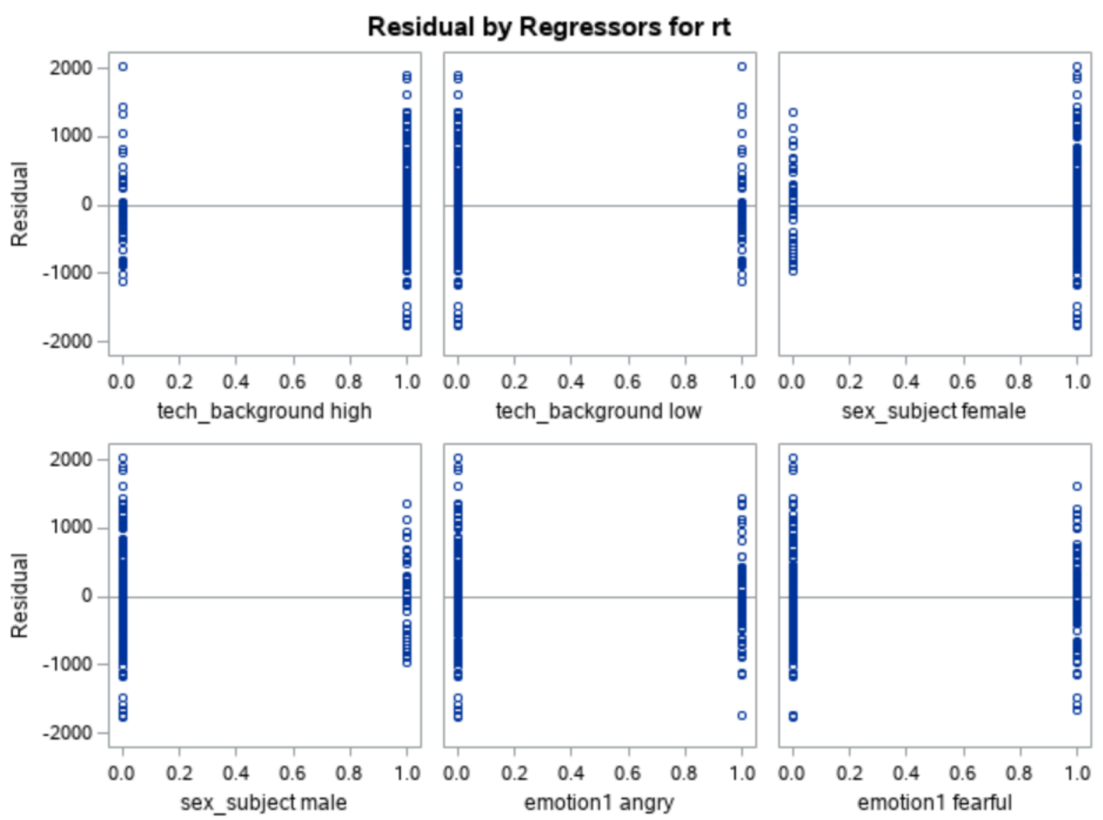

Figure 7: Plots of Residual by Regressors for Reaction Time in Session 1 (1)

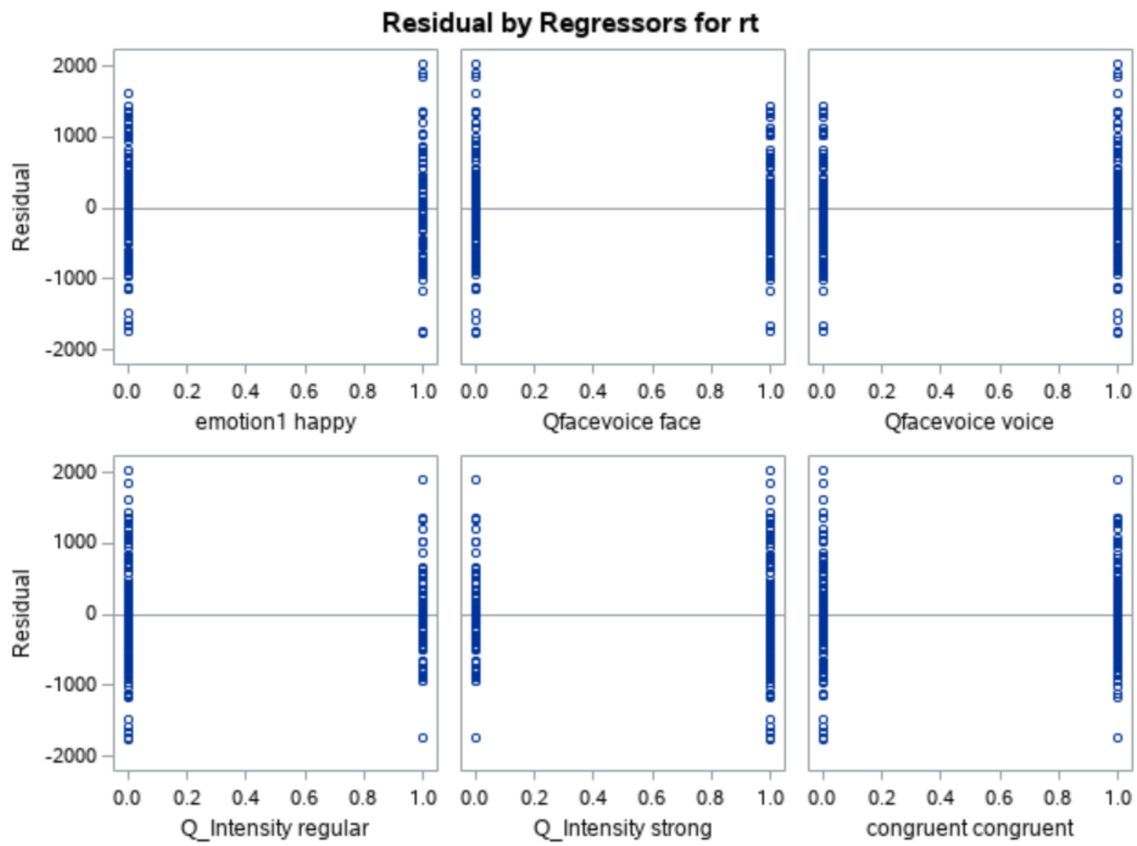

Figure 8: Plots of Residual by Regressors for Reaction Time in Session 1 (2)

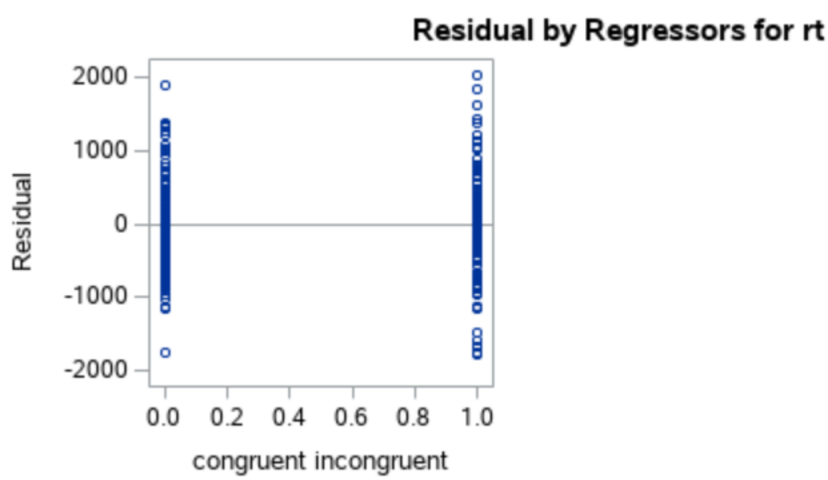

Figure 9: Plots of Residual by Regressors for Reaction Time in Session 1 (3)

Influential Outliers.

To identify and count the outliers, assessment of standardized and studentized deleted residuals, Cook's D, Leverage, and Studentized Dffit values was used. The results demonstrated the presence of influential outliers because extreme values (studentized deleted residuals >2) surpassed a threshold of Cook's D (4/217 = .018), Leverage (2*6/217 = .055) and DfFit (2*√ (6/217) = .333). Ten influential outliers were detected in the outlier data set, 6 with positive and 4 with negative studentized deleted residuals (See Figure 10 and 11). Besides, the Diffts influence diagnostics (see Figure 12) for reaction time showed that there are two main concern cases at the top (#4, #181). The above results showed there are more than 0.92% significant outliers in the dataset. Therefore, it was necessary to utilize a robust estimation to address the influential outlier.

cookd_	h_	rstudent_ ▾	dffits_
0.04956798	0.0433505828	3.0148856203	0.641788462
0.0317556489	0.0327192076	2.7844260592	0.512107099
0.0260293705	0.0286410453	2.6970885444	0.4631266394
0.0184372445	0.0261542324	2.369234652	0.3882701244
0.0273496393	0.0474813984	2.1123371365	0.4716156974
0.026258477	0.050058796	2.0110747128	0.4616576564
0.0165847398	0.032738021	1.9939544178	0.3668338288
0.0147541465	0.0300860223	1.9639693564	0.3458999387
0.014666508	0.0301589291	1.9555333894	0.3448441855

Figure 10: Influential Outliners (positive) for MLR in Session 1

cookd_	h_	rstudent_ ▴	dffits_
.	0.0327192076	.	.
0.0240278637	0.0286410453	-2.587842174	-0.444367558
0.0245160527	0.0297860689	-2.560925723	-0.448714211
0.0225908607	0.0277492371	-2.549260543	-0.430675931
0.0201800562	0.027522734	-2.415837197	-0.406418736
0.0175467355	0.0261542324	-2.309805314	-0.378530846
0.0154636945	0.0261542324	-2.165078418	-0.354813005
0.0114983648	0.0315846983	-1.686802798	-0.30462943
0.0097440751	0.0277492371	-1.659563413	-0.280369153
0.0152391337	0.0432766981	-1.648421217	-0.350592062

Figure 11: Influential Outliners (negative) for MLR in Session 1

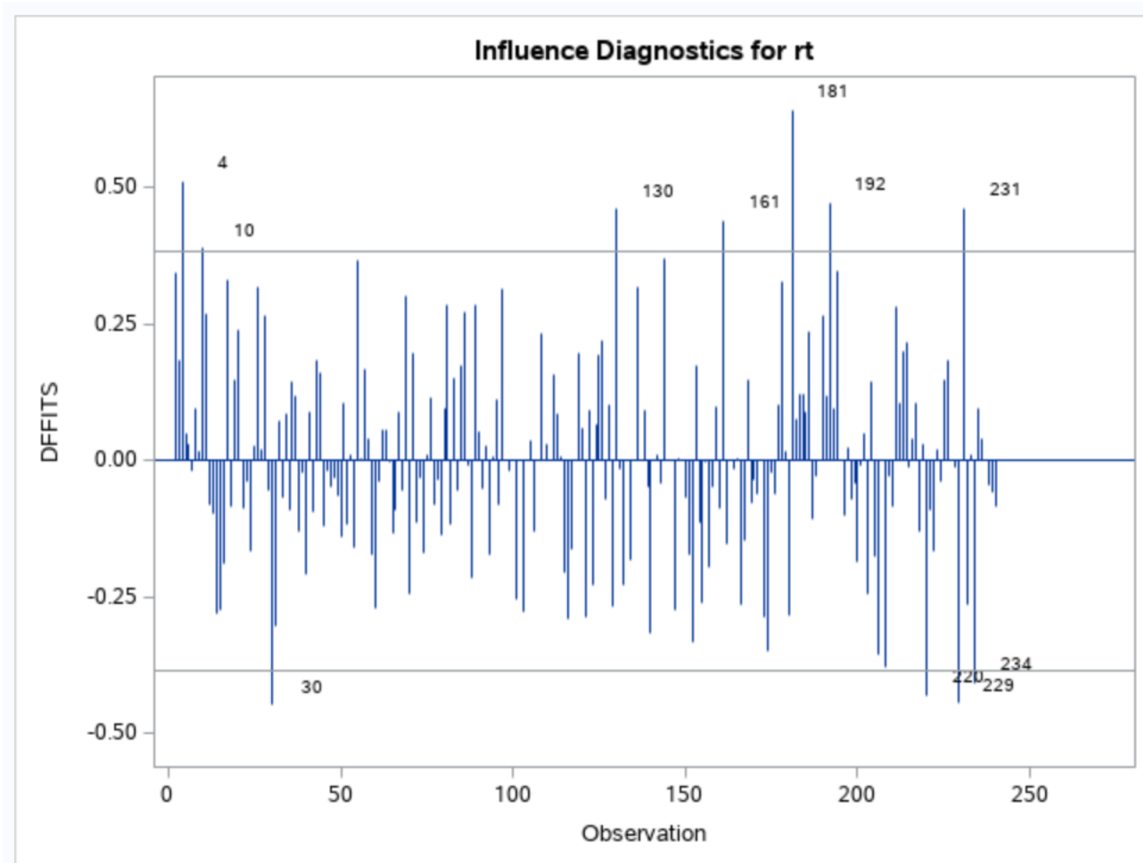

Figure 12: Studentized Dffit Influence Diagnostics for Reaction Time in Session 1

Independent variables were added to the model one by one from step 1 to step 6 as table 7 shows. The order of joining was determined by the degree of interest and the degree of correlation between each independent and dependent variable and is shown in table 7. The first model with only multimodality background as a predictor was not significant, F (1, 293) = 2.40, p = .04 and accounted for .47 % of the variability in reaction time. With the next variable joins, the second model was not a significant model. From the step 3, the model for predicting reaction time became significant, and the third model with multimodality background, emotion and gender as predictors was significant, F (5, 289) = 6.80, p < .0001 and accounted for 8.97% of the variability in reaction time. The final model with all six predictors was significant, F (7, 209) = 5.06, p < .0001 and accounted for 11.62% of the variability in reaction time. The residual-fit spread plots indicated that the model does not explain much variability in the data (i.e., the range of the residual plot is substantially larger than the range of the fit-mean plot) and therefore can be improved (see Figure 13).

Table 7: Model Fit for MLR in Session 1

Step	**Df**	***F***	***p***	***Adj R^2***
1 multimodality background	1	2.40	.12	.0047
2 multimodality background + emotion	4	1.78	.13	.0106
3 multimodality background + emotion + gender	5	6.8	<.0001	.0897
4 multimodality background + emotion + gender + congruency	6	5.69	<.0001	.0874
5 multimodality background + emotion + gender + congruency + question type	7	5.15	<.0001	.0900
6 multimodality background + emotion + gender + congruency + question type + question intensity	7	5.06	<.0001	.1162

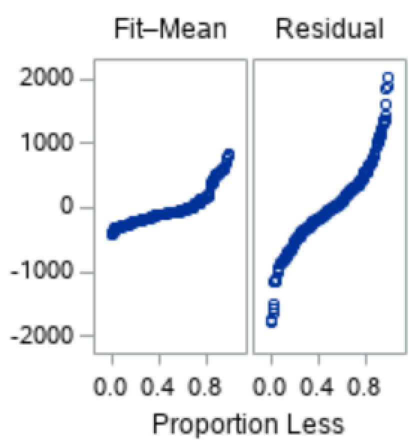

Figure 13: The Residual-fit Spread Plots for Final MLR Model in Session 1

Main Analysis.

The results for the main analysis were shown in Table 7. Among all predictors, multimodality background was the one of most interested predictors, so it was first added into the model. The results showed that in step 1, the multimodality background could not significantly predict the reaction time (p = .12). For step 2, emotion type was added as the second predictor because it was assumed as a strong predictor, but the results showed that both multimodality background and emotion are not significant predictors in predicting the reaction time. For the third step, gender was added as it has significant relationship with reaction time. The results showed that gender was a strong predictor in this step (p <. 0001), females had slower reaction times compared with male subjects, with the difference of 3560.54 ms. The addition of gender caused the significant level of multimodality background to change from .47 to .27, which means that with the addition of gender, multimodality background became more significant. For step 4, the congruency of stimulus was added as the fourth predictor as it was also seen as a strong predictor. However, it was not a significant predictor (p = .61), and the addition of this predictor did not have much influence on the influence of other predictors. For step 5, another insignificant predictor (p = .18) – question type was added into the model and this predictor did not have much influence on other predictors. For the last step, the intensity of the questioned stimulus emotion was added with the significance level of .38, meaning that the intensity was not a significant predictor. The results showed that even though some predictors are not significant to predict the model, they could have an influence on other predictors to perform a better model. Additionally, with the addition of the last predictor, the neutral emotion would disappear from the model because there was no intensity of neutral emotion.

Table 8: Multiple Linear Regression Model Predicting Reaction Time from Multimodality background, Emotion Type, Gender of Participants, Congruency, Question Type and Question Intensity

Step	**Variable**	***B***	***SE(B)***	***t***	***p***	**Semi-partial r^2**	**95% CI**	
1	**Multimodality_high**	164.16	105.94	1.55	.12	.008	-44.33	372.66

Step	Variable	*B*	*SE(B)*	*t*	*p*	Semi-partial r^2	95% CI	
2	**Multimodality_high**	151.07	105.84	1.43	.15	.007	-57.24	359.37
	Emotion_angry	87.17	119.59	.73	.47	.002	-148.20	322.53
	Emotion_fearful	-115.70	116.97	-.99	.32	.003	-345.92	114.51
	Emotion_happy	-146.77	119.05	-1.23	.22	.005	-381.09	87.55
3	**Multimodality_high**	27.91	104.32	.27	.79	<.001	-177.42	233.24
	Emotion_angry	103.96	114.75	.91	.37	.003	-121.89	329.81
	Emotion_fearful	-89.89	112.30	-.80	.42	.002	-310.93	131.14
	Emotion_happy	-121.12	11430	-1.06	.29	1.45	-346.09	103.84
	Gender_female	-560.54	109.47	-5.12	<.0001	.081	-775.98	-345.09
4	**Multimodality_high**	28.54	104.46	.27	.78	<.001	-177.07	234.15
	Emotion_angry	103.33	114.90	.90	.37	.003	-122.82	329.48
	Emotion_fearful	-89.35	112.45	-.79	.43	.002	-310.68	131.98
	Emotion_happy	-120.83	114.45	-1.06	.29	.003	-346.09	104.43
	Gender_female	-560.34	109.60	-5.11	<.0001	.081	-776.07	344.61

Step	Variable	*B*	*SE(B)*	*t*	*p*	Semi-partial r^2	95% CI	
	Congruent	-41.62	81.18	-.51	.61	<.001	-201.40	118.16
5	**Multimodality_high**	28.62	104.32	.27	.78	<.001	-176.70	233.94
	Emotion_angry	104.55	114.74	.91	.36	.003	-121.30	330.39
	Emotion_fearful	-88.89	112.29	-.79	.43	.002	-309.92	132.13
	Emotion_happy	-118.16	114.30	-1.03	.30	.003	-777.26	-346.39
	Gender_female	-561.82	114.30	-1.03	.30	.003	-343.14	106.83
	Congruent	-71.12	83.98	-.85	.40	.002	-236.41	94.17
	Question_face	-113.00	83.98	-1.35	.18	.006	-278.31	52.30
6	**Multimodality_high**	117.52	122.96	.96	.34	.003	-124.87	359.92
	Emotion_angry	215.26	118.59	1.82	.07	.013	-18.53	449.05
	Emotion_fearful	36.21	116.40	.31	.76	<.001	-193.26	265.68
	Gender_female	-633.07	131.45	-4.82	<.0001	.095	-892.21	-373.92
	Congruent	-53.12	96.20	-.55	.58	.001	-242.77	136.53
	Question_face	-153.38	95.99	-1.60	.11	.010	-342.62	35.85

Step	Variable	*B*	*SE(B)*	*t*	*p*	Semi-partial r^2	95% CI	
	Intensity_regular	87.66	99.46	.88	.38	.003	-108.42	283.74

Note. The reference group of multimodality background was low; the reference group of emotion was neutral for first five steps and was happy for the last step; the reference group of gender was male; the reference group of congruency was incongruent; the reference group of question type was voice; the reference group of intensity was high.

Robust Estimation.

Table 9 provided summary of parameter estimates and their significance and 95% confidence intervals for the model with robust estimation. Using robust estimation with Huber weights, emotion type and gender of participants remained significant predictors of reaction time. All estimates were adjusted. Those trials with angry emotion would lead to longer reaction time compared with happy emotion, with the difference of 231.61 ms ($p < .05$), taking other predictors into account, while the fearful emotion did not have significant difference with happy emotion ($p = .40$); besides, the female subjects would have a shorter reaction time compared with male subjects, with the difference of 613.31 ($p < .0001$), taking other predictors into account. Multimodality background ($p = .17$), congruency ($p = .42$), question type ($p = .15$) and question intensity ($p = .38$) still did not significantly predict the reaction time, taking other predictors into account.

Table 9: Robust Estimation for Independent Variables Against Reaction Time Using MLR in Session 1

Variable	*B*	*SE(B)*	*95%CI*		χ^2	*p*
Multi_high	168.56	121.74	-70.05	407.17	1.92	.17
Emotion_angry	231.61	117.42	1.47	461.75	3.89	<.05
Emotion_fearful	97.49	115.25	-128.39	323.38	.72	.40

Variable	*B*	*SE(B)*	*95%CI*		χ^2	*p*
Gender_female	-613.31	130.15	-868.41	-358.21	22.20	<.0001
Congruent	-76.75	95.25	-263.44	109.94	.65	.42
Question_face	-137.78	95.04	-324.06	48.50	2.10	.15
Intensity_regular	87.05	98.48	-105.97	280.07	.78	.38

Note. Adj R^2 *=.1326. The reference group of multimodality background was low; the reference group of emotion was neutral for first five steps and was happy for the last step; the reference group of gender was male; the reference group of congruency was incongruent; the reference group of question type was voice; the reference group of intensity was high.*

4.1.2 BLR model for the correctness

Preliminary Analysis.

All the frequencies of independent variables for stimulus trials have been calculated in Research question 1.1 (a). Therefore, only the frequencies of correct responses for stimulus trials were calculated in this step (see Table 10).

Table 10: Frequencies of Correct Responses for Stimuli Trials

Correct	Frequency	Percent	Cumulative Frequency	Cumulative Percent
No	65	22.03	65	22.03
Yes	230	77.97	295	100

Note. Missing values = 25

Relationships Between Independent Variables and Dependent Variable.

The bivariate relationships between independent variables and dependent variable were shown in Table 11. Pearson chi-square test was conducted to test the relationships between all independent variables and correctness. The relationship between multimodality background and correctness was not significant, $\chi^2(1) = .02$, $p = .89$ The relationship between emotion and correctness was not significant, $\chi^2(3) = 5.30$, $p = .15$. The relationship between gender of participants and correctness was not significant, $\chi^2(1) = 2.04$, $p = .15$. The relationship between congruency and correctness was significant, $\chi^2(1) = 53.83$, $p < .0001$. The relationship between question type and correctness was significant, $\chi^2(1) = 6.07$, $p = .01$. The relationship between intensity and correctness was not significant, $\chi^2(1) = .0006$, $p = .98$.

Table 11: ***Frequencies for Predictor Variables as a Function of Correctness***

Variable	**Incorrect (*n* = 87)**	**correct (*n* = 269)**	**$\chi^2(1)$ or $\chi^2(3)$**	***p***
Multimodality background (%) of Participants			.12	.73
Low	17.29	62.71		
High	4.75	15.25		
Emotion Type (%)			3.29	.35
Happy	6.10	17.97		
Angry	5.08	18.64		
Fearful	6.78	18.98		
Neutral	4.07	22.37		
Gender (%)			.03	.87
Female	18.31	64.07		
Male	3.73	13.90		
Congruency (%)				
Incongruent	18.98	30.85	44.00	<.0001
Congruent	3.05	47.12		
Question type (%)				
Voice-related	13.56	35.59	5.11	.02
Face-related	8.47	42.37		
Intensity (%)				
Regular	10.14	29.49	.10	.75
Strong	14.29	46.08		

Collinearity Detection.

To check for collinearity among predictors, Pearson chi-square tests were conducted to test the relationships between two categorical variables, multimodality background and gender of participants. Similar to Research question 1.1 (a), other independent variables were the properties of stimulus and was set by experiment designer, which meant they are already independent from each other. The relationship between gender and multimodality background was significant, $\chi^2(1) = 20.00$, $p < .0001$ (see Table 5).

However, all standard errors in the model were less than 2.0 (see Table 12). Therefore, there was no severe multicollinearity among predictors in this model.

Table 12: Summary of Logistic Regression Analysis Predicting Correctness

Variable	***B***	***SE***	***OR***	**95% CI**	**Wald statistic**	***p***
Multi_background high vs. low	-.26	.77	.83	[0.32, 2.20]	.12	.73
Emotion angry vs. happy	.42	.49	1.53	[0.59, 3.98]	.75	.39
Emotion fearful vs. happy	-.21	.46	.81	[0.33, 2.00]	.21	.65
Gender_subject female vs. male	.13	.53	1.13	[0.40, 3.20]	.06	.81
Congruent vs. incongruent	3.40	.57	30.06	[9.83, 91.94]	35.6	<.0001
Question type face vs. voice	1.72	.44	5.60	[2.37, 13.21]	15.46	<.0001
Intensity regular vs. strong	-1.11	.44	.33	[0.14, 0.79]	6.21	.01

Note. CI = confidence interval for odds ratio (*OR*).

Checking Assumptions.

Correctness had a sample size of 320. However, some of trials did not have answers, which caused 25 missing values; besides, the neutral trials did not have intensity, which caused more missing values ($N = 78$). Therefore, the final sample size for this model was 217. By dividing 217 by 30 (217/30 = 7.23), the maximum number of predictors were 7 in this model. This model has 6 predictors, which means this model can be used to do further analysis.

The two categories of dependent variable were mutually exclusive and exhaustive, because each trail can either be correct or incorrect.

The independence of residuals was violated to some extent because although the participants did not know each other, there were lots of trials belonged to one participant. However, the further analysis would still be done because most of the assumptions were satisfied.

Influential outliers were assessed based on Pearson and Deviance residuals, Leverage, DfBetas and C statistics. Based on the Influence and predicted Probability Diagnostics plots (see Figure 14 - 20), case 36, 282 were the most influential because they seemed significantly departed from the main pattern. The decision was made to keep these cases in the model, because the number of influential outliers was small enough to have slight influence on final model.

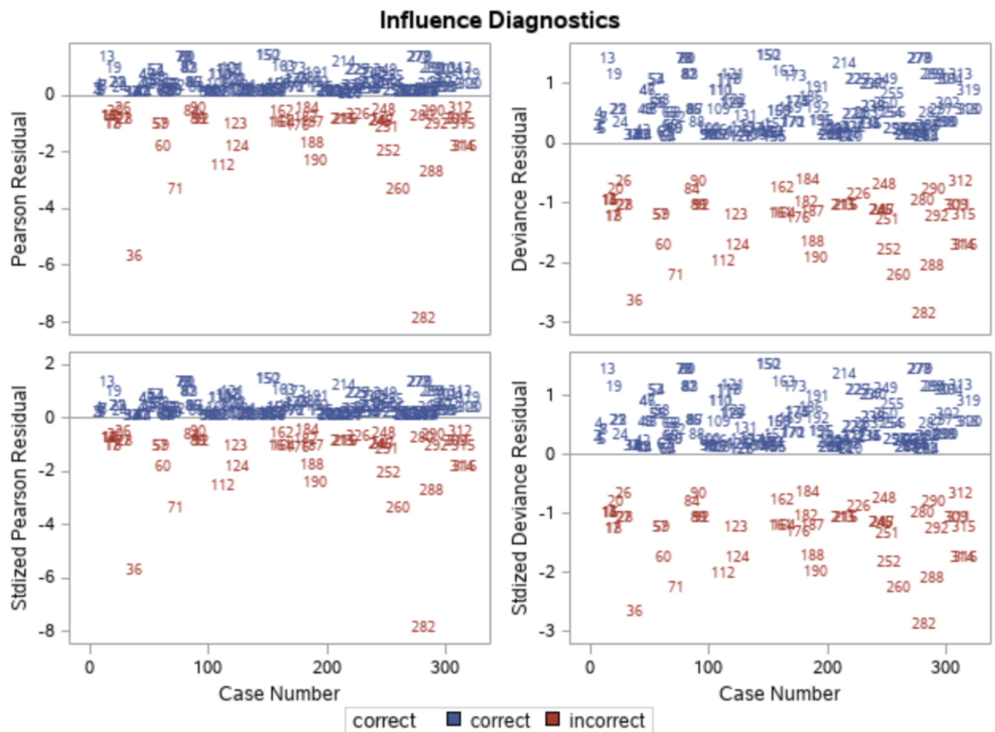

Figure 14: Pearson and Deviance Residuals Influence Diagnostics Plots for BLR in Session 1

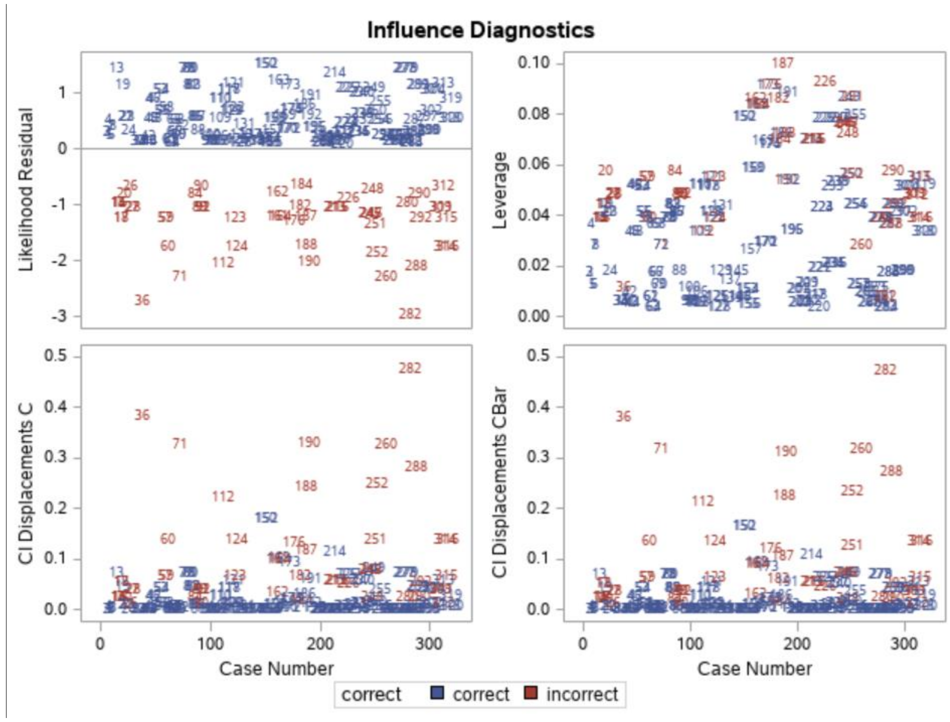

Figure 15: Leverage and C Influence Diagnostics Plots for BLR in Session 1 (1)

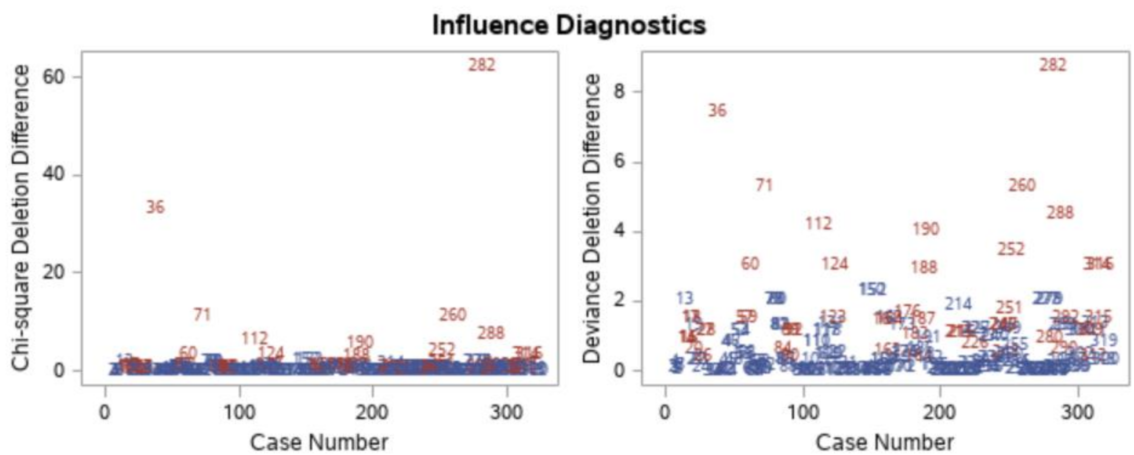

Figure 16: Leverage and C Influence Diagnostics Plots for BLR in Session 1 (2)

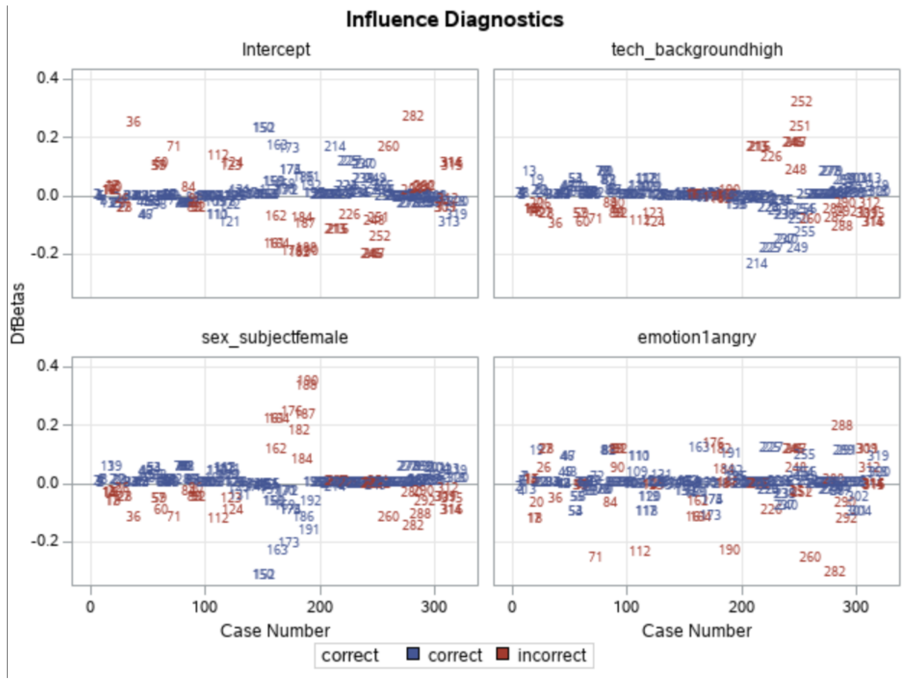

Figure 17: DfBetas Diagnostics Plots for BLR in Session 1 (1)

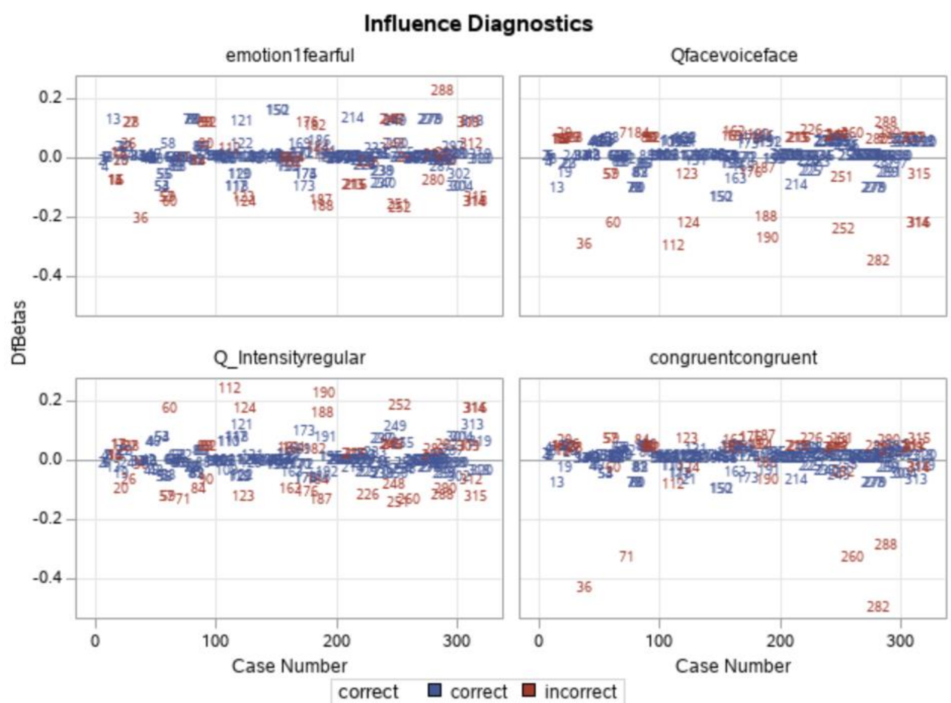

Figure 18: DfBetas Diagnostics Plots for BLR in Session 1 (2)

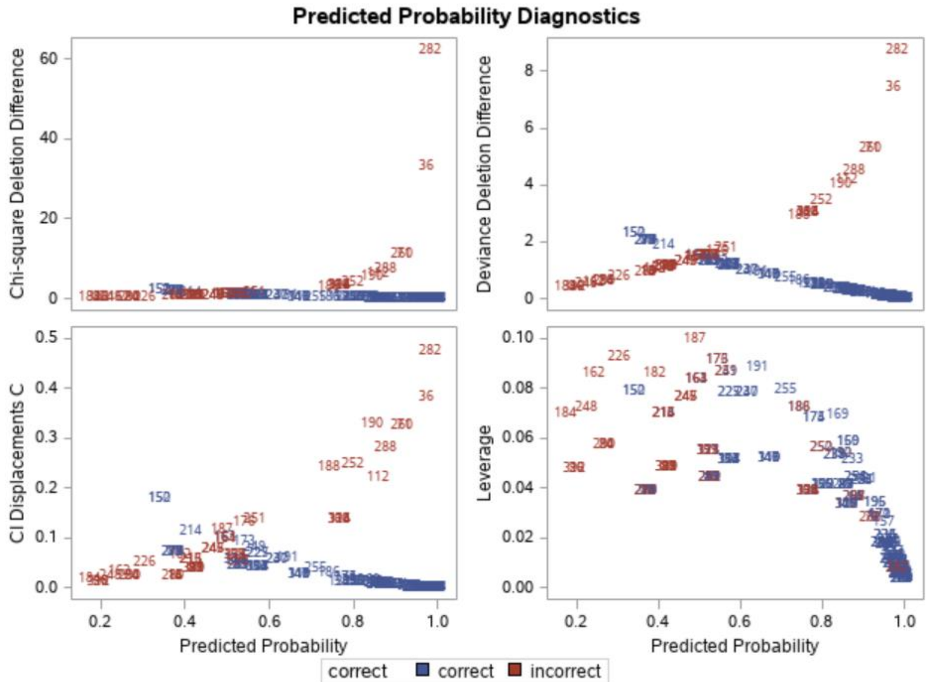

Figure 19: Predicted Probability Diagnostics Plots for BLR in Session 1

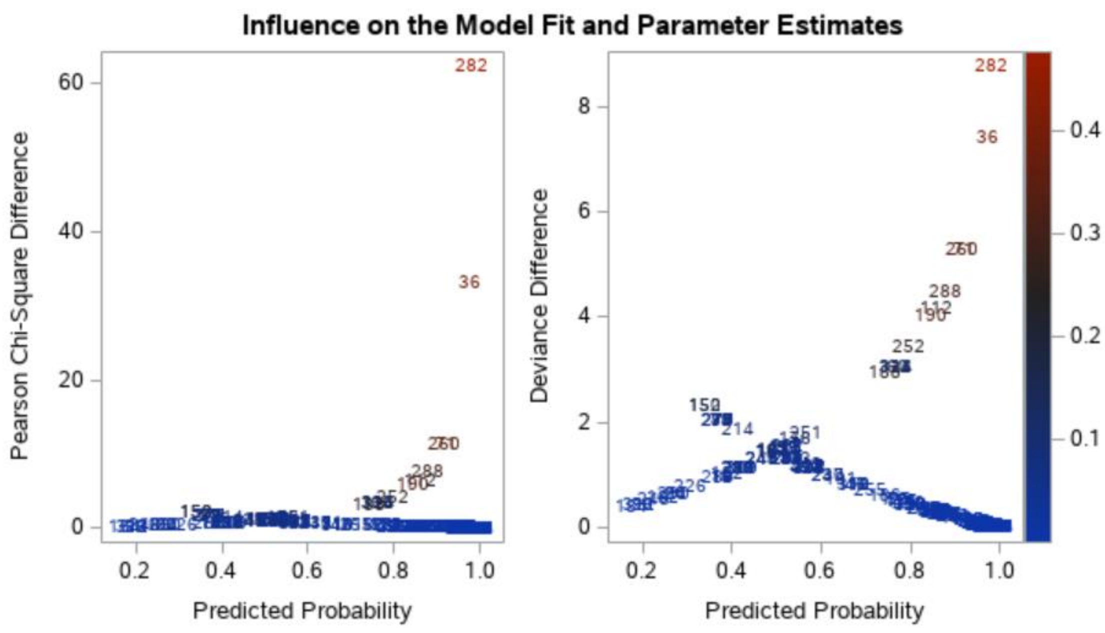

Figure 20: Influence on the Model Fit and Parameter Estimates Plots

Main Analysis.

A binary logistic regression was conducted using 6 predictors. The overall model was statistically significant compared to the null model, Likelihood ratio $\chi^2(7) = 73.63$, p < .0001, Max-rescaled $R^2 = 0.\ 288$. The model was able to discriminate between the trails that were correct and the trials that were incorrect at 86.4% accuracy.

In the model with multimodality background, emotion type, gender of participants, congruency, question type and intensity, multimodality background of low or high level, emotion type and gender of participants were not significantly related to correctness.

Congruency significantly was significantly related to the correctness: compared to incongruent trials, congruent trials expected difference in the log-odds of correct is 3.40 ($p < .0001$), holding all other independent variables constant. It corresponded to a trial with congruent stimulus being 30.06 times more likely to be correct compared with a trial with incongruent stimulus, or 2906% increase in odds.

Question type significantly predicted the chances to be correct: compared with trials with voice-related questions, trials with face-related questions expected difference in the log-odds of being correct is 1.72, holding all other independent variables constant. It corresponded to a trial with face-related questions being 5.58 times more likely to be correct compared to a trial with voice-related questions, or 458% increase in odds.

Emotion intensity was significantly related to the chance of being correct, controlling for other variables in the model: compared to stimulus with strong emotion, stimulus with regular emotion expected difference in the log-odds of being correct is -1.11. It corresponded to a trial with strong emotion being 0.33 times less likely to be correct compared to a trial with voice-related questions, or 67% decrease in odds.

Therefore, the hypothesis that in a multivariate model, congruent stimulus (vs. incongruent stimulus), strong intensity of stimulus (vs. regular intensity of stimulus) and face-related question (vs. voice-related question) were more likely to be correct for each test trials was supported, while the other 3 predictors did not have much difference in predicting the correctness for different categories.

4.2 Research Question 1.2 How does the Relationship between Behaviour Data and Independent Variables Change after Multiliteracies learning?

4.2.1 Preliminary analysis for both MLR and BLR

Preliminary Analysis.

Table 13 showed the frequencies table for all independent variables in session 2 for stimuli trials.

Table 13: Frequencies for Independent Variables in Session 2

Variable	Frequency	Percent	Cumulative frequency	Cumulative percent
Multimodality background				
High	256	80.00	256	80.00
Low	64	20.00	320	100.00
Emotion Type				
Happy	80	25.00	80	25.00
Angry	80	25.00	160	50.00
Fearful	80	25.00	240	75.00
Neutral	80	25.00	320	100.00
Congruency				
Congruent	160	50.00	160	50.00
Incongruent	160	50.00	320	100.00
Question Type				
Face-related	160	50.00	160	50.00
Voice-related	160	50.00	320	100.00
intensity				
Regular	92	38.33	92	38.33
Strong	148	61.67	240	100.00
Sex				
Female	256	80.00	256	80.00
Male	64	20.00	320	100.00
Correct				
No	45	14.80	45	14.80
Yes	259	85.20	304	100.00

4.2.2 MLR Model for Reaction Time

T-tests and ANOVA were used to check the relationship between each independent variables and dependent variable. The results were showed in table 14. Congruency, question type and emotion intensity did not show a significant correlation with the dependent variable, while multimodality background (t (301) = 3.85, p = .0001), emotion type (F (3, 299) = 8.69, p <.0001) and gender of subject (t (301) = 3.85, p < .0001) was significantly related to reaction time. Although some of independent variables did not show significant relationship with dependent variables, further analysis was still performed because no other independent variable could be involved.

Table 14: Bivariate Relationships between Independent Variables against Reaction Time

Variable	**Df**	***t/F***	***p***
Multimodality background	301	3.85	.0001
Emotion type	3	8.69	<.0001
Gender of Subject	301	-5.50	<.0001
Congruency	301	-.79	0.43
Question Type	301	-0.80	0.42
Emotion Intensity	222	1.11	0.27

Collinearity Detection.

All independent variables except multimodality background and gender of subjects were considered separately and the properties were fixed when designing the experiment. Therefore, all independent variables except multimodality background and gender of subjects will not have a relationship with each other, and Chi-square only need to be conducted between gender and multimodality background (see Table 15). The relationship between gender and multimodality background in session 2 was significant, $\chi^2(1) = 20.00$, p <.0001. Besides, the statistics of collinearity (VIF) were all acceptable (<5, see Table 16); besides, none of the Condition indexes exceeded 10. These results indicated that although there was a significant relationship between gender and multimodality background and there was no collinearity issue in this model.

Table 15: Collinearity of Gender of Subjects against Multimodality Background

Variable	Tech_high	Tech_low	Total	$\chi^2(1)$	*p*
Female	60.00	20.00	80.00	20.00	<.0001
Male	20.00	0.00	20.00		
Total	80.00	20.00	100.00		

Table 16: Multiple Linear Regression Analysis Summary for Variables Predicting Reaction Time

Variable	Df	Parameter estimate	*SE(B)*	*t*	*p*	Variance inflation	95 % Confidence Interval	
Intercept	B	1857.39	166.82	11.13	<.0001	0	1528.60	2186.19
High multimodality background	B	283.78	103.75	2.74	.007	1.06	79.29	488.26
Low multimodality background	0	0						
Emotion_angry	B	501.37	99.47	5.04	<.0001	1.35	305.31	697.43
Emotion_fearful	B	386.96	100.52	3.85	.0002	1.35	188.83	585.09
Emotion_happy	0	0						
Female subject	B	-315.55	108.49	-2.91	.004	1.06	-529.39	-101.72
Male subject	0	0						
Face-question	B	-41.17	81.69	-.50	.62	1.01	-202.19	119.85
Voice-question	0	0						

Regular intensity	B	107.41	84.16	1.28	.20	1.02	-58.47	273.30
Strong intensity	0	0						
Congruent stimulus	B	19.20	82.05	.23	.82	1.02	-142.53	180.93
Incongruent stimulus	0	0						

Note. Adjusted R^2 = 0.1636

Validation and Influential Observation Detection.

The independence of observations and residuals was satisfied to some extent because the participants did not know each other.

The assumption of linearity does not need to be check because all the independent variables were categorical variables.

The assumption of normality of residuals was evaluated using Kolmogorov-Smirnov test of normality. The distribution of residuals satisfied the assumption (Kolmogorov-Smirnov D = 0.04, p >.150). Besides, normal probability and Q-Q plots of residuals (see Figure 21) indicated no strong departures from normality. Therefore, the assumption of normality of residuals was totally satisfied, so the data could be further analyzed.

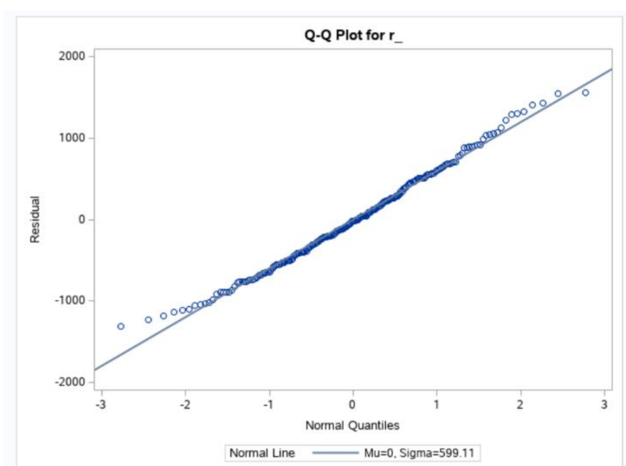

Figure 21: Q-Q Plots of Residuals for MLR in Session 2

The assumption of homogeneity of variance of residuals was examined using plots of residuals against predicated values and residuals against the independent variables which indicated no clustering or patterns (see Figure 22). The results of White test showed that the heteroscedasticity was not significant, $\chi 2$ (27, N = 224) = 31.30, p = .79. The plots of residual by regressors for reaction time was showed in Figure 23 – Figure 25. Therefore, the assumption of constant variance was satisfied.

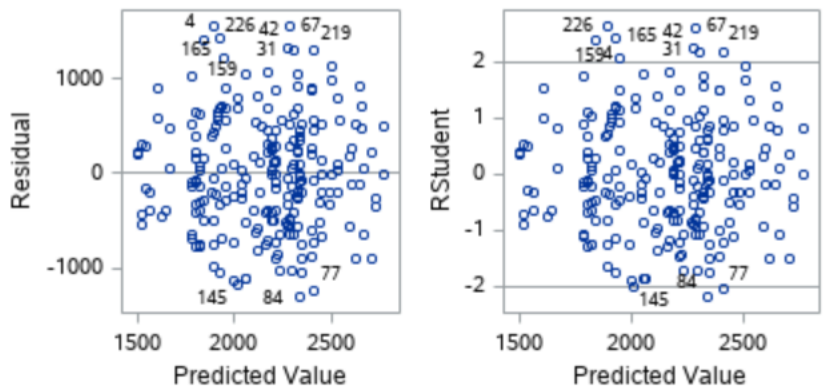

Figure 22: Plots of Residuals against Predicated Values and Independent Variables for MLR in Session 2

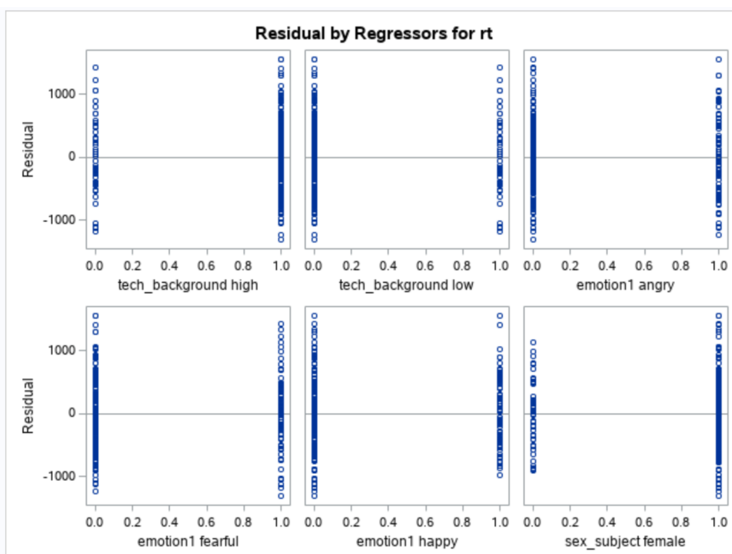

Figure 23: Plots of Residual by Regressors for Reaction Time for MLR in Session 2 (1)

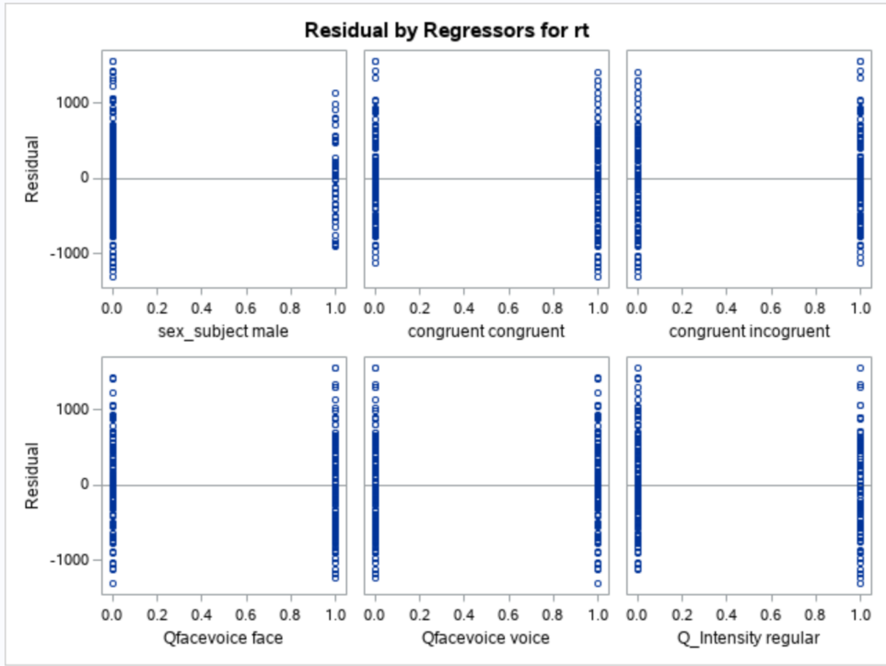

Figure 24: Plots of Residual by Regressors for Reaction Time for MLR in Session 2 (2)

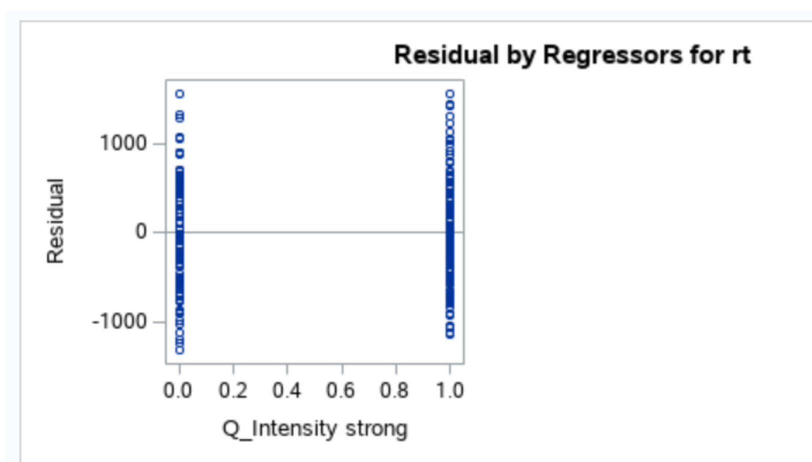

Figure 25: Plots of Residual by Regressors for Reaction Time for MLR in Session 2 (3)

Influential Outliers.

To identify and count the outliers, assessment of standardized and studentized deleted residuals, Cook's D, Leverage, and DfFit values were used. The results demonstrated the presence of influential outliers because extreme values (studentized deleted residuals >2) surpassed a threshold of Cook's D (4/224 = 0.018), Leverage (2*6/224 = 0.054) and Studentized Dffit (2*√ (6/224) = 0.327). Nine influential outliers were detected in the outlier data set, 6 with positive and 3 with negative studentized deleted residuals (See Figure 26 and Figure 27). Besides, the studentized dfFit values influence diagnostics (see Figure 28) for reaction time showed that there are three main concern cases at the top (#159, #165, #226). The above results showed there are more than 1.34% significant outliers in the dataset. Therefore, it was necessary to utilize a robust estimation to address the influential outlier.

cookd_	h_	rstudent_	dffits_
0.028006791	0.032274501	2.6270986455	0.4797666507
0.0230979089	0.0271766778	2.6061301996	0.435589402
0.0305077381	0.0409005658	2.4190266082	0.4995436999
0.021107742	0.0297482044	2.3718032543	0.4153046669
0.0209076504	0.0330033483	2.2341224502	0.4127370814
0.017622813	0.0293509717	2.1778766262	0.3787157822
0.0174311458	0.0293231705	2.1668215988	0.3766095141
0.0235955605	0.0429086664	2.0674322825	0.4377509626
0.0210699219	0.045241574	1.8973723993	0.4130234231
0.0187243721	0.0449600877	1.7929195306	0.3890125498
0.0189306696	0.0461708135	1.7776250423	0.3911007236
0.0105937883	0.0271649654	1.7504546484	0.2925067149

Figure 26: Influential Outliners (positive) in MLR in Session 1

cookd_	h_	rstudent_ ▲	dffits_
.	0.05102154	.	.
0.0196345424	0.0318326697	-2.205175017	-0.399856706
0.0159193403	0.0293231705	-2.068768218	-0.359567116
0.0237758001	0.0459761039	-2.000428291	-0.439146519
0.0196152944	0.0417406207	-1.909629296	-0.398553824
0.0213745556	0.0461708135	-1.890680407	-0.41597438
0.0190269986	0.0424767294	-1.862939884	-0.392373535
0.0166557208	0.0409005658	-1.776439048	-0.366845462
0.0112157282	0.0287137999	-1.75046015	-0.300970517

Figure 27: Influential Outliners (Negative) in MLR in Session 1

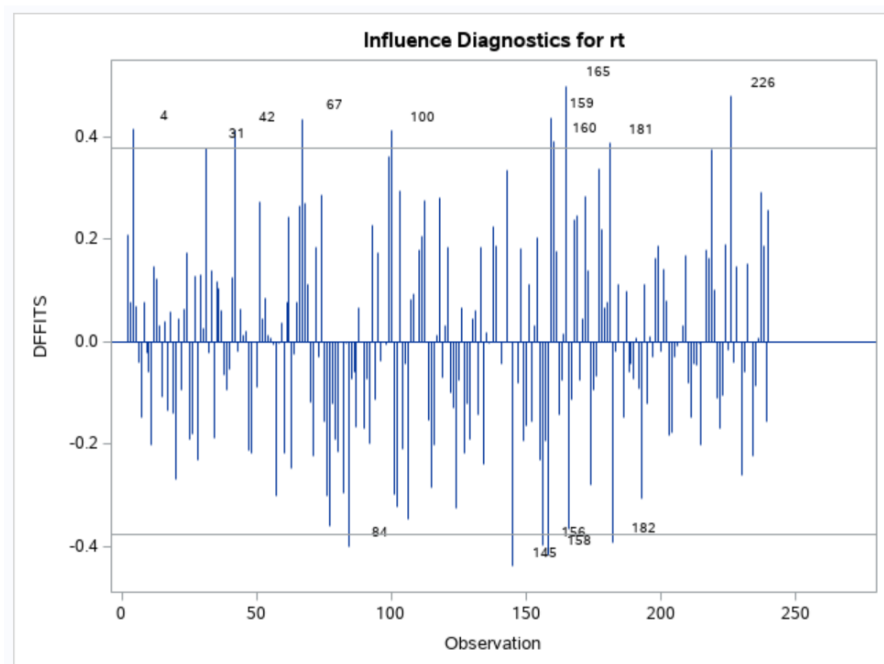

Figure 28: Studentized Dffit Influence Diagnostics for Reaction Time

Model fit.

Independent variables were added to the model one by one from step 1 to step 6 as table 17 showed. The order of joining was determined by the degree of interest and the degree of correlation between each independent and dependent variable and was shown in table 7. The first model with only multimodality background as a predictor was significant, *F* (1,

301) = 14.83, p = .0001 and accounted for 4.38% of the variability in reaction time. Emotion joined as the second predictor, and the second model with two predictors was still significant, F (4, 298) = 10.87, p < .0001 and accounted for 11.56% of the variability in reaction time, which was improved compared to first step. For the step 3, the model with multimodality background, emotion and gender as predictors was significant, F (5, 297) = 14.21, p < .0001 and accounted for 17.95% of the variability in reaction time, which was improved again. However, with the fourth variable – congruency joins, the model accounted for less variability (17.88%) in reaction time, but the model was still significant, F (5, 296) = 11.96, p < .0001. With the fifth variable which is question type joined, the proportion that the model could accounted for variability in reaction time slightly decreased again, from 17.88% to 17.69%, and the model was still significant, F (7, 295) = 10.27, p < .0001. The sixth model with all six predictors was significant, F (7, 216) = 7.23, p < .0001 and accounted for 16.36% of the variability in reaction time.

Although the third model in step 3 could accounted for largest variability in reaction time, from the step 2 to step 5, the plots of residuals against predicated values and residuals against the independent variables (see Figure 29-31) for these models indicated clustering, which will violated the model assumptions; besides, as the comparison of the MLR model in session 1 and session 2 will be made, the final decision was to keep all 6 variables. The residual-fit spread plots for third model indicated that the model does not explain much variability in the data, and therefore can be improved (see Figure 32).

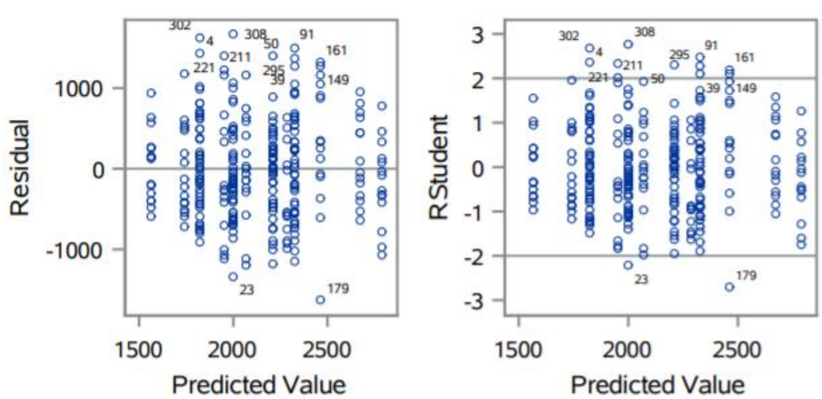

Figure 29: Plots of Residuals against Predicated Values and Independent Variables for MLR in Session 2 (step 3)

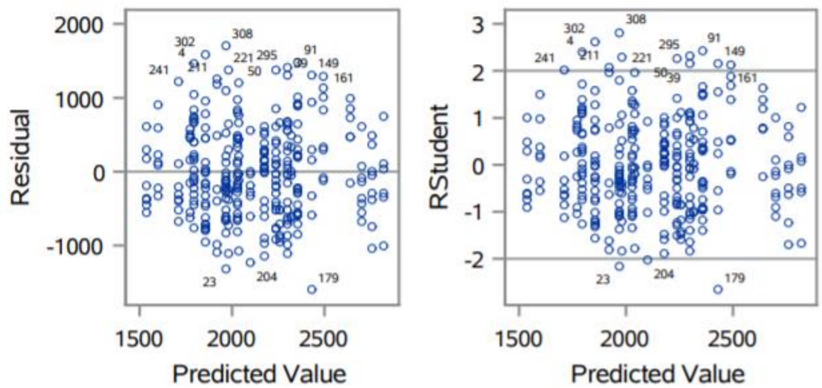

Figure 30: Plots of Residuals against Predicated Values and Independent Variables for MLR in Session 2 (step 4)

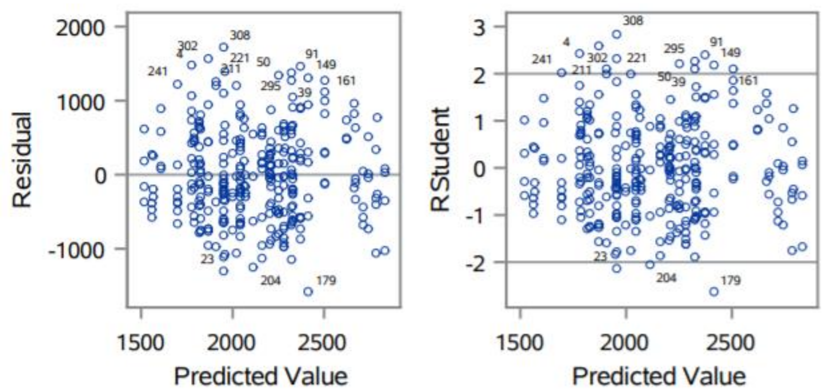

Figure 31: Plots of Residuals against Predicated Values and Independent Variables for MLR in Session 2(step 5)

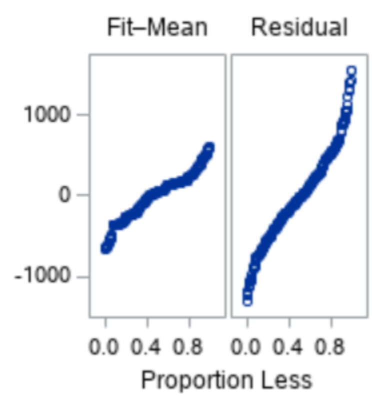

Figure 32: ***The Residual-fit Spread Plots for Final Model for MLR in Session 2***

Table 17: Model Fit for Reaction Time in Session 2

Step	Df	*F*	*p*	*Adj R^2*
1 Multimodality background	1	14.83	.0001	.0438
2 Multimodality background+emotion	4	10.87	<.0001	.1156
3 Multimodality background+emotion+gender	5	14.21	<.0001	.1795
4 Multimodality background+emotion+gender+congruency	6	11.96	<.0001	.1788
5 Multimodality background+emotion+gender+congruency+question type	7	10.27	<.0001	.1769
6 Multimodality background+emotion+gender+congruency+question type+question intensity	61	7.23	<.0001	.1636

Main Analysis.

The main analysis results could be seen in table 18. Among all predictors, multimodality background was the one of most interest predictors, so it was firstly added into the model. The results showed that in step 1, the multimodality background could significantly predict the reaction time (p = .0001), compared with low multimodality background, those with high multimodality background had longer reaction time, with a difference of 364.96, taking other predictors into account.

For step 2, emotion type was added as the second predictor because it was assumed as a strong predictor and have significant relationship with reaction time, and the results showed that both multimodality background, angry and fearful emotion were significant in predicting the reaction time, which meant both multimodality background and emotion type were strong predictors for step 2, and the significance level of multimodality background became higher, while the happy emotion was not significant (p = .08). For multimodality background, those with high multimodality background had longer reaction time than those with low multimodality background, with a difference 365.73, which did not change much from step 1; for emotion type, trials with angry and fearful stimulus had longer reaction time for trials with neutral stimulus, with the difference of 323.71ms (p =.002) and 209.02ms (p = .04) respectively, taking other predictors into account.

For the third step, gender of subjects was added as it also had significant relationship with reaction time. The results showed that gender of subject was a strong predictor in this step (p <. 0001), female have less reaction time compared with male subjects, with the difference of 462.60ms; besides, the join of this predictor did not have much influence on the influence of other predictors.

For step 4, the congruency of stimulus was added as the fourth predictor as it was also seen as a strong predictor. The results showed that it was not a significant predictor ($p = .39$), and the join of this predictor did not have much influence on the influence of other predictors.

For step 5, question type was added into the model and it was still not a significant predictor ($p = .57$), and the join of this predictor did not have much influence on the influence of other predictors.

For the last step, the intensity of emotion was added with the significance level of .20, indicating that the intensity is not a significant predictor. However, with this predictor joined, the significance level for angry and fearful emotion and high multimodality background has increased a lot, which meant this predictor did have some influence for the model. The last three predictors were all non-significant predictors for the model, but the congruency and question type did not have much influence for the model while the intensity had an influence on other predictors and made the ability of the model to accounted for the variability of reaction time decreased. Besides, with the join of the last predictor, the level of neutral emotion was gone because neutral emotion has no intensity.

Compared to the MLR model in session 1, the model in session 2 could explain much more variability of reaction time (from 11.62% to 16.36%). Besides, the multimodality background changed from an insignificant predictor to a strong predictor. The congruency, question type and emotion intensity still performed as an insignificant predictor. The change of the model and the significant predictors may indicate that the multiliteracies learning between session 1 and session 2 have some influence on the model, and the multimodality background may influence the learning outcome of multiliteracies learning.

Table 18: Multiple Linear Regression Predicting Reaction Time from Multimodality Background, Emotion Type, Gender of Participants, Congruency, Question Type and Question Intensity

Step	Variable	*B*	*SE(B)*	*t*	*p*	Semi-partial r^2	95% CI	
1	**Multi_high**	364.96	94.77	3.85	.0001	.05	178.45	551.47
2	**Multi_high**	365.73	91.15	3.16	<.0001	.05	186.36	545.10
	Emotion_angry	323.71	102.50	2.02	.002	.03	121.99	525.42
	Emotion_fearful	209.02	103.55	-1.74	.04	.01	5.25	412.80
	Emotion_happy	-180.77	103.91		.08	.01	-385.26	23.72
3	**Multi_high**	258.26	90.47	2.85	.005	.02	80.22	436.31
	Emotion_angry	326.87	98.73	3.31	.001	.03	132.57	521.17
	Emotion_fearful	209.32	99.74	2.10	.04	.01	13.04	405.60
	Emotion_happy	-175.63	100.09	-1.75	.09	.01	-372.62	21.35
	Gender_female	-462.60	94.04	-4.92	<.0001	.07	-647.66	-277.54
4	**Multi_high**	258.10	90.51	2.85	.005	.02	79.97	436.23
	Emotion_angry	327.65	98.78	3.32	.001	.03	133.25	522.05
	Emotion_fearful	208.89	99.78	2.09	.04	.01	12.51	405.26
	Emotion_happy	-174.83	100.14	-1.75	.08	.01	-371.92	22.25
	Gender_female	-462.78	94.08	-4.92	<.0001	.07	-647.93	-277.63
	Congruent	-60.62	70.88	-.86	.39	.002	-200.11	78.87
5	**Multi_high**	257.56	90.62	2.84	.005	.02	79.22	435.91
	Emotion_angry	326.93	98.90	3.31	.001	.03	132.29	521.58
	Emotion_fearful	209.23	99.90	2.09	.04	.01	12.62	405.83
	Emotion_happy	-176.75	100.32	-1.76	.08	.01	-374.17	20.68
	Gender_female	-461.04	94.24	-4.89	<.0001	.07	-646.50	-275.58
	Congruent	-49.38	73.66	-.67	.50	.001	-194.35	95.59
	Question_face	41.96	73.79	.57	.57	.001	-103.27	187.19
6	**Multi_high**	283.78	103.75	2.74	.007	.03	79.29	488.26
	Emotion_angry	501.37	99.47	5.04	<.0001	.10	305.31	697.43
	Emotion_fearful	386.96	100.52	3.85	.0002	.06	188.83	585.09

Step	Variable	*B*	*SE(B)*	*t*	*p*	Semi-partial r^2	95% CI	
	Gender_female	-315.55	108.49	-2.91	.004	.03	-529.39	-101.72
	Congruent	19.20	82.05	.23	.82	.0002	-142.53	180.93
	Question_face	-41.17	81.69	-.50	.61	.0009	-202.19	119.85
	Intensity_regular	107.41	84.16	1.28	.20	.006	-58.47	273.30

Note. The reference group of multimodality background was low; the reference group of emotion was neutral for first five steps and was happy for the last step; the reference group of gender was male; the reference group of congruency was incongruent; the reference group of question type was voice; the reference group of intensity was high.

Robust Estimation.

Table 19 provided summary of parameter estimates and their significance and 95% confidence intervals for the model with robust estimation. Using robust estimation with Huber weights, multimodality background, emotion type, gender of participants remained significant predictors of reaction time. All estimates were adjusted, and the model with robust estimation could explain 18.03% of the variability of reaction time. The trials with participants of high multimodality background would cause longer reaction time compared with trials with participants of low multimodality background, with the difference of 264.17ms (p = .02). Those trials with angry emotion and fearful emotion would lead to longer reaction time compared with happy emotion, with the difference of 506.10ms (p <.0001) and 402.85ms (p = .0001) respectively, taking other predictors into account; besides, the female subjects would have a shorter reaction time compared with male subjects, with the difference of 324.53 (p = .005), taking other predictors into account. Congruency (p = .65), question type (p = .52) and question intensity (p = .18) still did not significantly predict the reaction time, taking other predictors into account.

Compared with the MLR model with robust estimation in session 1, similar to the comparison without robust estimation, multimodality background changed from a insignificant predictor to a significant predictor from session 1 to session 2, which may indicate that multimodality background may have influences on the learning of multiliteracies ESL, which will be further discussed in next chapter.

Table 19: Robust Estimation for Independent Variables Against Reaction Time in Session 2

Variable	***B***	***SE(B)***	***95%CI***		χ^2	***p***
Multi_high	264.17	109.41	49.73	478.62	5.83	.02
Emotion_angry	506.10	104.90	300.49	711.71	23.27	<.0001
Emotion_fearful	402.85	106.01	195.07	610.63	14.44	.0001
Gender_female	-324.53	114.41	-548.78	-100.29	8.05	.005
Congruent	39.58	86.54	-130.02	209.19	.21	.65
Question_face	-55.20	86.16	-224.06	113.67	.41	.52
Intensity_regular	119.57	88.76	-54.39	293.53	1.81	.18

Note. Adj R^2 *= .1803. The reference group of multimodality background was low; the reference group of emotion was neutral for first five steps and was happy for the last step; the reference group of gender was male; the reference group of congruency was incongruent; the reference group of question type was voice; the reference group of intensity was high.*

4.2.3 BLR model for the correctness

Relationships Between Independent Variables and Dependent Variable.

The bivariate relationships between independent variables and dependent variable in session 2 were shown in Table 20. Pearson chi-square test was conducted to test the relationships between all independent variables and correctness. The relationship between multimodality background and correctness was not significant, $\chi^2(1) = .53$, $p = .47$. The relationship between emotion and correctness was not significant, $\chi^2(3) = 11.81$, $p = .01$. The relationship between gender of participants and correctness was not significant, $\chi^2(1) = 3.56$, $p = .06$. The relationship between congruency and correctness was not significant, $\chi^2(1) = 1.17$, $p = .28$. The relationship between question type and correctness was significant, $\chi^2(1) = 8.92$, $p = .003$. The relationship between intensity and correctness was not significant, $\chi^2(1) = .72$, $p = .39$.

Table 20: Frequencies for Predictor Variables as a Function of Correctness

Variable	**Incorrect (*n* = 87)**	**correct (*n* = 269)**	**χ^2(1) or χ^2(3)**	***p***
Multimodality background (%)			.53	.47
Low	11.18	68.42		
High	3.62	16.78		
Emotion (%)			11.81	.01
Happy	4.61	19.74		
Angry	5.59	19.74		
Fearful	3.62	20.72		
Neutral	0.99	25.00		
Gender (%)			3.56	0.06
Female	10.53	70.72		
Male	4.28	14.47		
Congruency (%)			1.17	.28
Incongruent	8.55	41.78		
Congruent	6.25	43.42		
Question type (%)			8.92	.0003
Voice-related	10.20	38.16		
Face-related	4.61	47.04		
Intensity (%)			.72	.39
Regular	6.22	32.89		
Strong	12.44	48.44		

Collinearity Detection.

To check for collinearity among predictors, Pearson chi-square tests were conducted to test the relationships between two categorical variables, multimodality background and gender of participants. Like Research question 1.1 (a), other independent variables were the properties of stimulus and was set by experiment designer, which meant they were already independent from each other. The relationship between gender and multimodality background was significant, $\chi^2(1) = 20.00$, $p < .0001$ (see Table 15).

However, all standard errors in the model were less than 2.0 (see Table 21). Therefore, there was no severe multicollinearity among predictors in this model.

Table 21: Summary of Logistic Regression Analysis Predicting Correctness

Variable	***B***	***SE***	***OR***	**95% CI**	**Wald statistic**	***p***
Multi_background high vs. low	.57	.43	1.78	[0.76, 4.16]	1.75	.19
Emotion angry vs. happy	-.19	.42	.83	[0.36, 1.89]	.20	.66
Emotion fearful vs. happy	.38	.46	1.46	[0.59, 3.56]	.67	.41
Gender_subject female vs. male	.63	.45	1.88	[0.78, 4.53]	1.97	.16
Congruent vs. incongruent	.49	.37	1.64	[0.79, 3.38]	1.77	.18
Question type face vs. voice	1.16	.37	3.05	[1.46, 6.36]	8.86	.003
Intensity regular vs. strong	.12	.38	1.13	[0.53, 2.39]	0.10	.76

Note. CI = confidence interval for odds ratio (*OR*).

Checking Assumptions.

Correctness had a sample size of 320 in session 2. However, some of trials did not have answers, which caused 16 missing values; besides, the neutral trials did not have intensity, which caused more missing values ($N = 79$). Therefore, the final sample size for this model was 225. By dividing 225 by 30 (225/30 = 7.5), the maximum number of predictors were 7 in this model. This model had 6 predictors, which meant this model could be used to do further analysis.

The two categories of dependent variable were mutually exclusive and exhaustive, because each trail can either be correct or incorrect.

The independence of residuals was violated to some extent because although the participants did not know each other, there are lots of trials belonged to one participant. However, the further analysis will still be done because most of the assumptions were satisfied.

Influential outliers were assessed based on Pearson and Deviance residuals, Leverage, DfBetas and C statistics. Based on the Influence and predicted Probability Diagnostics plots (see Figure 33 – 39), case #6, #30, #39 and #50 were the most influential. The decision was made to keep these cases in the model because the sample size is small, and the number influential outliers is small.

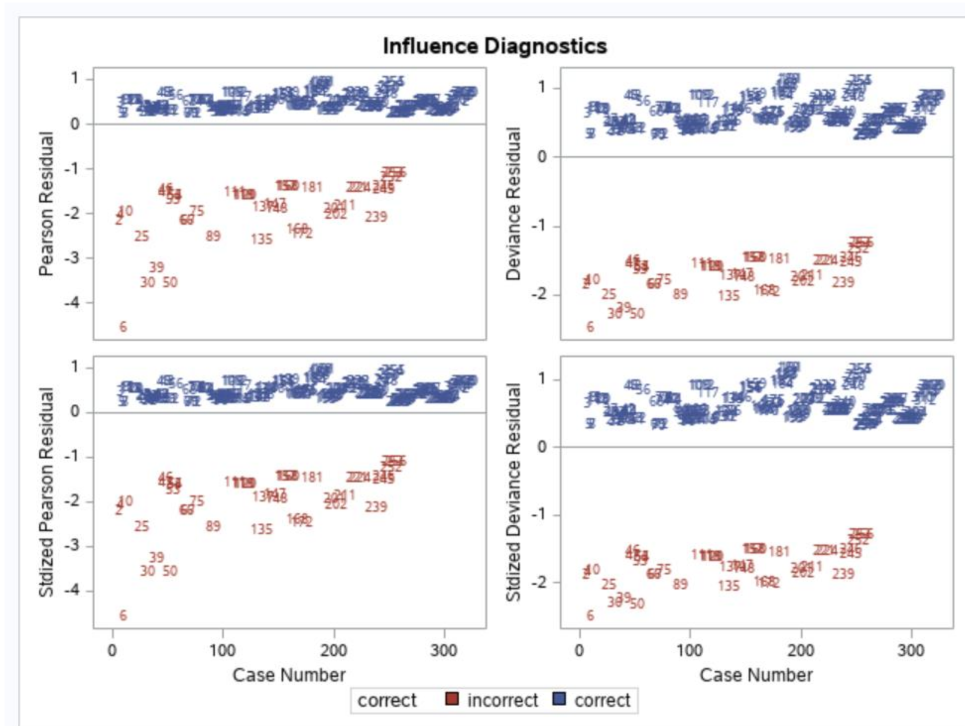

Figure 33: Pearson and Deviance Residuals Influence Diagnostics Plots

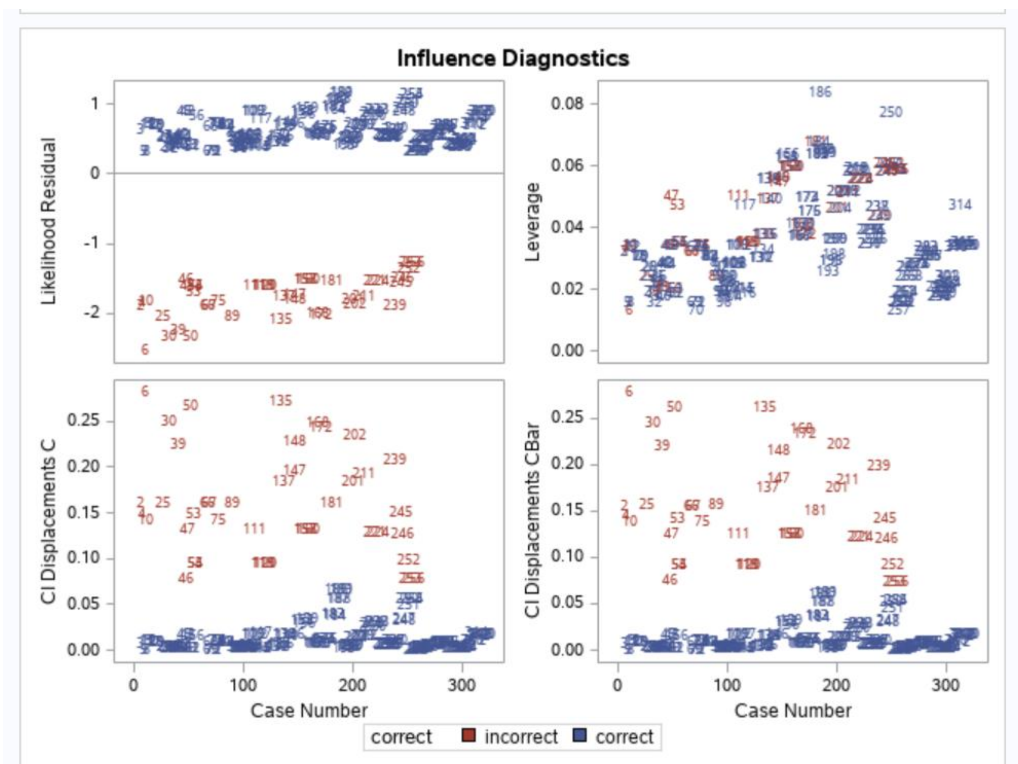

Figure 34: Leverage and C Influence Diagnostics Plots (1)

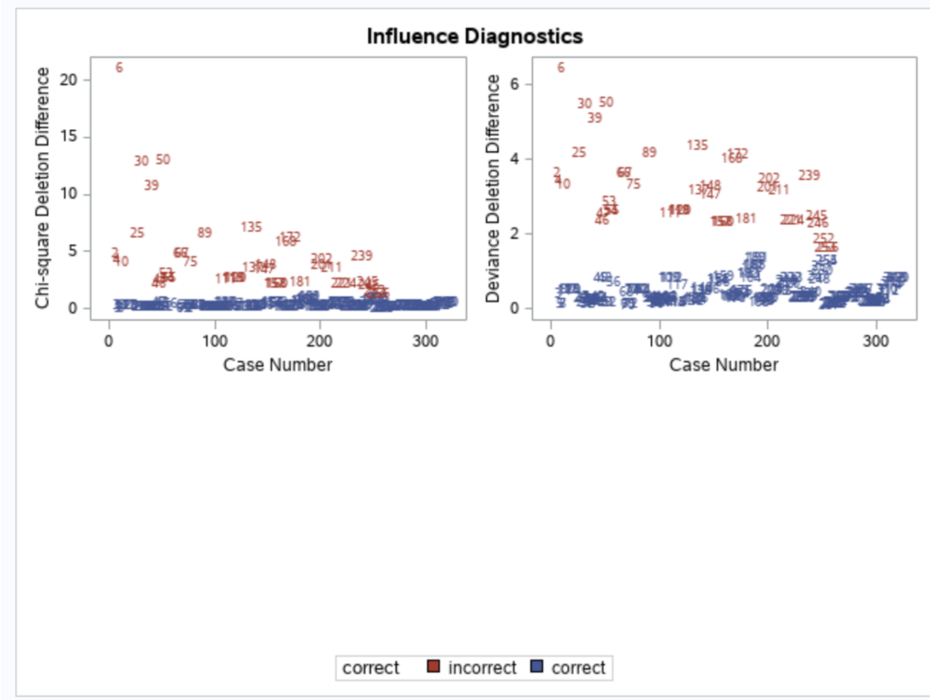

Figure 35: Leverage and C Influence Diagnostics Plots (2)

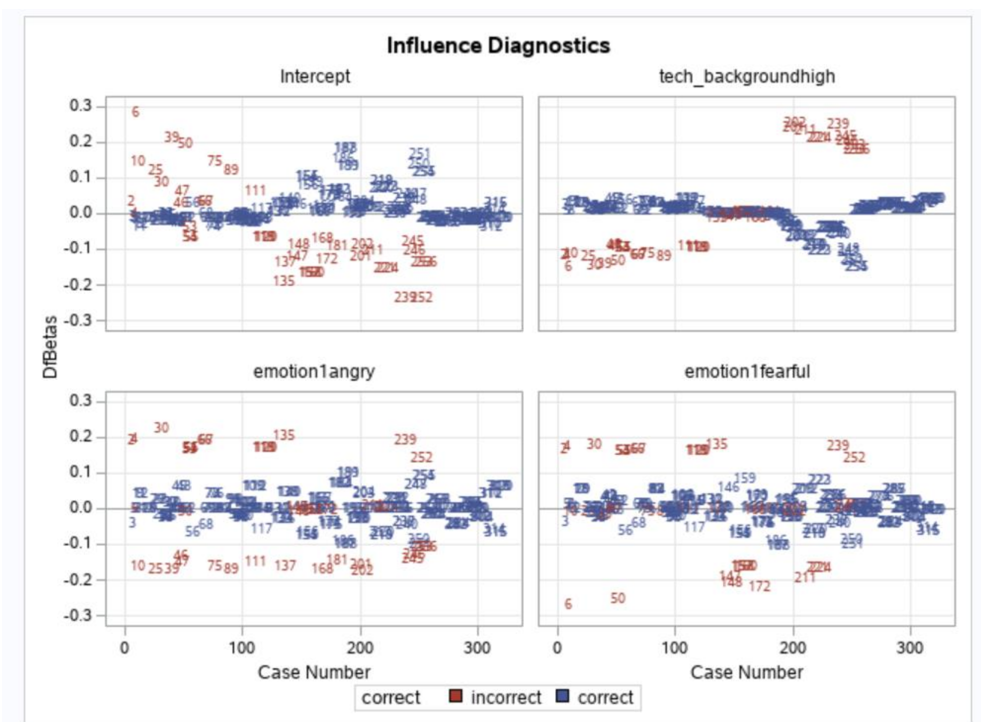

Figure 36: DfBetas Diagnostics Plots (1)

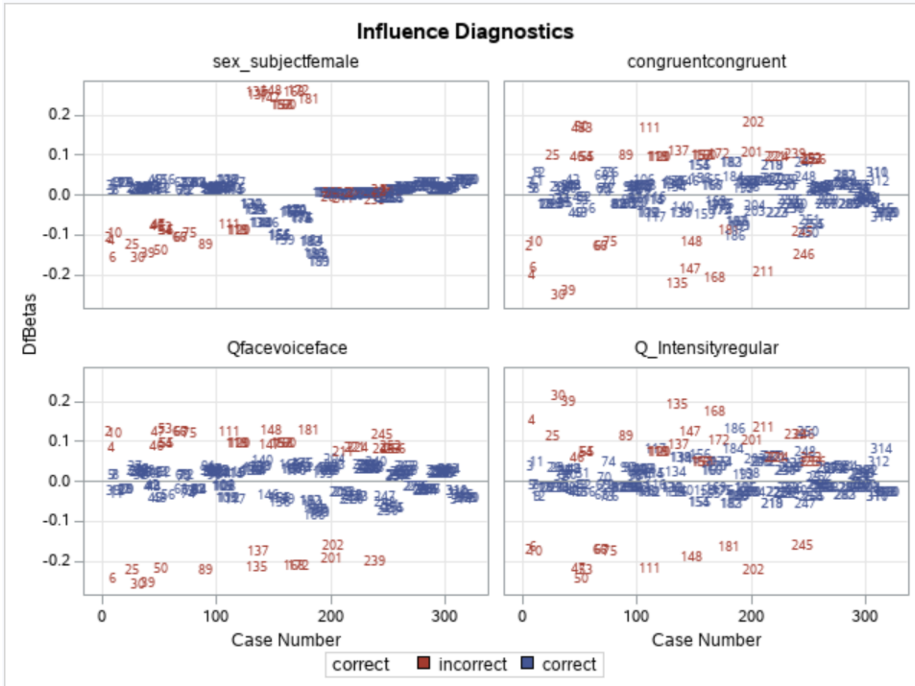

Figure 37: DfBetas Diagnostics Plots (2)

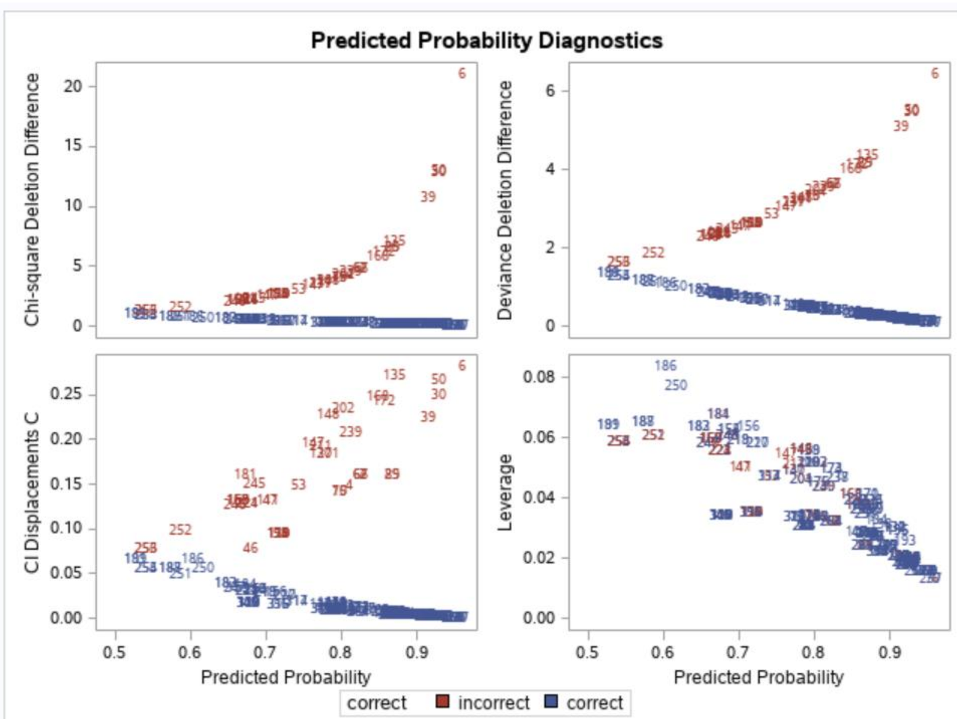

Figure 38: Predicted Probability Diagnostics Plots

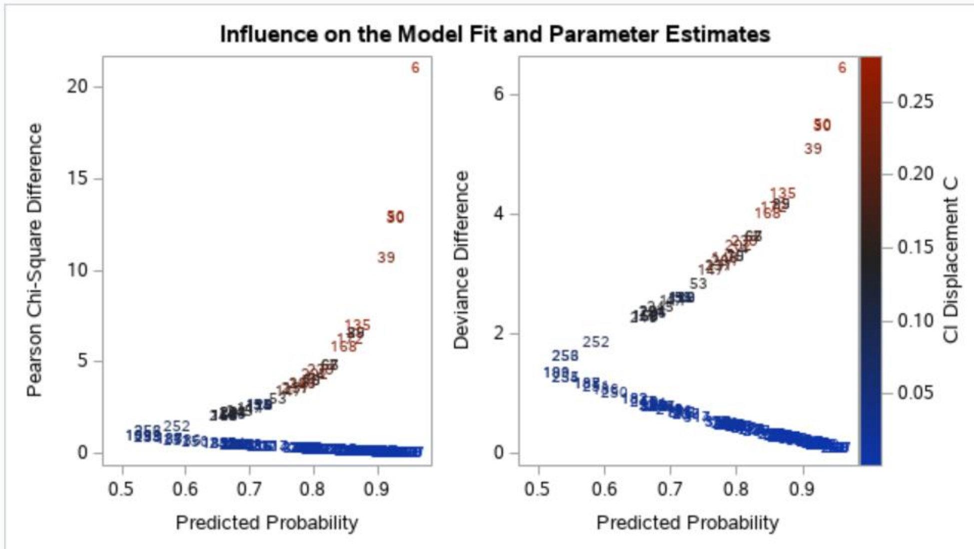

Figure 39: Influence on the Model Fit and Parameter Estimates Plots

Main Analysis.

A binary logistic regression was conducted using 6 predictors. The overall model was statistically significant compared to the null model, Likelihood ratio $\chi^2(7) = 15.79$, p = .03, Max-rescaled R^2 = 0.110. The model was able to discriminate between the trails that are correct and the trials that are incorrect at 70.3% accuracy.

In the model with multimodality background, emotion type, gender of participants, congruency, question type and intensity, multimodality background, emotion type, gender of participants, congruency and intensity was not significantly related to correctness.

Only the question type was significantly related to the correctness: compared with trials with voice-related questions, trials with face-related questions expected difference in the log-odds of being correct is 1.12, holding all other independent variables constant. It corresponded to a trial with face-related questions being 3.05 times more likely to be correct compared to a trial with voice-related questions, or 205% increase in odds.

Therefore, the hypothesis that in a multivariate model, face-related question (vs. voice-related question) were more likely to be correct for each test trials was supported, while the other 5 predictors did not have much difference in predicting the correctness for different categories.

Compared with BLR model of correctness in session 1, technology, emotion type and gender of participants were still not significantly related to correctness; however, in the BLR model in session 1, congruency and emotion intensity were significantly related to the chance of being correct, while for the BLR model in session 2, these two variables were not significantly related to the correctness; only the question type was still significantly related to correctness, but the difference of the two levels of question type (i.e., face-related or voice-related) decreased from 1.68 to 1.12. Besides, the value of max-rescaled R^2 for BLR models in session 1 were larger than that in session 2. Therefore, it was possible that after multiliteracies learning, there were some different variables that can be related to the chances of being correct; additionally, multiliteracies learning may enhance the ability to using parallel attention to both listening and watching and the ability to judge of emotions contained in language, and therefore lead to the insignificant relationship between congruency or emotion intensity and correctness, which will be further discussed in next chapter.

4.2.4 Simple comparisons between session 1 and session 2 for reaction time and accuracy

The t-test was used to check if there was a difference between session 1 and session 2 in reaction time and accuracy.

The mean of reaction time for session 1 (M = 2189.2) was more than that for session 2 (M = 2124.2), but the results show that t (657) = 1.16, p = .25, which meant there was not a significant difference for reaction time between session 1 and session 2 and our hypothesis was violated. That is to say, although there was a decrease in the reaction time in the session 2 compared that in session 2, this decrease was not significant, indicating that the multiliteracies learning did not have significant influence on reaction time of this experiment for the selected subjects.

Accuracy with missing values and without missing values was calculated for each participant in each session and t-test was used to compare the means of accuracy in session 1 and session 2. For accuracy without missing values, the results showed that t (9) =-2.09, p = .07, which meant although the mean of accuracy in session 1 (M = .76) was less than the mean of accuracy in session 2 (M = .85), the difference was not significant. For accuracy with missing values, the results showed that t (9) =-2.19, p = .06, which meant although the mean of accuracy in session 1 (M = .70) was less than the mean of accuracy in session 2 (M = .81), the difference is not significant.

With the following test results in Research Question 1.2 (c), it can be assumed that there was some influence of multiliteracies learning on increasing accuracy and decreasing reaction time, this influence was not significant.

4.3 Research Question 2.1 What is the Relationship between fNIRS Data and Students' Multimodality Background and Other Possible Factors Using Emotional Videos?

4.3.1 High Multimodality Group 1 vs. Low Multimodality Group 2: Congruent Stimuli

The brain regions that showed significant difference in oxyhemoglobin between group 1 and group 2 include superior frontal gyrus (SFG) - channel 17 (t (4) = 10.14, p < 0.01), premotor cortex (PMC) – channel 19 (t(4) = 4.73. p < 0.01), primary motor cortex (M1) – channel 26 (t(4) = 3.46, p = 0.03), superior parietal lobule (SPL) including channel 33 (t(4) = 3.45, p = 0.03) and 34 (t(4) = 4.05, p = 0.02) in frontal, temporal and parietal lobes (see Figure 40 (a)).

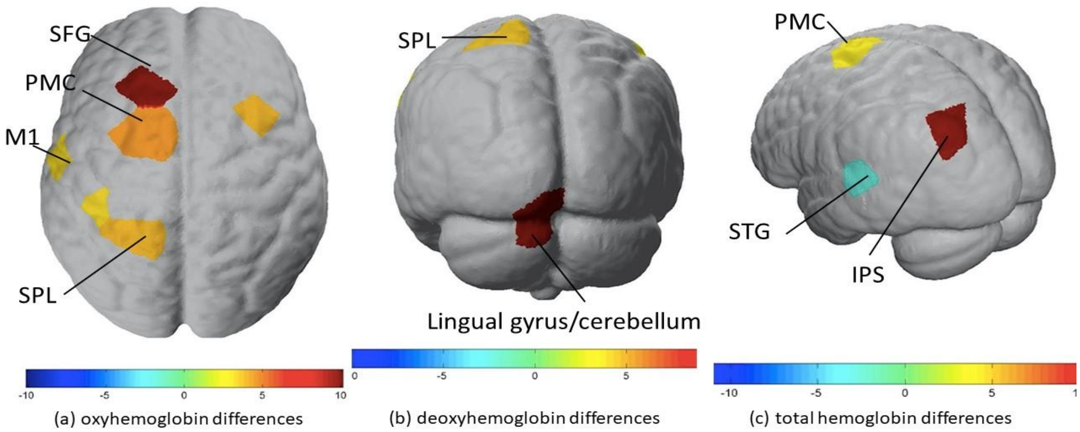

Figure 40: Session 1: High vs. Low Multimodality Group (between Group Contrast): Congruent Stimuli

Note. SPL, superior parietal lobule, M1 primary motor cortex, SFG, Superior frontal gyrus, PMC, premotor cortex, STG, superior temporal gyrus, IPS, intraparietal sulcus.

For deoxyhemoglobin differences, there are significant differences in superior parietal lobule – channel 34 ($t(4) = 4.63$, $p < 0.01$) and lingual gyrus – channel 96 ($t(4) = 12.5$, $p < 0.01$). Besides, channel 26 ($t(4) = 3.74$, $p = 0.02$), 57 ($t(4) = 3.64$, $p = 0.02$), 71 ($t(4) = 3.42$, $p = 0.03$) also showed significant difference between high and low multimodality group but they were not in the interested area (see Figure 40 (b)). For total hemoglobin differences, although there are significant differences in premotor cortex - channel 19($t(4) = 4.37$, $p = 0.01$), superior temporal gyrus - 38($t(4) = -2.78$, $p < 0.05$) and intraparietal sulcus – channel 43($t(4) = 14.63$, $p < 0.01$). In particular, the left superior temporal gyrus and the intraparietal sulcus were activated in the high multimodality group compared to the low multimodality group.

4.3.2 High Multimodality Group 1 vs. Low Multimodality Group 2: Incongruent Stimuli

The brain regions that showed significant difference in oxyhemoglobin between group 1 and group 2 in interested brain areas include primary somatosensory cortex (S1) - channel 27 ($t(4) = 4.86$, $p < 0.01$) and middle occipital gyrus (MOG) - channel 47($t(4) = 4.78$, $p < 0.01$) (see Figure 41(a)). Besides, channel 65($t(4) = 3.56$, $p = 0.02$) also showed significant difference between two groups. For deoxyhemoglobin differences, there are significant differences in inferior frontal gyrus (IFG) - channel 56($t(4) = -4.09$, $p = 0.01$) (see Figure 41(b)). Besides, channel 59($t(4) = 3.25$, $p = 0.03$), channel 89($t(4) = 9.14$, $p < 0.01$), channel 91($t(4) = 5.06$, $p < 0.01$), channel 94($t(4) = 3.35$, $p = 0.03$), channel 96($t(4) = 12.9$, $p < 0.01$) and channel 97($t(4) = 26.18$, $p < 0.01$) also showed significant difference in uninterested area. For total hemoglobin differences, there are significant differences in inferior frontal gryus – channel 56($t(4) = 3.34$, $p = 0.03$) and superior parietal lobule – channel 83($t(4) = 3.96$, $p = 0.02$) (see Figure 41(c)). In addition, channel 15($t(4) = -3.06$, $p = 0.04$) and 27($t(4) = 3.47$, $p = 0.03$) also showed significant difference between high and low multimodality groups.

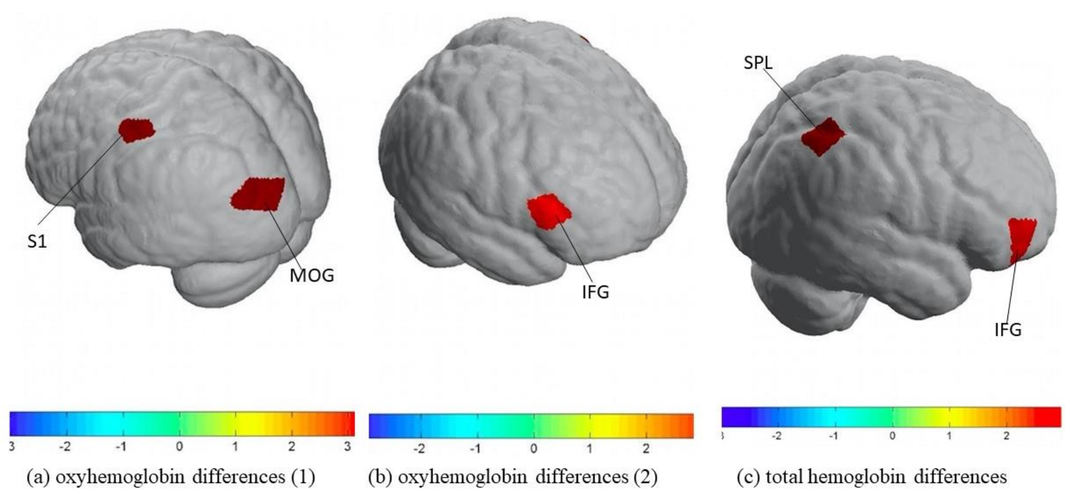

Figure 41: Session 1: High vs. Low Multimodality Group (between Group Contrast): Incongruent Stimuli

Note. S1, primary somatosensory cortex, MOG, middle occipital gyrus, IFG, inferior frontal gyrus, SPL, superior parietal lobule

4.3.3 High Multimodality Group 1 vs. Low Multimodality Group 2: Congruent vs. Incongruent Stimuli

For oxyhemoglobin differences, there are significant differences in channel 29 which is in superior temporal gyrus and middle temporal gyrus (see Figure 42(a)). For deoxyhemoglobin differences, there are significant differences in inferior frontal gyrus - channel 56. (see Figure 42(b). Besides, channel 96 in occipital gyrus also showed significant difference for deoxygenated hemoglobin. For total hemoglobin differences, there are significant differences in channel 26, 27, 31, 36 in primary somatosensory cortex, angular gyrus and middle temporal cortex (see Figure 42(c)).

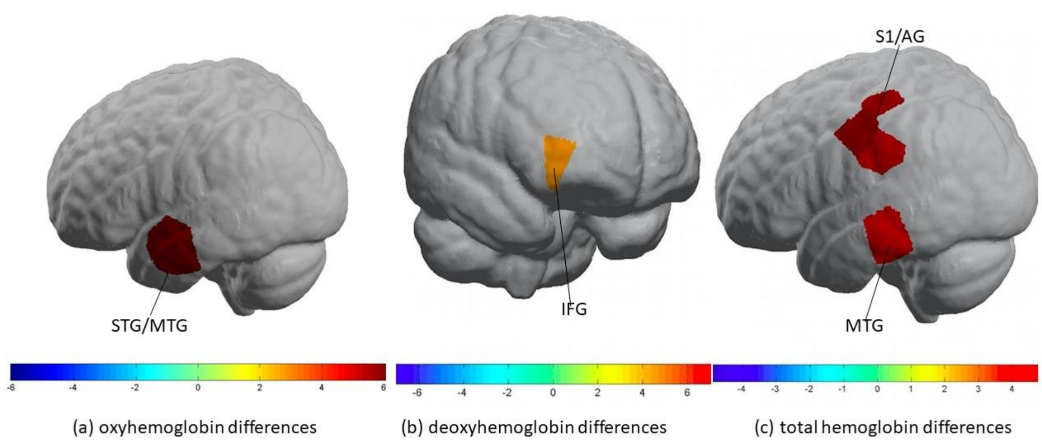

Figure 42: Session 1: High vs. Low Multimodality Group (between Group F-Contrast): Congruent vs. Incongruent Stimuli

Note. STG, superior temporal gyrus, MTG, middle temporal gyrus, IFG, inferior frontal gyrus, AG, angular gyrus, S1, primary somatosensory cortex

4.3.4 High Multimodality Group 1 vs. Low Multimodality Group 2: Congruent Stimuli - Emotions (Angry, Fearful and Happy) vs. Neutral

There is no significant brain region for this comparison in all three types of hemoglobin data: oxyhemoglobin, deoxyhemoglobin and total hemoglobin.

4.3.5 High Multimodality Group 1 vs. Low Multimodality Group 2: Face-related Question vs. Voice-related Question

There is no significant brain region for this comparison in both oxyhemoglobin and total hemoglobin data, but there showed significant difference in channel 49 and 96 in occipital lobe in left hemisphere for deoxyhemoglobin data.

4.4 Research Question 2.2 How does Participants' fNIRS Data Change after Multiliteracies ESL Learning?

4.4.1 Before Multiliteracies Learning Group 1 vs. After Multiliteracies Learning Group 2: Congruent Stimuli

The brain regions that showed significant difference in oxyhemoglobin between group 1 and group 2 are the channel 20($t(8) = -2.76$, $p = 0.02$) in middle and/or inferior frontal gyrus (MFG/IFG) and 29($t(8) = -2.68$, $p = 0.03$) in superior and/or middle temporal gyrus (STG/MTG) (see Figure 43(a)).

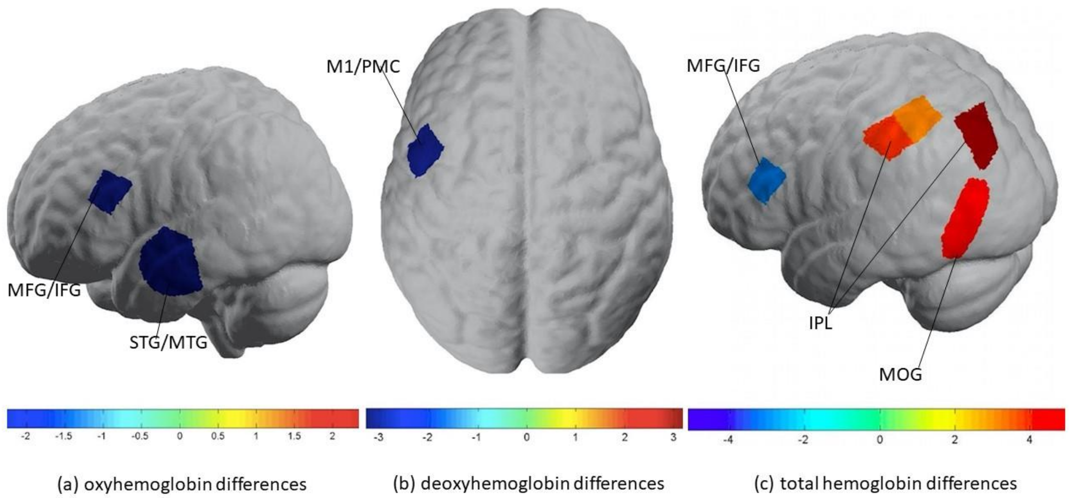

Figure 43: Before vs. After Multiliteracies Learning Group (between Group Contrast): Congruent Stimuli

Note. MFG/IFG, middle/inferior frontal gyrus, STG/MTG, superior/middle temporal gyrus, M1, primary motor cortex, PMC, premotor cortex, MFG/IFG, middle/inferior frontal gyrus, IPL, inferior parietal lobule, MOG, middle occipital gyrus

For deoxyhemoglobin differences, there is one channel (channel 24, $t(8) = -3.29$, $p = 0.01$) in primary motor cortex and/or premotor cortex in left hemisphere that showed significant difference (see Figure 43(b)). For total hemoglobin differences, there are some regions showed significant difference including superior and/or middle temporal gyrus - channel 20($t(8) = -3.11$, $p = 0.01$), inferior parietal lobule including channel 37($t(8) = 3.95$, $p < 0.01$), 40($t(8) = 3.06$, $p = 0.02$) and 43($t(8) = 6.49$, $p < 0.01$) and middle occipital gyrus – channel 46($t(8) = 4.58$, $p < 0.01$) (see Figure 43(c)). Besides, channel 63($t(8) = 2.64$, $p = 0.03$), channel 68($t(8) = -2.55$, $p = 0.03$), channel 74($t(8) = -4.53$, $p < 0.01$) and channel 94($t(8) = 2.84$, $p = 0.02$) also showed significant differences.

4.4.2 Before Multiliteracies Learning Group 1 vs. After Multiliteracies Learning Group: Answering Questions for Stimuli Trials

The brain regions that showed significant difference in oxyhemoglobin between group 1 and group 2 are the channel 28($t(8) = -2.43$, $p = 0.04$), channel 54($t(8) = -2.41$, $p = 0.04$), channel 56($t(8) = -2.32$, $p < 0.05$) and channel 72($t(8) = -2.32$, $p < 0.05$). For deoxyhemoglobin differences, channel 60($t(8) = -3.10$, $p = 0.02$), channel 64($t(8) = -2.71$, $p = 0.03$), channel 78($t(8) = -2.45$, $p = 0.04$) and channel 95($t(8) = 4.30$, $p < 0.01$) showed significant differences. For total hemoglobin differences, the channel showed significant difference includes channel 20($t(8) = -2.41$, $p = 0.04$), channel 66($t(8) = -2.39$, $p = 0.04$), channel 68($t(8) = -2.71$, $p = 0.03$) and channel 72($t(8) = -2.61$, $p = 0.03$).

4.4.3 Before Multiliteracies Learning Group 1 vs. After Multiliteracies Learning Group: Incongruent Stimuli - Emotions (Angry, Fearful and Happy) vs. Neutral

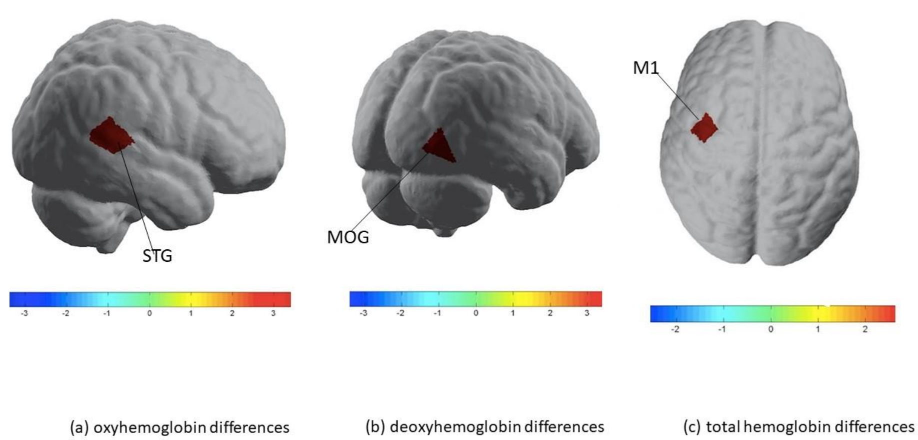

Figure 44: Before vs. After Multiliteracies Learning Group (between Group F-Contrast): Congruent Stimuli – Emotions (Angry, Fearful and Happy) vs. Neutral

Note. STG, superior temporal gyrus, MOG, middle occipital gyrus, M1, primary motor cortex

The channel 81 in superior temporal gyrus is the only channel that showed significant difference in oxyhemoglobin before and after multiliteracies learning. For deoxyhemoglobin differences, the channel 94 in middle occipital gyrus is the only channel showed significant difference. For total hemoglobin differences, the primary motor cortex – channel 25 showed significant difference.

4.5 Considerations for Mirror Tracing Task

T-tests was used to check if there were significant differences in the time spent on finishing mirror tracing tasks before and after multiliteracies learning. Because the sixth participant did not participate in the session 2, the data for mirror tracing task for the sixth participant was excluded. Table 22 showed the descriptive statistics for the experimental time for initial drawing task (M = 11.40, SD = 2.70 for session 1; M = 9.20, SD = 2.05 for session 2) and mirror tracing drawing task (M = 12.40, SD = 4.72 for session 1; M = 10.60, SD = 4.67 for session 2) in session 1 and 2 respectively.

Table 22: ***Descriptive Statistics for Time Spent on Mirror Tracking Task***

Session	**Variable**	**Mean**	**Std.Dev**	**Minimum**	**Maximum**	**N**
1	**Time spent on initial drawing task**	11.40	2.70	7.00	14.00	5
	Time spent on mirror tracing task	12.40	4.72	6.00	17.00	5
2	**Time spent on initial drawing task**	9.20	2.05	7.00	11.00	5
	Time spent on mirror tracing task	10.60	4.67	6.00	17.00	5

Table 23 showed the t-test results for mirror tracing task. According to the t-tests results, there was no significant change for time spent on drawing task for both initial drawing task (p = .18) and mirror tracking task (p = .56).

Table 23: T-tests Results for Comparing Mirror Tracing Task Performance between Session 1 and 2

Variable	**Df**	***t* (8)**	***p***
Time spent on initial drawing task	8	1.45	.18
Time spent on mirror tracing task	8	.61	.56

Chapter 5

5 Conclusion

The overall purpose of this study was to understand the influences of multiliteracies learning for ESL learners on their multiliteracies task performance (i.e., behavioural data) and brain activities (i.e., fNIRS data). To achieve this purpose, an E-prime experiment with multimodality emotional stimuli was designed to collect participants' behavioural data and fNIRS data during ESL participants' completion of the experiment both during and after multiliteracies learning. The data analysis for behavioural data used MLR and BLR models to establish the relationship between reaction time or correct responses and the six independent variables during and after multiliteracies learning: participants' multimodality background/digital literacy background; the gender of participants; the emotion types, the intensity and congruency of stimuli; and the question types regarding either face or voice. Results showed that although there is no significant difference in reaction time and accuracy during and after multiliteracies learning, the models for predicting the reaction time and correct responses have changed. The data analysis for fNIRS data used NIRSlab to make comparisons between high multimodality background group and the low multimodality background group, and between the session 1 and session 2 regarding congruency or emotion types. The results showed that superior and middle temporal gyrus (STG/MTG), inferior frontal gyrus (IFG), primary motor cortex (M1) and premotor cortex (PMC) were the main areas that showed significance difference between the groups. There were also a few channels in occipital lobes that showed significance, but they did not get discussed in this thesis because the significant channels in occipital lobes were considered to be related to visual information processing and the aim of the experiment was to study more complex aspects of multimodal and multisensory processing.

This chapter begins with a summary of the data analysis results in chapter 4 and discusses the similarities and differences between this study and previous study findings. Then, the limitations of this study were discussed. The third part reviews the possible implications based on the findings of this study. Finally, this study provides possible directions for future data analysis and future research and ends with a summary of the thesis's main findings.

5.1 Summary and Discussion of the Main Findings

The mirror tracing task was used as a control task to make sure there was no significant changes in participants' procedural memory. Training in procedural memory could cause changes in brain structures, which means more consideration of the training in procedural memory need to be considered to analyze the changes in fNIRS data if there is a significant change happen in the mirror tracing task performance. The results showed that students' multiliteracies learning did not significant influence in procedural memory, which meant the influence of procedural memory did not need to be considered when analyzing the behavioural and fNIRS data.

The first research questions drew upon the relationship between behavioural data and the independent variables and the changes in the relationships both during and after multiliteracies learning. According to the results of preliminary analysis, only the gender of participants has a significant relationship with reaction time in session 1, and only congruency and question types have significant relationships with correctness without considering the influence of other possible factors using t-test, ANOVA or Chi-square. When using the MLR model to establish the relationship between reaction time and all six independent variables, the results showed that the emotion types and the gender of participants could be significantly related to the reaction time in the established model, while multimodality background, congruency, question types and intensity did not have a significant relationship with reaction time. As mentioned in the literature review in Chapter 2, a significant number of findings have demonstrated that technology usage can help students develop digital literacy and multimodality(e.g., Beach, 2012), which may ultimately help participants to react more quickly, but the findings cannot support this inference. The possible reason is that the tasks were too difficult or too easy for the participants to finish in a limited time, and thus that they did not show significant differences in different levels of the insignificant predictors; the other reason can be the questions in technology questionnaire could not reflect students' multimodality and ability on audio-visual contents correctly. The significant difference in reaction time between the angry emotion and the happy emotion (i.e., the baseline emotion in the model) may be anger is more difficult to distinguish than fear and happiness for ESL learners before multiliteracies learning, but the further reason still need to be explored.

The gender difference coincides with previous research findings from Beavis et al. (2015) that suggested that females are more likely to experience personality changes during the game. From this experiment, it can probably be inferred that females are more sensitive to changes in emotion, and thus they can react more quickly during the multiliteracies experimental tasks. However, due to the small sample size and the unbalanced number of female and male participants, the individual differences can also cause the results.

For the BLR model for correctness in session 1, multimodality background, emotion type and gender of participants did not show a significant relationship with correctness in the model with all 6 predictors, while the congruency and intensity of stimuli and question types showed a significant relationship with correctness. Although it may be surprising that multimodality background, emotion types and gender of participants were not significantly related to correctness, it is reasonable that congruency and intensity of stimuli as well as question types could be significantly related to correctness given the following: a) before multiliteracies learning, participants' ability to pay attention to both face and voice in English simultaneously would not be sufficient enough to answer equally well on both congruent and incongruent trials; b) participants would pay more attention to face than voice when distinguishing emotions in an unfamiliar language and their listening ability would be improved after multiliteracies learning (e.g., Winke, 2013); and c) participants can response better to stimuli with strong intensity because their ability to distinguish emotions was often not strong sufficient to discern the emotion from regular intensity stimuli.

After multiliteracies learning, although the simple comparison results showed that there is no significant change in accuracy, the MLR model for predicting reaction time and BLR model for predicting correctness for session 2 changed compared with models in session 1. For reaction time, although the congruency, question type and intensity still remained insignificant predictors in the model, multimodality background has become the significant predictor, and both angry and fearful emotions have a significant influence on reaction time compared with the happy emotion. It can be inferred that although the level of multimodality background did not significantly affect the reaction time in MLR model in session 1, it may influence the multiliteracies learning process. This influence coincidences with the stipulation that prior knowledge can have an influence on a student's ability to learn new material. Additionally, the theory of "funds of knowledge" (e.g., Ana, 2004) also called for the integration of students' prior backgrounds into the classroom and argued that teachers should recognize the importance of students' prior knowledge when learning. The findings that multimodality background changes from being an insignificant influencer to a significant predictor supports the previous findings. For BLR models in session 2, although multimodality background, emotion types of stimuli, and gender of participants remained as the insignificant predictors and question type remained a significant predictor, the congruency and intensity of stimuli changed from significant predictors to insignificant predictors, which likely infers that students' parallel attention was improved to be able to distinguish the congruency and the regular intensity of stimuli. The above findings of behavioural data demonstrated that multiliteracies learning did have a positive influence on students' parallel attention demonstrated, and their ability to distinguish emotions in foreign language.

For fNIRS data in session 1, for the t-test for comparing the hemoglobin differences when viewing and listening congruent or incongruent stimulus between high multimodality group and low multimodality group in session 1, channels in SFG, IFG, SPL, M1, S1, AG, PMC, SPG and IPS showed significant differences in brain activities. The different activation of these brain regions was reasonable considering the stimulus content, and supported the previous research findings that a) IFG and STG are related to emotional processing and language processing (e.g., Balconi, Grippa, & Vanutelli, 2015; Balaguer and Rodríguez Fornells, 2010); b) AG is important to language understanding and visual memory (e.g., Seghier, 2012); c) technology use can have a influence on temporal lobes (Gottschalk, 2019); d) IPS is greatly involved in emotional face perception and processing (e.g., Fan, Wan, Zhang, Jin & Li, 2018) and e) STG area is related to multisensory processing (e.g., Balconi, Grippa, & Vanutelli, 2015). The *t* value was negative for STG but is positive for the IPS (see Figure 40), which may indicate that technology use could help the development of STG but may inhibit the development of IPS. For F-contrasts which compared the differences between viewing and listening congruent and incongruent stimulus in group 1 versus group 2 (i.e., the group 1 is the high multimodality background group and the group 2 is the low multimodality background group), the STG, IFG and S1 were main areas that showed significant difference.

The above findings strongly supported the previous findings that STG area is strongly connected to multisensory processing (e.g., Gentile et al., 2017) and the experience of multimodality could help the development of multisensory area in brain. The possible reason for why there are significant difference for F-contrasts in IFG, and S1 may be these regions are related to sensory processing and working memory, but further reasons still need to be explored. For the F-contrast that considering both multimodality background and emotion type and the F-contrast considering both multimodality background and question type, no significant channel was found, which may indicate that the multimodality background did not have significant influence on the ability on emotional perception and the preference on visual or audio information based on the fNIRS data in this experiment.

For comparing fNIRS data between session 1 and session 2, there were significant changes in activity in IFG/MFG, IPL, M1/PFC and STG/MTG brain regions. The results were inline with previous findings, because IFG/MFG is related to the processing of speech and language (e.g., Greenlee et al., 2007), IPS is involved in the processing of the facial emotional processing (e.g., Radua et al., 2010), M1/PFC is related to the control the behaviour of arms, legs and human body and STG/MTG is involved in both multisensory and emotional processing.

For t-contrasts, the *t* values were negative for most of the significant channels except for the ones in IPL, which meant the hemoglobin states were stabler in session 2 than that in session 1, and it can be inferred that these important areas gets developed after multiliteracies learning. However, the *t* values for IPL were positive, which meant participants spent more efforts on facial emotional processing that is related to IPL, which coincides with our hypothesis that they will be better in distinguishing facial emotions. In addition, according to the analysis results of behavioral data, question type was an insignificant predictor for reaction time both during and after multiliteracies learning and it was a significant predictor for correctness both during and after multiliteracies learning, while the correctness for face-related questions increased after multiliteracies learning. The reason for it should be further explored. For the F-test that considered both emotion types and time (i.e., session 1 and session 2, both STG and M1 areas showed significant difference, which may indicate the impact of multiliteracies learning on STG and M1 and may indicate that students could make quicker body response (make a choice with keyboard, which can be controlled by M1) and could have better ability in dealing with multisensory.

5.2 Limitations

This study has 4 main limitations that will be discussed in this section. These limitations include the small sample size and the selection of the sample, the recruitment of the participant, the lack of qualitative data on the practice of multiliteracies learning and the limitations of fNIRS data analysis.

The first limitation that needs to be addressed is the small sample size and the selection of participants. The minimum sample size was estimated to be 10 participants for both sessions, but the recruitment process did not proceed well, and there were only 6 participants enrolled in session 1 by the time the COVID-19 crisis hit London. One participant could not participate in session 2 experiment because of the lockdown restrictions, and there was another participant whose fNIRS data in session 2 was damaged. These factors ultimately resulted in only 6 participants completing the first session, only 4 samples of fNIRS data collected in session 2, and only 5 samples of behavioural data collected in session 2. This small sample size could indicate that the recruited body of participants may not be fully representative of ESL learners in the experimental area, and therefore the data and calculated models obtained from this experiment lead to the less reliable results and may lead to the Type II error for the analysis for the control task – mirror tracing task. Additionally, since this experiment could only be performed in the laboratory in time-intensive sessions, the selection of participants was greatly restricted. First, ESL learners residing far from Western campus may not be able to participate. Second, all participants of the experiment expressed interest in the experiment, and it is possible that these interested ESL learners may have some characteristics fundamentally different than uninterested ESL learners, and that these differences may affect the experimental results. Thirdly, the unbalanced sample size for female and male participants may lead to the results that showed gender differences may be caused only by individual differences. Finally, the method of recruitment way for this study mainly involved displaying posters in ESL buildings or libraries and posting advertisements on Wechat and Facebook. Two participants were recruited through Wechat and four participants were recruited through posters. These different sources of participants may also suggest that these study participants have different characteristics. When a sample size is too small, it is possible that differences in characteristics may have a greater impact on the experimental results.

The second limitation is the lack of qualitative data. This research was initially planned to be a mixed-design research and should have included qualitative interview data to understand participants' real multiliteracies learning in real classrooms. However, following the outbreak of COVID-19, these interviews could not be conducted and therefore the findings cannot be fully related to real multiliteracies practice. The ESL courses that participants choose were different from one another given that participants are not in the same ESL program, thus multiliteracies and multimodality content in these courses can be dissimilar. Therefore, differences in curriculum may strongly impact a participant's performance in this experiment and their brain development following multiliteracies learning. In addition, as mentioned in Chapter 2, traditionally there has always been a persistent view in the field of education that the neuroscience findings are usually separate from classroom settings and cannot be applied to real teaching and learning. By including interview information to the research data, we can better combine teaching practice with experimental research, and thus the conclusions obtained may be more practical. Without qualitative data on participants' curriculum, the cause-effect relations between multiliteracies learning and the study outcome is uncertain. In view of our inadequate understanding of the participants' classroom activities and daily activities between the two sessions of the experiment, we may not be able to attribute the experimental results to multiliteracies learning, because participants were also exposure to other multimodal information and multimodality learning in their daily life. Therefore, there are certain flaws in the discussion of the experimental results and should be further explored.

The third limitation is the design of digital technology questionnaire and participants' multimodality background. According to the literature review, digital technologies can greatly enhance the students' multimodality ability because they contain many forms of multimodal information. However, the study results showed that the multimodality score through technology questionnaire did not predict students' performance in multimodal tasks significantly. This may indicate that the design of this questionnaire is not comprehensive enough to understand participants' multimodality background. For example, our experiment mainly used audio-visual tasks, but the questionnaire did not ask specific question about students' audio-visual ability.

The last limitation is limited fNIRS data analysis. For the analysis of fNIRS data, nirsLAB software was used. This software can provide basic information on fNIRS data, and compare the data using t-test and F-tests. Despite these advantages, nirsLAB software also has its limitations; for example, it can only analyze the fNIRS data of two wavelengths (785nm and 850nm), which consequentially may lose some information from the other two wavelengths. In addition, given that the software cannot directly output the significance level of the comparisons, it is necessary to use the degrees of freedom and t or F value to calculate the significance level. However, the F-tests performed in the software did not appear to be a simple ANOVA. If the calculation of significance level were completed with the degrees of freedom of a simple ANOVA, the significant channel output, completed by the software would no longer be significant. This is the reason why the F value and p value were not reported in Chapter 4.

5.3 Implications

Although this study has the above limitations, these research findings can still have some meaningful implications. Firstly, these findings provided evidences that multiliteracies and technology use can probably improve the development of the STG area and the ability of parallel attention, and also demonstrated that more multimodal teaching materials and technology can be added into real teaching practices and curriculum design. Secondly, these findings verified the importance of the prior knowledge, and suggested that educators should consider students' prior knowledge, including their first language, cultural background, and multimodality background, in multiliteracies curriculum design. Finally, this research supported the view that emotions are related to language learning, and that there is strong evidence that suggest the perception of emotions in language can be added to the assessment of language learning. The main purpose of multiliteracies language learning is to be applied in real life, and the perception of another's emotions is an important aspect of this style of communication. Therefore, multiple forms of language learning assessment may help educators better understand student's learning situations. This kind of assessment not only echoes the multiliteracies' view that learning must be conducted in this style of contexts and must pay attention to students' experience when learning, but also supports the promotion of multiple forms of assessment.

5.4 Directions for Future Data Analysis and Research

5.4.1 Directions for Future Data Analysis

In addition to the data used in this thesis, eye-tracking data was also collected to better understand the cognitive processes of participants during the experiment. Analyzing eye-tracking data and combining it with existing experimental findings may provide researchers with a deeper understanding of the processing of multimodal information, and an abundance of questions regarding participant learning processes, including inquiries such as: when the participants were viewing stimuli videos, were they more interested in the actor's eyes or the mouth to distinguish the emotions? Would this interest change after multiliteracies learning? Is interest in different face regions related to multimodal tasks performance and different brain activities?

In addition to eye-tracking data, there were other sources of collected data, including questionnaire information that can be used for analysis to support or modify existing conclusions because the information covered by other questionnaires can be quantified and may help to better modify the existing MLR and BLR model. For example, the LEAP-Q questionnaire can be coded to quantify the participant's English ability and then this data can be added as a predictor in the model of reaction time and correctness.

5.4.2 Directions for Future Research

For future research, the most important direction for future research is to include more information on the authentic teaching practice. Possible methods could include: working with an ESL programmer to design a specific multiliteracies ESL curriculum for an ESL program; interviewing student participants to understand their experiences in multiliteracies classroom; or collaborating with ESL teachers to better understand the teaching practices, etc. While this study demonstrated that multiliteracies can have a positive effect and can also improve brain development, there are also many studies that have also demonstrated that the effect of technology use on learning and brain development can be negative if used incorrectly. Thus, further research is needed to determine what kind of multiliteracies course design is the most beneficial for learning. Therefore, future research should concentrate on the relationship between the real multiliteracies practice and students' brain development. Additionally, there is also the possibility of using fNIRS in classrooms settings to study the brain's immediate response to classroom content, considering the portability and low noise properties of fNIRS. While it may be difficult to employ simultaneously given budgetary concerns, there remains a strong potential for designing and conducting in a single subject experimental design to better understand the entire learning process.

Another recommendation for future research is to include the usage of brain-imaging techniques in future experiments on learning. For example, there have been many studies that have demonstrated the possibility of collecting data from EEG and fNIRS simultaneously, which can provide the experiment with both good temporal and spatial resolution. Using more brain imaging technologies in a single study can increase the reliability of the study while correcting the shortcomings of each brain imaging technique. For example, fNIRS can only achieve a depth sensitivity of approximately 1.5 cm, and a spatial resolution up to 1 cm. Thus, while it cannot be used to observe brain activity within the insular cortex, fMRI can help to achieve a deeper sensitivity and higher spatial resolution.

5.5 Conclusion

This study uses a relatively novel neuroimaging technique – fNIRS – to understand the influence of multiliteracies learning on ESL adult learners. Through establishing models of behaviour data and comparing the fNIRS data, this study provides some evidence on how students' multimodality background could be related to multimodal task performance and brain development using emotional stimuli. This is the first neuroscience study to understand multimodal ESL learning through a multiliteracies perspective and to highlight the potential for using emotional stimuli to measure multiliteracies performance.

The findings of this study make a great contribution to both the neuroscience field and the multiliteracies field. To be more specific, for multiliteracies research, this study used emotional stimuli which are commonly used in psychological research within educational fields to understand the impact of learning, and also used neuroimaging tools to more deeply understand the neural mechanism of multiliteracies learning. Consequently, the results demonstrated that the brain areas related to processing of multisensory, language, body motor and emotions can be significantly developed. For neuroscience research, this study has broadened the neuroscience research in educational fields, and has demonstrated that the use of neuroscience in education is not only related to FL or the use of technology in education, but also related to multiliteracies, which is one of the most important pedagogy for literacy learning in recent years. Although this study has some limitations in research methods and sample size, the results of the study still provide significant understanding and suggest possible methods of studying multiliteracies using neuroscience techniques.

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Appendices

Appendix A: Technology Questionnaire

Please answer the following questions about your computer use and experience. For each statement below, please select the option that best describes you.

Information Navigation

Q1 I get tired when looking for information online.

- ☐ Not at all true of me
- ☐ Not very true of me
- ☐ Neither true nor untrue of me
- ☐ Mostly true of me
- ☐ Very true of me

Q2 Sometimes I end up on websites without knowing how I got there.

- ☐ Not at all true of me
- ☐ Not very true of me
- ☐ Neither true nor untrue of me
- ☐ Mostly true of me
- ☐ Very true of me

Q3 I find it hard to find a website I visited before.

- ☐ Not at all true of me
- ☐ Not very true of me
- ☐ Neither true nor untrue of me
- ☐ Mostly true of me
- ☐ Very true of me

Q4 I find the way in which many websites are designed confusing.

- ☐ Not at all true of me
- ☐ Not very true of me
- ☐ Neither true nor untrue of me
- ☐ Mostly true of me
- ☐ Very true of me

Q5 I find it hard to decide what the best keywords are to use for online searches.

- ☐ Not at all true of me

- ☐ Not very true of me
- ☐ Neither true nor untrue of me
- ☐ Mostly true of me
- ☐ Very true of me

Q6 I should take a course on finding information online.

- ☐ Not at all true of me
- ☐ Not very true of me
- ☐ Neither true nor untrue of me
- ☐ Mostly true of me
- ☐ Very true of me

Q7 All the different website layouts make working with the Internet difficult for me.

- ☐ Not at all true of me
- ☐ Not very true of me
- ☐ Neither true nor untrue of me
- ☐ Mostly true of me
- ☐ Very true of me

Q8 Sometimes I find it hard to verify information I have retrieved.

- ☐ Not at all true of me
- ☐ Not very true of me
- ☐ Neither true nor untrue of me
- ☐ Mostly true of me
- ☐ Very true of me

Social Skills

Q9 I know when I should and shouldn't share information online.

- ☐ Not at all true of me
- ☐ Not very true of me
- ☐ Neither true nor untrue of me
- ☐ Mostly true of me
- ☐ Very true of me

Q10 I am careful to make my comments and behaviours appropriate to the situation I find myself in online.

☐ Not at all true of me

☐ Not very true of me

☐ Neither true nor untrue of me

☐ Mostly true of me

☐ Very true of me

Q11 I know how to remove friends from my contact lists.

☐ Not at all true of me

☐ Not very true of me

☐ Neither true nor untrue of me

☐ Mostly true of me

☐ Very true of me

Q12 I know which information I should and shouldn't share online.

☐ Not at all true of me

☐ Not very true of me

☐ Neither true nor untrue of me

☐ Mostly true of me

☐ Very true of me

Q13 I know how to change who I share content with.

☐ Not at all true of me

☐ Not very true of me

☐ Neither true nor untrue of me

☐ Mostly true of me

☐ Very true of me

Q14 I feel comfortable deciding who to follow online.

☐ Not at all true of me

☐ Not very true of me

☐ Neither true nor untrue of me

☐ Mostly true of me

- Very true of me

Creative Skills

Q15 I know how to design a website.

- Not at all true of me
- Not very true of me
- Neither true nor untrue of me
- Mostly true of me
- Very true of me

Q16 I would feel confident putting video content I have created online.

- Not at all true of me
- Not very true of me
- Neither true nor untrue of me
- Mostly true of me
- Very true of me

Q17 I know which different types of licences apply to online content.

- Not at all true of me
- Not very true of me
- Neither true nor untrue of me
- Mostly true of me
- Very true of me

Q18 I know how to make basic changes to the content that others have produced.

- Not at all true of me
- Not very true of me
- Neither true nor untrue of me
- Mostly true of me
- Very true of me

Q19 I know how to create something new from existing online images, music or video.

- Not at all true of me
- Not very true of me
- Neither true nor untrue of me

- Mostly true of me
- Very true of me

Q20 I know which apps/software are safe to download.

- Not at all true of me
- Not very true of me
- Neither true nor untrue of me
- Mostly true of me
- Very true of me

Q21 I am confident about writing a comment on a blog, website or forum.

- Not at all true of me
- Not very true of me
- Neither true nor untrue of me
- Mostly true of me
- Very true of me

Q22 I would feel confident writing and commenting online.

- Not at all true of me
- Not very true of me
- Neither true nor untrue of me
- Mostly true of me
- Very true of me

Operational Skills Q23 I know how to open downloaded files.

- Not at all true of me
- Not very true of me
- Neither true nor untrue of me
- Mostly true of me
- Very true of me

Q24 I know how to download/save a photo I found online.

- Not at all true of me
- Not very true of me
- Neither true nor untrue of me

- Mostly true of me
- Very true of me

Q25 I know how to open a new tab in my browser.

- Not at all true of me
- Not very true of me
- Neither true nor untrue of me
- Mostly true of me
- Very true of me

Q26 I know how to use shortcut keys.

- Not at all true of me
- Not very true of me
- Neither true nor untrue of me
- Mostly true of me
- Very true of me

Q27 I know how to bookmark a website.

- Not at all true of me
- Not very true of me
- Neither true nor untrue of me
- Mostly true of me
- Very true of me

Q28 I know where to click to go to a different webpage.

- Not at all true of me
- Not very true of me
- Neither true or nor untrue of me
- Mostly true of me
- Very true of me

Q29 I know how to complete online forms.

- Not at all true of me
- Not very true of me
- Neither true nor untrue of me

- Mostly true of me
- Very true of me

Q30 I know how to connect to a WIFI network.

- Not at all true of me
- Not very true of me
- Neither true nor untrue of me
- Mostly true of me
- Very true of me

Q31 I know how to upload files.

- Not at all true of me
- Not very true of me
- Neither true nor untrue of me
- Mostly true of me
- Very true of me

Q32 I know how to adjust privacy settings.

- Not at all true of me
- Not very true of me
- Neither true nor untrue of me
- Mostly true of me
- Very true of me

Mobile Internet Skills

Q33 I know how to install apps on my mobile device.

- Not at all true of me
- Not very true of me
- Neither true nor untrue of me
- Mostly true of me
- Very true of me

Q34 I know how to download apps to my mobile device.

- Not at all true of me
- Not very true of me

☐ Neither true nor untrue of me

☐ Mostly true of me

☐ Very true of me

Q35 I know how to keep track of the costs of mobile app use.

☐ Not at all true of me

☐ Not very true of me

☐ Neither true nor untrue of me

☐ Mostly true of me

☐ Very true of me

Please answer the following questions about your computer use and experience.

Q36 Do you own a computer?

☐ Yes

☐ No

Q37 If you have a computer, how often do you use it?

☐ Never

☐ Once or twice a year

☐ Monthly

☐ Weekly

☐ Daily

☐ I don't have a computer

Q39 Since what grade have you been using computers at school?

____

Q40 In an average school year, how often have you been using computers at school?

☐ Never

☐ Once or twice a year

☐ Monthly

☐ Weekly

Q41 How often do you decide you want to use computers to work on school assignments?

☐ Always

- ☐ Often
- ☐ Sometimes
- ☐ Rarely
- ☐ Never

Q42 How often do you use a computer to complete the following tasks? Check the response that most accurately describes **how often you use** each of the following software programs.

	Never	Once or twice a year	Monthly	Weekly	Almost daily
Play Games	○	○	○	○	○
Do schoolwork	○	○	○	○	○
Wordprocess a document	○	○	○	○	○
Perform calculations with spreadsheet	○	○	○	○	○
Create presentations	○	○	○	○	○
Create a computer game	○	○	○	○	○
Create a database	○	○	○	○	○
Produce multimedia projects	○	○	○	○	○
Use the Internet	○	○	○	○	○
Search for information on the web	○	○	○	○	○
Communicate through e-mail	○	○	○	○	○
Work with graphics and pictures	○	○	○	○	○
Watch videos and/or TV	○	○	○	○	○

Communicate through Skype, FaceTime, iMessage, etc.	○	○	○	○	○
Use tutorials/drill & practice software	○	○	○	○	○

Q43 When using each of the following software programs, check the statement that most accurately describes **how much help** you need.

	I do not use this software program.	I always need help.	I sometimes need help.	I can help other people. I am an expert.
Games	○	○	○	○
Word processing (e.g. Word, WordPerfect)	○	○	○	○
Presentation software (e.g. PowerPoint)	○	○	○	○
Databases (e.g. Access)	○	○	○	○
Multimedia (e.g. Hyperstudio)	○	○	○	○
Internet (e.g. Web pages)	○	○	○	○
E-mail (e.g. Outlook, Express, Gmail)	○	○	○	○
Working with graphics and pictures	○	○	○	○
Tutorials/drill & practice software	○	○	○	○

Please check the response that most accurately describes your level of agreement with the following statements.

Q45 Computers make schoolwork easier to do.

□ Strongly disagree

□ Disagree

□ Neither agree nor disagree

☐ Agree

☐ Strongly agree

Q46 I prefer to use computers to do schoolwork instead of using pencil and paper.

☐ Strongly disagree

☐ Disagree

☐ Neither agree nor disagree

☐ Agree

☐ Strongly agree

Q47 Using computers for schoolwork can also have disadvantages.

☐ Strongly disagree

☐ Disagree

☐ Neither agree nor disagree

☐ Agree

☐ Strongly agree

Q48 Computers make schoolwork more fun/interesting.

☐ Strongly disagree

☐ Disagree

☐ Neither agree nor disagree

☐ Agree

☐ Strongly agree

Q49 Computers help me improve the quality of my schoolwork.

☐ Strongly disagree

☐ Disagree

☐ Neither agree nor disagree

☐ Agree

☐ Strongly agree

Q50 Computers help me understand my classes better.

☐ Strongly disagree

☐ Disagree

☐ Neither agree nor disagree

☐ Agree

☐ Strongly agree

Q51 I look forward to computer use in my classes.

☐ Strongly disagree

☐ Disagree

☐ Neither agree nor disagree

☐ Agree

☐ Strongly agree

Q52 I need to learn many new skills to use computers for my schoolwork.

☐ Strongly disagree

☐ Disagree

☐ Neither agree nor disagree

☐ Agree

☐ Strongly agree

Q53 I want to learn more about computers.

☐ Strongly disagree

☐ Disagree

☐ Neither agree nor disagree

☐ Agree

☐ Strongly agree

Q54 Having a computer is an advantage when it comes to learning.

☐ Strongly disagree

☐ Disagree

☐ Neither agree nor disagree

☐ Agree

☐ Strongly agree

Q55 I think my ability with computers will affect the grades I get.

☐ Strongly disagree

☐ Disagree

☐ Neither agree nor disagree

- ☐ Agree
- ☐ Strongly agree

Q56 I would be equally prepared to enter university without a computer.

- ☐ Strongly disagree
- ☐ Disagree
- ☐ Neither agree nor disagree
- ☐ Agree
- ☐ Strongly agree

Appendix B: Results of PCA

First PCA.

Rotated Component Matrix[a]

	Component				
	1	2	3	4	5
In an average school year, how often have you been using computers at school?	.980				
How often do you decide you want to use computers to work on school assignments?	-.951				
How often do you use a computer to complete the following tasks? Check the response that most acc... - Play Games				.736	
How often do you use a computer to complete the following tasks? Check the response that most acc... - Do schoolwork	.980				
How often do you use a computer to complete the following tasks? Check the response that most acc... - Wordprocess a document	.864				
How often do you use a computer to complete the following tasks? Check the response that most acc... - Perform calculations with spreadsheet		-.576	.680		
How often do you use a computer to complete the following tasks? Check the response that most acc... - Create presentations	.553			.803	
How often do you use a computer to complete the following tasks? Check the response that most acc... - Create a computer game		-.631	.572		
How often do you use a computer to complete the following tasks? Check the response that most acc... - Create a database			.835		
How often do you use a computer to complete the following tasks? Check the response that most acc... - Produce multimedia projects	.562	-.686			
How often do you use a computer to complete the following tasks? Check the response that most acc... - Use the Internet	.980				
How often do you use a computer to complete the following tasks? Check the response that most acc... - Search for information on the web	.980				
How often do you use a computer to complete the following tasks? Check the response that most acc... - Communicate through e-mail	.980				

	Component				
	1	2	3	4	5
How often do you use a computer to complete the following tasks? Check the response that most acc... - Work with graphics and pictures	.625			.685	
How often do you use a computer to complete the following tasks? Check the response that most acc... - Watch videos and/or TV	.925				
How often do you use a computer to complete the following tasks? Check the response that most acc... - Communicate through Skype, FaceTime, iMessage, etc.	.968				
How often do you use a computer to complete the following tasks? Check the response that most acc... - Use tutorials/drill & practice software		-.533			.679
Information NavigationI get tired when looking for information online.			.863		
Sometimes I end up on websites without knowing how I got there.				-.862	
I find it hard to find a website I visited before.		-.570		-.562	
I find it hard to decide what the best keywords are to use for online searches.		-.714			
I should take a course on finding information online.					.888
All the different website layouts make working with the Internet difficult for me.					.964
Sometimes I find it hard to verify information I have retrieved.		-.521	.769		
Social Skills I know when I should and shouldn't share information online.			.867		
I am careful to make my comments and behaviours appropriate to the situation I find myself in online.		.930			
I know which information I should and shouldn't share online.		.763			.628
I know how to change who I share content with.	.679	.702			
I feel comfortable deciding who to follow online.				-.594	.710

	Component				
	1	2	3	4	5
Creative SkillsI know how to design a website.		-.923			
I would feel confident putting video content I have created online.			.930		
I know which different types of licences apply to online content.			.889		
I know how to make basic changes to the content that others have produced.		.773			-.519
I know how to create something new from existing online images, music or video.			.587		-.646
I am confident about writing a comment on a blog, website or forum.	.752				
I would feel confident writing and commenting online.		.506	.821		
I know how to use shortcut keys.			.941		
I know how to bookmark a website.		.984			
I know how to complete online forms.	.679	.702			
I know how to adjust privacy settings.		.913			
I know how to keep track of the costs of mobile app use.		.984			
Please check the response that most accurately describes your level of agreement with the following statements. Computers make schoolwork easier to do.					.884
I prefer to use computers to do schoolwork instead of using pencil and paper.				.598	.636
Using computers for schoolwork can also have disadvantages.			.779		
Computers make schoolwork more fun/interesting.				.880	
Computers help me improve the quality of my schoolwork.	.625			.685	
I look forward to computer use in my classes.			.528	.544	
I need to learn many new skills to use computers for my schoolwork.	-.850				
I want to learn more about computers.				.787	
Having a computer is an advantage when it comes to learning.				.660	
I think my ability with computers will affect the grades I get.		-.564			.555
I would be equally prepared to enter university without a computer.	.724				

Second PCA.

Rotated Component Matrix[a]

	Component 1	2	3	4
In an average school year, how often have you been using computers at school?	.962			
How often do you decide you want to use computers to work on school assignments?	-.921			
How often do you use a computer to complete the following tasks? Check the response that most acc... - Do schoolwork	.962			
How often do you use a computer to complete the following tasks? Check the response that most acc... - Wordprocess a document	.825		.508	
How often do you use a computer to complete the following tasks? Check the response that most acc... - Create presentations	.541			
How often do you use a computer to complete the following tasks? Check the response that most acc... - Produce multimedia projects	.640	-.665		
How often do you use a computer to complete the following tasks? Check the response that most acc... - Use the Internet	.962			
How often do you use a computer to complete the following tasks? Check the response that most acc... - Search for information on the web	.962			
How often do you use a computer to complete the following tasks? Check the response that most acc... - Communicate through e-mail	.962			
How often do you use a computer to complete the following tasks? Check the response that most acc... - Work with graphics and pictures	.577		.691	
How often do you use a computer to complete the following tasks? Check the response that most acc... - Watch videos and/or TV	.959			
How often do you use a computer to complete the following tasks? Check the response that most acc... - Communicate through Skype, FaceTime, iMessage, etc.	.936			
I should take a course on finding information online.			.922	
All the different website layouts make working with the Internet difficult for me.			.943	
I would feel confident putting video content I have created online.				.912
I know which different types of licences apply to online content.				.856
I know how to create something new from existing online images, music or video.				.681
I would feel confident writing and commenting online.				.821
I know how to bookmark a website.		.973		
I know how to complete online forms.	.621	.768		
I know how to adjust privacy settings.		.949		
I know how to keep track of the costs of mobile app use.		.973		
Computers help me improve the quality of my schoolwork.	.577		.691	
I need to learn many new skills to use computers for my schoolwork.	-.831	-.545		
I would be equally prepared to enter university without a computer.	.793			

Third PCA.

Rotated Component Matrix[a]

	Component 1	2	3	4
In an average school year, how often have you been using computers at school?	.986			
How often do you decide you want to use computers to work on school assignments?	-.957			
How often do you use a computer to complete the following tasks? Check the response that most acc... - Do schoolwork	.986			
How often do you use a computer to complete the following tasks? Check the response that most acc... - Create presentations	.556			
How often do you use a computer to complete the following tasks? Check the response that most acc... - Use the Internet	.986			
How often do you use a computer to complete the following tasks? Check the response that most acc... - Search for information on the web	.986			
How often do you use a computer to complete the following tasks? Check the response that most acc... - Communicate through e-mail	.986			
How often do you use a computer to complete the following tasks? Check the response that most acc... - Watch videos and/or TV	.939			
How often do you use a computer to complete the following tasks? Check the response that most acc... - Communicate through Skype, FaceTime, iMessage, etc.	.950			
I should take a course on finding information online.				.914
All the different website layouts make working with the Internet difficult for me.				.982
I would feel confident putting video content I have created online.			.895	
I know which different types of licences apply to online content.			.859	
I know how to create something new from existing online images, music or video.			.617	-.629
I would feel confident writing and commenting online.			.838	
I know how to bookmark a website.		.975		
I know how to complete online forms.	.609	.780		
I know how to adjust privacy settings.		.957		
I know how to keep track of the costs of mobile app use.		.975		
I would be equally prepared to enter university without a computer.	.742		-.554	

Fourth PCA.

Rotated Component Matrix[a]

	Component			
	1	2	3	4
In an average school year, how often have you been using computers at school?	.984			
How often do you decide you want to use computers to work on school assignments?	-.961			
How often do you use a computer to complete the following tasks? Check the response that most acc... - Do schoolwork	.984			
How often do you use a computer to complete the following tasks? Check the response that most acc... - Create presentations	.574			
How often do you use a computer to complete the following tasks? Check the response that most acc... - Use the Internet	.984			
How often do you use a computer to complete the following tasks? Check the response that most acc... - Search for information on the web	.984			
How often do you use a computer to complete the following tasks? Check the response that most acc... - Communicate through e-mail	.984			
How often do you use a computer to complete the following tasks? Check the response that most acc... - Watch videos and/or TV	.936			
How often do you use a computer to complete the following tasks? Check the response that most acc... - Communicate through Skype, FaceTime, iMessage, etc.	.949			
I should take a course on finding information online.				.911
All the different website layouts make working with the Internet difficult for me.				.977
I would feel confident putting video content I have created online.			.907	
I know which different types of licences apply to online content.			.875	
I know how to create something new from existing online images, music or video.			.610	-.635
I would feel confident writing and commenting online.			.831	
I know how to bookmark a website.		.976		
I know how to complete online forms.	.610	.779		
I know how to adjust privacy settings.		.957		
I know how to keep track of the costs of mobile app use.		.976		